

Systematic Review

A Systematic Review for Reducing Risky, Demanding and Repetitive Labor in Agriculture Through Digital and Automated Technologies

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Abstract

The modern agricultural sector faces a multidimensional crisis, mainly consisting of an aging workforce, labor shortages, exhausting working conditions, and high rates of work-related accidents. In response, the authors carried out a systematic literature review (SLR), to explore the latest research on smart agricultural technologies, their effects on occupational safety, ergonomics, and worker health, and pinpoint obstacles to sustainable adoption. A thorough search was performed solely in the Scopus database, covering peer-reviewed publications from 2020 to 2026, strictly following the PRISMA 2020 guidelines. Based solely on Scopus, this study provides a focused synthesis, with the results suggesting that hazards such as chemical exposure and musculoskeletal strain are significantly reduced with the use of innovations such as unmanned vehicles, exoskeletons, and collaborative robots. These technologies also show great promise in cutting down resource waste, helping farmers practice sustainable agriculture. However, a recurring gap between research and real-life deployment exists, as adoption is hindered by cost considerations, reliability issues, and ergonomic problems. To achieve a sustainable technological transition in agriculture, it is necessary to simultaneously bridge three critical gaps: technological (ensuring robust field performance), ergonomic (design and testing processes based on real end-users and their needs), and socio-economic (addressing adoption barriers).

Keywords: agriculture 4.0; occupational safety; agricultural ergonomics; technology acceptance; sustainable agriculture; smart farming; human–robot collaboration; automation; systematic literature review



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1. Introduction

The agricultural sector is in the midst of a transformation that is being termed the fourth industrial revolution in agriculture (Agriculture 4.0). Conventional approaches are being transformed by the integration of state-of-the-art perception systems, Artificial Intelligence (AI), and robotics. Although agriculture has always been dependent on manual labor and empirical knowledge, the sector is now experiencing a multidimensional crisis that threatens its long-term sustainability. Key factors, including an aging workforce, labor shortages, and the perception of farming as an unattractive career path for younger generations, have led to a major demographic bottleneck, compounded by the sector's demanding working conditions. Furthermore, agriculture is still considered to be one of

the most hazardous sectors in the world, with the International Labor Organization (ILO) estimating that each year, about 210,000 farmers lose their lives in work-related accidents, facing up to three times the mortality risk that workers in other industries do [1]. These hazards are often attributed to the use of outdated machinery and long working hours under extreme weather conditions.

In addition to occupational health, the sector is faced with a big challenge: meeting the food needs for a global population of 9.6 billion by 2050 while simultaneously reducing the consumption of finite natural resources, such as land, water, and energy [2]. Climate change adds to this challenge by presenting the sector with unpredictable weather patterns, extended periods of drought, and resistant pests. In this context, the use of technology becomes a structural need for resilience and global food security. Achieving true global sustainability, however, is not necessarily only a matter of stabilizing the existing structure, as it may often require breakthroughs in fundamental scientific discovery, a radical rethinking of consumption patterns in agriculture, and the integration of broader food systems, such as aquaculture. The widespread digitalization of agri-food systems is the means to safeguard the sustainability of the planet and ensure that resources are available for future generations, as highlighted by both the Food and Agriculture Organization (FAO) [3] and the European Green Deal, in the form of the “Farm to Fork” strategy [4]. It is worth noting that the EU’s legislative goals of reducing the use of chemical pesticides by 50% and fertilizers by 20%, by 2030, have already prompted innovation in the field of Precision Agriculture, including the development of autonomous drones for targeted pesticide spraying, thereby minimizing groundwater contamination.

However, in alignment with the UN Sustainable Development Goals (particularly SDG 3: Good Health and Well-being, and SDG 8: Decent Work and Economic Growth [5]), this review’s main focus area is how the Agriculture 4.0 technologies can enhance specific aspects of social sustainability by addressing systemic problems like occupational safety, ergonomic burden, and vulnerable groups’ exclusion from the sector. It is acknowledged that social sustainability is a broad and complex concept and thus, these technological interventions may occasionally introduce contradictory socio-economic dynamics, such as job displacement or digital divides. At the same time, however, it should be noted that new job positions are created in agriculture (e.g., remote equipment operators, data analysts, and robotic technicians), while traditionally limiting factors such as gender or physical strength are no longer considered barriers to entry. This ensures that the explored technologies are not viewed just as technological advancements, but as practical tools that can be used to bridge the gap between laboratory theory and real-world application, aiming to provide a viable solution to the many human-centric problems that are prevalent in the agricultural sector, transforming farming into a more attractive and sustainable profession. In order to achieve this, the Main Research Question (MRQ) that is addressed is: “How can technological transformation address the operational challenges of agricultural labor, and what is the current level of technological readiness and acceptance by stakeholders?”. For a more in-depth analysis, the three core pillars, stated in the MRQ, are examined through three Specific Research Questions (SRQs), as listed below:

- SRQ 1: What are the primary operational challenges, ergonomic constraints, and safety risks currently faced by agricultural workers?
- SRQ 2: Which modern technological solutions aim to mitigate or replace hazardous, harmful, and unattractive agricultural tasks?
- SRQ 3: What are the technical limitations and factors influencing technology acceptance among agricultural workers, particularly regarding ergonomic integration and operational drawbacks of automated solutions?

By conducting a systematic literature review, using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses—PRISMA 2020 guidelines [6], the authors aim to map the current state of the agricultural technological transition, compiling the main operational hazards, the technological innovations aimed at mitigating these hazards, and the socio-economic barriers to incorporating these technologies.

The key conclusions are that in order to achieve a truly sustainable technological transition in agriculture, all three gaps (technological, ergonomic and socio-economic) have to be bridged at the same time, firmly supported by continuous advancements in fundamental science. This review is designed to offer a structured approach towards promoting solutions that are technically innovative and socially as well as environmentally sustainable.

2. Materials and Methods

2.1. Eligibility Criteria

A formal review protocol was not prepared prior to conducting this review. Instead, specific criteria for inclusion and exclusion were predefined.

The inclusion criteria for this review were based on six (6) axes. The papers were limited to peer-reviewed journal articles and conference proceedings to ensure the data's universal eligibility, as these sources have already undergone expert review. This was deemed necessary, given the research fields examined, especially AI and robotics. The papers were also required to be exclusively in English to avoid information corruption during translation. Moreover, the timeframe was set to 2020–2026 to document the current frontier of technological solutions and agricultural challenges, avoiding outdated data.

The thematic eligibility criteria for this research, which were applied both during the initial search phase (while formulating the query keywords) and throughout the subsequent screening process, are listed below:

1. The papers had to address Agriculture 4.0 (Robots, UAVs, AI, IoT) within the context of agricultural labor, while maintaining a human-centric approach. Industrial robots and other solutions developed for manufacturing applications or generic automation, with no potential for integration into agriculture to assist humans in their tasks, were excluded from the search, because the way a robot is built to operate in such “caged” environments differs fundamentally from the way it needs to operate in “unstructured” environments (mud, rain, slopes), like those in real-world agricultural scenarios.
2. Regarding the human element, the studies had to contextualize—at least—or explicitly address occupational safety, ergonomics, and labor in agriculture, as well as technology acceptance among key stakeholders within the sector. Building on that, studies focusing exclusively on crop genetics, soil chemistry, or yield optimization without a human or safety link, were rejected.
3. The selected studies were required to include references to, or specifically address, agricultural tasks such as harvesting, pruning, weeding, spraying, irrigation, and livestock management. Studies that appeared relevant in a more general sense, such as those on forestry or industrial food processing, were excluded, during both the initial screening phase and the final selection.

2.2. Information Sources and Search Strategy

For the search, only one database was used to avoid further data fragmentation, given the abundance of information on the review's primary focus areas. The Scopus database was selected as the information source, as it offers broad interdisciplinary coverage, is reliable, and is widely acknowledged by the scientific community. The search results provided by the Scopus database were deemed adequate for this review's scope, and no further search in different databases was conducted. The Scopus database was last accessed

on 18 March 2026, and the search results, including the initial number of the identified records, are relevant as of that date.

The search strategy implemented in the Scopus database was developed using a multi-pillar Boolean approach and is outlined as follows.

The first step was to extract the thematic pillars from the SRQs and form the query's keywords. To synthesize the search string, four main pillars were extracted from the SRQs to achieve the desired depth of analysis.

- The first pillar captured the review's broader context, and the keywords assigned to it were variations of the words "agriculture", "farming", and "greenhouse".
- The second pillar was technology-related, ensuring the inclusion of both hardware (robotics, UAVs, drones) and automation, utilizing variations of the mentioned technological solutions or exact terms such as "smart farming" and "precision agriculture".
- The third pillar aimed to filter out purely technical papers that lacked any safety, ergonomic, or socio-technical impact on agricultural workers. Thus, variations of words related to ergonomics, safety, and occupational hazards were included, alongside terms like "worker perception," "technology acceptance," and "technology readiness".
- Finally, the fourth pillar focused on the workforce and the "labor crisis," captured by variations of words such as "labor," "worker," and "workforce".

The next step was the Scopus query formation. The final query string followed a strict logical structure to balance sensitivity—in terms of finding all relevant papers—and specificity, excluding sources not directly connected to the SRQs. Within each pillar, the keywords were connected with the "OR" operator to ensure no article would be excluded for not containing all terms simultaneously. However, the external logic connecting the different pillars was based on the "AND" operator. This structure ensured that every retrieved article contained at least one term from each of the four pillars, focusing on the key areas of the review and integrating the need for interconnectivity.

To further facilitate the search and screening process, specific fields and keywords that caused research "noise" were excluded using the "EXCLUDE" operator. After experimenting with different queries, it was determined that these areas did not offer the required granular level of information for the scope of this review. The excluded terms and fields were:

- Risk Assessment;
- Industrial Robots/Industrial Hygiene;
- Sustainable Development;
- Wages;
- Social Robots;
- Climate Change;
- Food Safety/Food Supply;
- Forestry;
- Manufacture;
- Construction Sites/Construction Industry;
- Maintenance;
- Major Clinical Study;
- Algorithm.

The final query string that originated following the above-mentioned steps is shown below.

(agricultur* OR farm* OR greenhouse) AND (robot* OR automat* OR "smart farming" OR "precision agriculture" OR uav OR drone) AND (ergonom* OR safety OR hazard* OR

“occupational risk” OR “worker perception*” OR “technology acceptance” OR “technology readiness”) AND (labor OR labour OR worker* OR workforce).

2.3. Study Selection and Data Extraction Process

The initial database search yielded 311 records, and after removing one duplicate record, the remaining 310 records proceeded to the screening process.

To guarantee that each record was subjectively assessed as per the inclusion criteria, the PRISMA 2020 guidelines were followed, during the selection process of the final corpus of this review. The full PRISMA checklist [6] is presented in Supplementary Table S1. The screening process was performed in two phases with intermediate checks. No tool was used to automate the process.

In the first phase, two of the authors performed a title-and-abstract screening for all the 310 retrieved records. The screening resulted in the exclusion of 111 papers (mainly due to focusing on industrial environments or non-technological improvements on conventional tools). For a number of papers whose relevance was not 100% clear, a secondary check by the remaining three authors was conducted to determine whether they should progress to the next phase and to help ensure consistent application of the general criteria established at the beginning of the research.

Of the 199 remaining articles, only 177 full texts were successfully retrieved and were subjected to full-text screening. This process led to the exclusion of 68 studies, for the following specific reasons:

- Exclusive focus on system architecture without substantial connection to agricultural labor (n = 26).
- Absence of a clear connection between Agriculture 4.0 technologies and the human factor (n = 27).
- Weak thematic relevance to the review’s scope (n = 15).

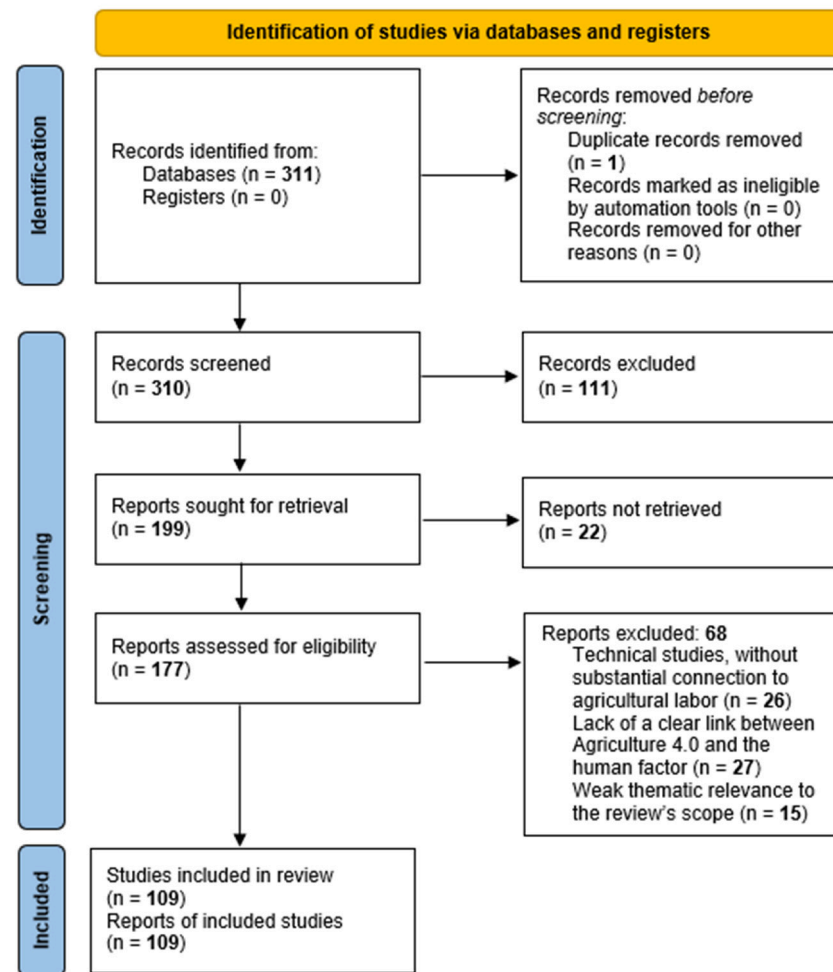
Ultimately, 109 studies were included in the final review corpus. The described exclusion and inclusion process is shown in detail in Scheme 1, following the PRISMA 2020 flow diagram [6].

The final 109 studies were thematically categorized based on the framework shown in Figure 1. To this end, a standardized, pre-designed bibliographic matrix was created and used with the assistance of the software Microsoft Excel 2024, which was organized in three main dimensions:

1. Operational Field of Agricultural Activity.
2. Technology Application Domain.
3. Degree of Human Involvement and Technological Autonomy.

Based on the first dimension, each study was assigned to the operational field that was mostly related to its focus area. Each study that proposed at least one technological solution was then evaluated regarding the type of proposed technology and its role within the agricultural ecosystem, falling into one or more of the categories of the second dimension. Finally, the systems proposed in the literature were evaluated regarding the role of the workers themselves and the extent to which technology supports or replaces them. The relevant articles were assigned to one or more of the categories of the third dimension.

During the data extraction process, apart from the operational field of agricultural activity, technology application domain, and degree of human involvement (as mentioned above), additional parameters were extracted per study and incorporated into the Excel matrix. These included the technologies utilized, the Technology Readiness Level (TRL) of the proposed solutions, and the geographical context of the studies.



Scheme 1. The PRISMA flowchart showing the screening and the final selection process. (Source: Adapted from [6]. Licensed under CC BY 4.0.)

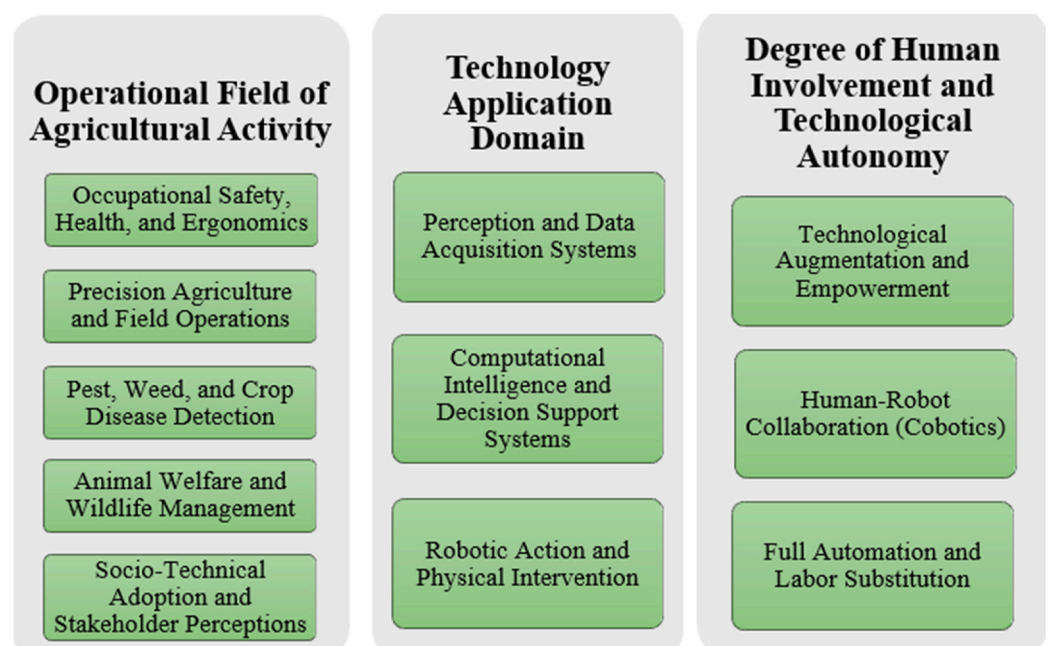


Figure 1. The three-dimensional methodological framework developed for the thematic classification and analysis of the selected studies.

The extraction and cross-checking of the data was carried out by comparing the majority of the above-mentioned parameters with the “Results” and “Conclusions” sections of each paper, while more general information was verified through the “Introduction”. The data extraction was performed manually, without the use of automation tools, to ensure the accuracy of the recording and to detect any data that could be omitted by automated extraction systems.

In addition to data extraction, risk of bias and certainty evaluations were conducted, in order to assess the validity of the results from the included studies. Supplementary Table S2 provides detailed information for the data extraction, classification and appraisal of each paper. Whenever results were presented in different incompatible formats (e.g., quantitative accuracy metrics and qualitative descriptions of success or failure), results were harmonized into the categorical classification scheme (operational field, technology domain, TRL, RoB, certainty, etc.), and not pooled numerically. Due to the diversity of study designs, outcome measures and reporting style of the included studies, a quantitative meta-analysis was not conducted; instead, the results were narratively summarized within the three-dimensional thematic framework outlined above.

2.4. Risk of Bias Assessment Methodology

The research that this review is based on comprises: (a) technical engineering studies on the design, development and testing of the proposed technological solutions, (b) literature reviews, and (c) social science surveys that provide mapping the perceptions and concerns of the agricultural workers. Given this diversity, a quality assessment framework was developed to analyze the Risk of Bias (RoB), according to three parameters:

- Internal Validity: The soundness of the experimental design or research procedure, and sample size (e.g., social surveys must report at least 30 participants).
- External Validity: The extent to which the results may be replicated in real-world agricultural scenarios.
- Technical Reliability: Maturity of the technologies used in measurement, experimental setup and developed prototypes.

The studies were assessed, and classified as Low, Moderate, or High Risk of Bias based on these criteria. Publication Bias was evaluated simultaneously by checking the bias in papers where technological interventions were only reported as successful without reporting failures or technical problems during the testing. Given the qualitative nature of this review, a full statistical meta-analysis of the entire data set was not possible. Instead, Risk of Bias was assessed through a qualitative appraisal of methodological characteristics and evidence base of the included studies.

2.5. Certainty Assessment Methodology

The certainty of the evidence drawn from the studies was then categorized as Low, Moderate or High Certainty, depending on the following three factors:

- Consistency of results: Repeatability and reproducibility of the results across various crop types and environmental conditions.
- Degree of Precision: Technical detail and accuracy of the sensors and supporting technologies.
- Ecological Validity (Level of Simulation): Degree of similarity between the experimental setup and the real-world conditions in the field.

For example, findings derived from successful field tests in settings that closely mirror real-world conditions were assigned the “High” certainty rating. However, conclusions like those regarding the long-term effects of using an exoskeleton in agricultural work were

rated at “Low Certainty”, due to the absence of robust evidence gathered from extensive field testing.

3. Results

3.1. Quantitative Analysis and Paper Classification

3.1.1. General Structural Characteristics of the Included Studies

Figure 2 illustrates the Technology Readiness Levels (TRLs) of the solutions discussed in the selected studies. A Venn diagram is used, in order to reflect the multi-dimensional nature of Agriculture 4.0. Out of the 109 included studies, 12 are purely theoretical or algorithmic, 41 are focusing on mechanical engineering and prototype testing, and only 4 involve commercial solutions in real-world applications (which, given the limited number of relevant studies, highlights the need for stronger technological consolidation from TRL 6 through TRL 9 within the sector). The most important research areas lie, however, at the intersections of the TRL groups, as they reflect transitional phases driving progress in Agriculture 4.0. For that reason, the Venn diagram is a good way to visualize “hybrid” studies that bridge existing gaps, such as:

- Studies with a focus on theoretical computer science and practical engineering: Research that involves training of algorithms and their integration into physical prototypes or existing systems for field testing.
- Studies on experimental research and commercial reality: Studies that compare systems still in a developing phase with existing commercial products or test experimental or commercial solutions in real-world agricultural scenarios for further optimization.

Furthermore, comprehensive reviews ($n = 3$) naturally span the entire TRL spectrum. Studies with a sole focus on the current agricultural conditions without proposing any specific technological solutions (e.g., social surveys, $n = 6$) were excluded from this classification.

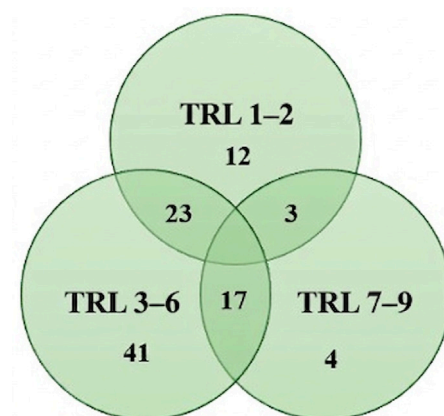


Figure 2. Classification of the literature’s technological solutions based on TRL.

The literature was also categorized based on underlying technology employed (Figure 3) to record the technological foundation of the proposed solutions. The data reveals the highly interdisciplinary nature of Agriculture 4.0, while also justifying the aforementioned TRL overlaps. Most of the studies focus on robotics (unmanned aerial and ground vehicles—UAVs, UGVs—and specialized hardware), indicating a shift from theoretical models to actual interventions that replace heavy manual labor and reduce ergonomic strain. Moreover, many articles employ Artificial Intelligence (AI) and Machine Learning (ML), often combined with Internet of Things (IoT) technologies and sensor networks to facilitate real-time data collection and provide accurate decision-making support. Finally,

wearable technologies (wearables—WT) for worker condition monitoring were considered part of the broader categories of sensors and IoT, while agricultural exoskeletons were classified as a smaller and more specific research subset.

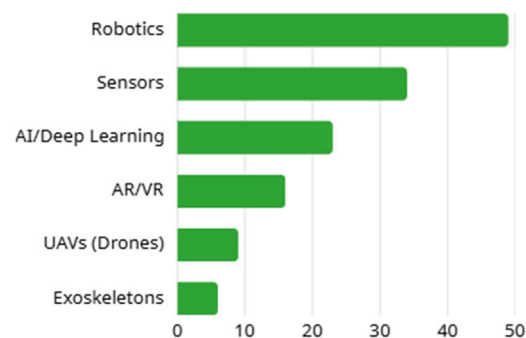


Figure 3. Distribution of the included studies based on the underlying technologies employed.

Regarding the geographical distribution of the research (Figure 4), the USA leads Agriculture 4.0, driven by the demands of large-scale commercial farming and extensive private sector investments in innovation. Asia follows, making a rapid shift towards automation, mostly due to the heavy demographic ageing of its agricultural workforce. Europe and Oceania account for a proportionately smaller share of research in this review’s sample; this could be due to fragmented funding, or because European literature tends to focus more on ergonomic improvements to existing tools than digital integration. Finally, little research data comes from developing areas of the Global South (such as Africa and South America). This marks a significant “digital divide”; despite agriculture being the economic backbone in these areas, the limited availability of the required infrastructure, the high acquisition costs of new technologies, and the lack of institutional frameworks regarding working conditions largely render technological change a privilege of the developed world.

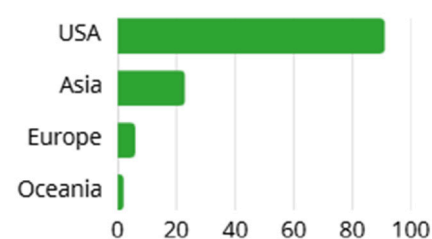


Figure 4. Geographical distribution of the selected studies.

3.1.2. Thematic Classification and Quantitative Data Across Research Dimensions

The aim of the developed thematic classification framework (Figure 1) was to organize the literature into three analytical dimensions that are highly specific yet interdependent. This approach was designed to map current technological trends, demonstrate functional overlaps, and highlight important research gaps in navigating towards a safe, automated, and sustainable Agriculture 4.0 ecosystem. A brief analysis of each dimension and its categories follows:

- **Dimension 1—Operational Field of Agricultural Activity:** This dimension categorizes the research according to the thematic field and the segment of the agricultural activity to which each study mainly refers. To provide a detailed analysis of the available data and accurately reflect the current agricultural reality, ergonomics and socio-technical adoption were analyzed as different categories of the dimension, alongside the primary sectors of traditional agricultural operations. The criteria for establishing

this dimension's categories were based on the main agricultural target entity of the proposed intervention (the physical worker, the crop, the livestock, or the overall farming community), alongside the problem area being addressed (e.g., occupational safety, operational efficiency, environmental protection, and psychological acceptance). These two axes were applied systematically across the full corpus, and no study was identified during classification that could not be accommodated within one of the five resulting categories, supporting the framework's comprehensiveness for the scope of this review. This dimension, therefore, allows for a multidimensional assessment of both the technological and human-related factors influencing technology adoption in agricultural activities through five categories:

- a. **Occupational Safety, Health, and Ergonomics:** Studies in this category are directly related to the physical health of the worker. The main focus points are the modern hazards and challenges faced by agricultural workers, as well as how technology can address and mitigate them.
- b. **Precision Agriculture and Field Operations:** This is a broad category that examines the use of a wide range of technologies and automated systems, built for the optimization of agricultural processes, core sector tasks, and sustainable resource utilization.
- c. **Pest, Weed, and Crop Disease Detection:** Articles within this category are primarily oriented towards the use of machine vision for the detection of crop threats. The aim is to avoid the manual inspections, and to replace the current widespread method of "blind", mass spraying—a labor-intensive, risky, and environmentally detrimental process. By mitigating such practices, these technologies directly foster sustainable agricultural practices.
- d. **Animal Welfare and Wildlife Management:** This category covers research into animal welfare and livestock (e.g., pigs, poultry) management for health monitoring. The proposed technological solutions aim to reduce the amount of time workers spend indoors in barns for cleaning, harvesting, and supervising livestock, while also addressing the sector's labor shortage issue. Some of these studies also focus on dealing with wildlife intrusions, suggesting the development of specific detection and tracking systems.
- e. **Socio-Technical Adoption and Stakeholder Perceptions:** This category discusses the human factor. It explores farmers' trust in automation, cost-benefit analyses, regulatory frameworks, and the psychological and social challenges hindering the widespread adoption of technological solutions in agriculture.

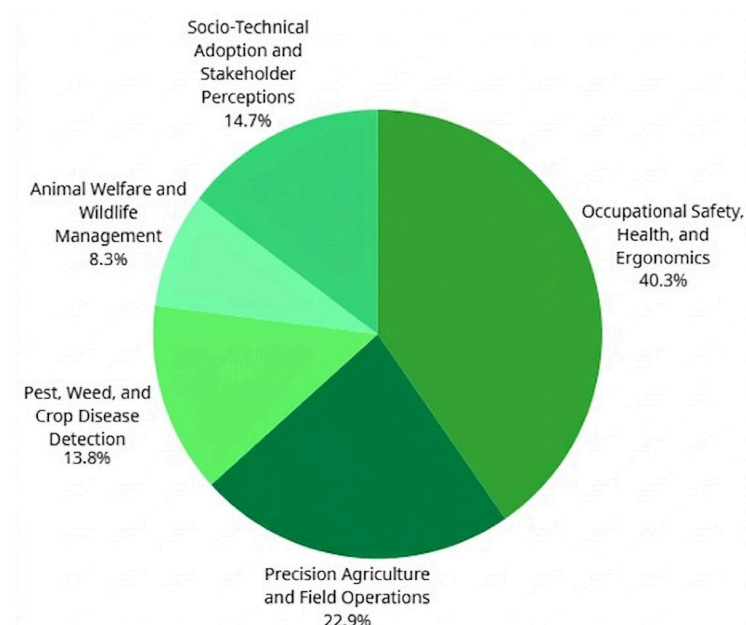
The classification of the papers based on this dimension's categories is shown in Figure 5.

To offer a more detailed analysis of this dimension's largest category, "Occupational Safety, Health, and Ergonomics", the most important studies were classified into four categories in Section 3.2.1 of this systematic review (as part of its dedicated synthesis), based on evidence type, to distinguish demonstrated health effects from technical performance metrics. The categories and their definitions are presented in Table 1 below:

Naturally, this additional classification can also apply to two other categories ("Pest, Weed, and Crop Disease Detection" and "Technological Augmentation and Empowerment"), in which similar accuracy- or efficiency-based hazard claims appear in some of their studies. Due to its higher relevance to the "Occupational Safety, Health, and Ergonomics" category, and since the purpose of this classification is to note rather than fully dive into this issue, it is presented only in that category.

Table 1. Definition of the four evidence categories regarding the type of the outcome measure.

Category	Definition	Practical Value
Direct occupational health outcomes (A)	Empirical data on actual injuries, fatalities, diagnosed disorders, etc., in agricultural worker populations.	Can support real-world hazard-reduction claims only when tied to a measured before/after or intervention effect. Descriptive fatality statistics alone identify the scale of the problem, but not a technology's effect on it.
Exposure-related or ergonomic proxy indicators (B)	Physiological, biomechanical, or biochemical measurements taken on human subjects to monitor indications that are recognized as risk factors for future harm (e.g., dermal pesticide residue in mg/kg, EMG muscle activation, heart rate/oxygen consumption, whole-body vibration, in contrast to ISO 2631-1 thresholds, RULA/REBA ergonomic scores, validated usability/comfort questionnaires).	Credible, literature-recognized proxies for injury/MSD/toxicity risk, but not a diagnosed health outcome. They can support estimations of potential future hazard caused by long-term exposure to risk factors.
Equipment/system safety performance (C)	Technical performance of the safety-relevant hardware or software itself.	Demonstrates that the tool functions as designed under the tested conditions. However, it is not considered sufficient to demonstrate any improvement in human exposure, injury rate, or MSD incidence.
Inferred potential benefit (D)	Claims of hazard or labor reduction extrapolated from productivity, cost/time-saving, qualitative statements, etc., with no direct exposure or safety-performance measurement.	Plausible but unverified hazard-reduction benefit, not actually measured.

**Figure 5.** Categorization of the included studies based on the operational field of agricultural activity.

- Dimension 2—Technology Application Domain: The proposed and existing solutions are classified according to the technological core that provides their functionality.

- a. Perception and Data Acquisition Systems: These systems act as the agricultural system's "sensory organs" and comprise cameras, IoT networks, and wearables that collect in-field data.
 - b. Computational Intelligence and Decision Support Systems: This category covers the "digital brain" of the solutions, represented by AI, ML, and Deep Learning (DL) algorithms. It also includes the data utilized and analyzed during algorithmic training, which connects theory to computational processing.
 - c. Robotic Action and Physical Intervention: Related to the "body" of the technologies, this category focuses on hardware, such as UGVs, UAVs, robotic harvesting arms, and automated platforms.
- Dimension 3—Degree of Human Involvement and Technological Autonomy: The third dimension assesses how agricultural workers and technology will interact, based on the end-use objective.
 - a. Technological Augmentation and Empowerment: This category features articles about systems that enhance the workers' physical abilities rather than replace them, while also facilitating task execution and increasing their safety. In this context technologies like Augmented Reality (AR) systems and motorized exoskeletons are examined.
 - b. Human–Robot Collaboration (Cobotics): Under this category fall technological solutions that involve human collaboration with robots in a shared workspace, while performing complementary tasks concurrently. It addresses, therefore, the concepts known as Human–Robot Collaboration (HRC) and Human–Machine Interaction (HMI).
 - c. Full Automation and Labor Substitution: Papers in this category propose solutions that can operate with full autonomy, aiming to eliminate the need for human presence on site, thereby mitigating operational risks.

It is important to note that many articles intersect two or more categories, since there are interconnections between Agriculture 4.0 technologies. For this reason, Venn diagrams were used to more precisely represent these identified overlaps in Dimensions 2 and 3. The following diagrams, therefore, show the categorization of the relevant studies according to the technology application domain (Figure 6) and the level of human involvement and technological autonomy (Figure 7).

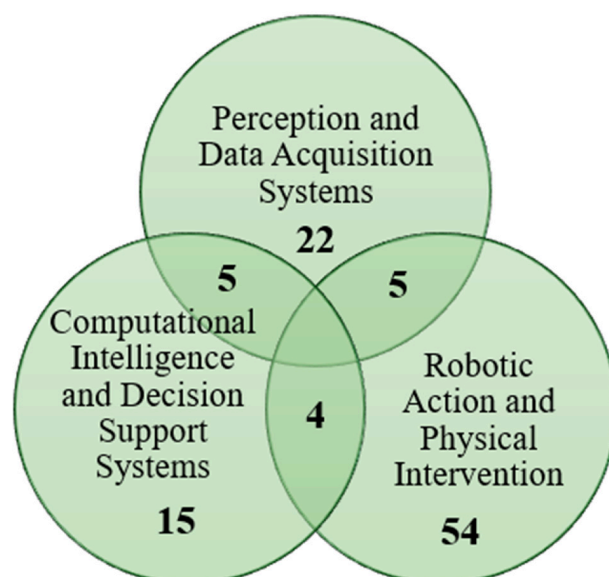


Figure 6. Categorization of the included studies based on the technology application domain.

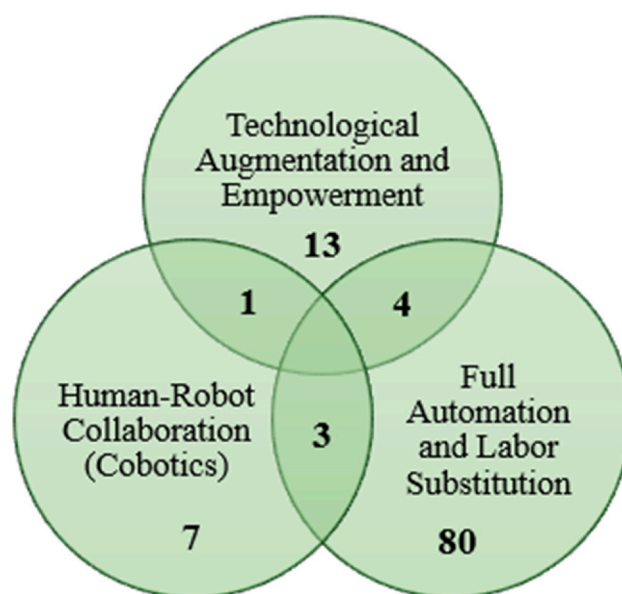


Figure 7. Categorization of the included studies based on the degree of human involvement and technological autonomy.

The synthetic approach described above aims to explore the intersection of technological innovation and socio-technical aspects of agricultural reality. An important concept explored is that of “closeness to the field” and the main challenges in transitioning to real-world application (TRL 7–9) from the experimental testing and prototyping phase (TRL 3–6). Moreover, this review considers technology beyond its functional performance and accuracy; it also addresses its ability to practically mitigate specific occupational risks and promote sustainable agricultural practices. This multi-dimensional analysis allows a structured mapping of the review’s findings, identifying the proposed and available solutions, as well as the research gaps and adoption barriers that prevent a complete transition to a sustainable Agriculture 4.0.

3.1.3. Quantification of Risk of Bias in the Included Studies

The 109 reviewed studies were evaluated based on the criteria defined in Section 2.4 to determine their quality and Risk of Bias (RoB) (Figure 8):

- **High RoB (8 studies):** These are mostly theoretical or early-stage algorithmic models that have not been tested in the field (TRL 1–2) and, therefore, have very limited external validity. Studies exhibiting publication bias (by neglecting to mention practical limitations or technical failures) were also included in this category.
- **Moderate RoB (87 studies):** Most studies had good internal validity (TRL 3–6 functional prototypes). However, their external validity was considered low, as most tests were performed under controlled conditions or on very specific samples, thus raising uncertainties about their performance under real-world agricultural scenarios.
- **Low RoB (14 studies):** Solutions that have been tested extensively in the field and proven to be successful, therefore exhibiting high external validity. These studies also transparently reported flaws in the sensors and limitations in the research.

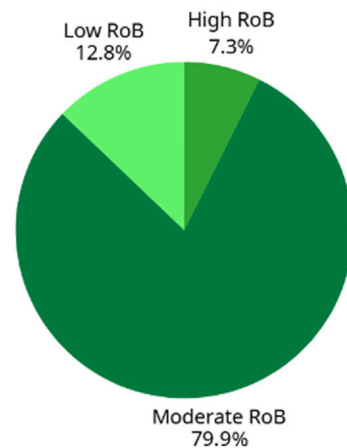


Figure 8. Risk of bias (RoB) assessment of the included studies.

3.1.4. Evidence Certainty

Accordingly, evidence certainty and validity (Figure 9) were assessed based on the parameters established in Section 2.5:

- High Certainty (19 studies): Studies that conducted real-world field trials, used high precision equipment (LiDAR, optical cameras, RTK-GPS), and produced highly applicable and consistent results.
- Moderate Certainty (79 studies): Even though these studies are technically precise (e.g., >90% AI success rate), certainty was downgraded because they lack generalizability. Algorithms and hardware trained on specific crops or under controlled conditions often lack adaptability in different environments and present low resilience to real-world factors such as extreme weather or changing soil conditions.
- Low Certainty (11 studies): Early-stage algorithmic designs and theoretical architectures. While potentially innovative, they lacked quantitative field measurement data.

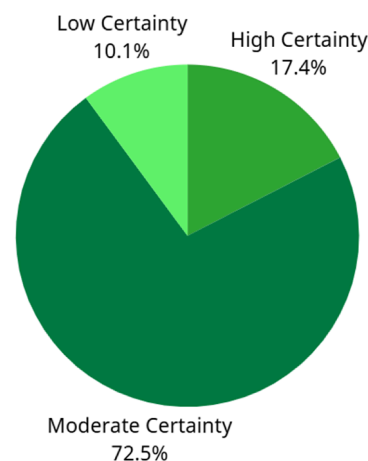


Figure 9. Assessment of the included studies regarding data certainty and validity.

3.1.5. Cross-Dimensional Synthesis of Technological Maturity and Evidence Quality

To connect the classifications analyzed in Section 3.1, Table 2 maps TRLs, RoB, and Certainty ratings for the 109 included studies to the review's three analytical dimensions, identifying which technology domains, operational fields, and human-involvement categories are the most advanced, most bias-prone, or best supported by high-certainty evidence.

Table 2. Cross-dimensional synthesis of technological maturity (TRL) and evidence quality (RoB, Certainty).

Category	Number of Examined Studies (n)	Indicator (s)	Value
Perception and Data Acquisition Systems (Dimension 2)	32	Share at TRL 7–9	31.2%
Computational Intelligence and Decision Support Systems (Dimension 2)	24	Share at TRL 7–9 Share still at TRL 1–2	16.7% 70.8%
Robotic Action and Physical Intervention (Dimension 2)	63	Share at TRL 7–9	25.4%
Occupational Safety, Health and Ergonomics (Dimension 1)	44	Share at High RoB Share at High Certainty	9.1% 18.2%
Precision Agriculture and Field Operations (Dimension 1)	25	Share at High RoB Share at High Certainty	4.0% (lowest) 16.0%
Pest, Weed and Crop Disease Detection (Dimension 1)	15	Share at High RoB Share at High Certainty	6.7% 13.3%
Animal Welfare and Wildlife Management (Dimension 1)	9 (n = small)	Share at High RoB Share at High Certainty	11.1% (highest) 0.0% (lowest)
Socio-Technical Adoption and Stakeholder Perceptions (Dimension 1)	16	Share at High RoB Share at High Certainty	6.2% 31.2% (highest)
Technological Augmentation and Empowerment (Dimension 3)	18	Share at TRL 7–9 Share at High RoB	27.8% 11.1%
Human–Robot Collaboration (Cobotics) (Dimension 3)	11 (n = small)	Share at TRL 7–9 Share at High RoB	36.4% (highest) 18.2% (highest)
Full Automation and Labor Substitution (Dimension 3)	87	Share at TRL 7–9 Share at High RoB	23.0% (lowest) 5.7% (lowest)

As already explained, TRL shares can exceed reasonable expectations within a domain because of TRL intersections in several studies (overlaps in Figure 2). An interesting observation is that from this review’s whole corpus (109 studies) there are only four studies that present technological solutions that are both of “High Certainty” and at TRL 7–9 [2,7–9], which is indicative of the lab-to-field gap that prevents the full commercialization and widespread adoption of these innovations in real-world agricultural contexts.

3.2. Synthesis of Findings

To avoid conceptual overlap, each category primarily presents findings from studies that have not been extensively examined in previous sections. It highlights specialized findings which, due to their specific thematic nature, could not be integrated into previous categories. However, repeated references to certain studies occur when their results are highly relevant to the examined category, ensuring a comprehensive presentation and thorough analysis.

3.2.1. Dimension 1—Operational Field of Agricultural Activity

- Occupational Safety, Health, and Ergonomics

The key findings and technological approaches of the most prominent studies within this category are summarized in Table 3 below.

While Table 3 summarizes the subjects of certain clustered studies, it does not distinguish between what type of evidence underlies each hazard-reduction claim. To avoid conflating technical performance with demonstrated occupational health benefits, the 28 studies referenced in Table 3 [6–33] were additionally classified according to the type of outcome measure they report, as shown in Table 4, using the four evidence categories described in Section 3.1.2.

Table 3. Structured overview of primary insights and studies focused on Occupational Safety, Health, and Ergonomics.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Reduction of agrochemical exposure and toxicity	Remote control (UGVs, UAVs) Automated sprayers Electromagnetic safety	Autonomous systems (especially drones) reduce operator exposure to pesticides by 90–99%, minimizing dermal exposure and inhalation of toxic chemicals. Additionally, sensor-activated robots achieve zero pesticide drift compared to manual applications, effectively mitigating chemical hazards.	[10–13]
Mitigation of physical strain and Musculoskeletal Disorders (MSDs)	Active exoskeletons Passive exoskeletons Wearable sensors (WT) IoT	Exoskeletons provide support during repetitive movements (e.g., bending, lifting, overhead work), significantly reducing muscle fatigue and injury risk (particularly in the lower back and shoulders). WT enables accurate activity recognition and fatigue monitoring to prevent long-term MSDs, heatstroke, etc.	[14–20]
Field accident avoidance and machinery rollover prevention	RTK-GNSS systems LiDAR sensors RFID tags Obstacle recognition algorithms	Precision navigation, coupled with obstacle detection sensors and centralized UAV-UGV coordination ensures centimeter-level accuracy, preventing path deviations and vehicle rollovers on uneven terrain or slopes. AI and vision models show high accuracy in detecting workers and obstacles, reducing crushing accidents.	[21–27]
Substitution of hazardous/strenuous manual labor	Robotic harvesting systems (UAVs, UGVs) Tree-climbing robots	Automating physically demanding or dangerous tasks (e.g., fruit harvesting, high-altitude pruning, climbing) removes the worker from the hazard zone (e.g., falls from ladders, cuts), radically improving safety and productivity.	[28–33]
Ergonomic machine design and workload evaluation	Biomechanical analysis Vibration assessment Redesigned tractor cabins	Evaluating and redesigning agricultural machinery (e.g., seating angles, steering interfaces) reduces whole-body vibration and physical discomfort. Additionally, optimized speeds and remote-controlled modes have been found to significantly lower operators' heart rates and fatigue levels.	[34–37]

Applying this four-category framework to the 28 studies in Table 3 shows that only one study reports a direct occupational health outcome, and even this is a retrospective description of existing fatality records rather than a measured intervention effect. Twelve studies rely on exposure-related or ergonomic proxy indicators, and nine studies report only the technical performance of the safety-relevant equipment, which demonstrates that a well-functioning tool does not, by itself, establish that human exposure or injury rate has undergone any change. The remaining six studies support their hazard-reduction claims only by inference from productivity, time-saving, or simulation results, with no exposure, physiological, or safety-performance data reported at all.

Table 4. Evidence-type classification of the references mentioned in Table 3.

Thematic Focus/Subject	References	Reported Metrics	Evidence Category
Reduction of agrochemical exposure and toxicity	[10]	Measured dermal exposure (mg/kg) PPE exposure reduction (%)	(B) Exposure-related indicator
	[11]	Potential dermal exposure (mL/h) (knapsack vs. robot) Operator heart rate and body-part discomfort score (BPDS)	(B) Exposure/ergonomic proxy
	[12]	Operator heart rate %VO ₂ max (workload) (robotic vs. manual sprayer)	(B) Ergonomic proxy
	[13]	Frequency-dependent hazard classification of SHF processing equipment (reflection coefficients, SWR)	(C) Equipment safety performance
Mitigation of physical strain and Musculoskeletal Disorders (MSDs)	[14]	EMG muscle activation and perceived exertion, measured on 15 farmers, with/without exoskeleton	(B) Ergonomic proxy
	[15]	Modeled/estimated peak and average lumbar load (biomechanical fatigue model)	(B) Ergonomic proxy (model-based)
	[16]	Early-stage prototype design description with no field ergonomic testing	(D) Inferred potential benefit
	[17]	Ground-reaction-force and center-of-pressure displacement (motion capture, lab-based)	(B) Ergonomic proxy
	[18]	Validated self-report usability questionnaire (effectiveness, wearability, safety, learnability)	(B) Ergonomic proxy (subjective/self-reported)
	[19]	F1-score of wearable sensors (activity-recognition classification accuracy)	(C) Equipment safety performance
	[20]	App functional reliability (BLE connection stability, data throughput)	(C) Equipment safety performance

Table 4. Cont.

Thematic Focus/Subject	References	Reported Metrics	Evidence Category
Field accident avoidance and machinery rollover prevention	[21]	RTK-GNSS vs. SA-GNSS path-tracking error Mission success rate	(C) Equipment safety performance
	[22]	RFID/BLE worker-detection range Trajectory-matching accuracy	(C) Equipment safety performance
	[23]	Obstacle-avoidance system detection performance (Bluetooth/RFID)	(C) Equipment safety performance
	[24]	Retrospective analysis of 171 fatal tractor-accident case reports (FACE database, 1999–2019)	(A) Direct occupational health outcome (descriptive; not an intervention effect)
	[25]	Obstacle-detection mAP Model size/speed Field warning-accuracy	(C) Equipment safety performance
	[26]	Human-detection recall Network/positioning reliability	(C) Equipment safety performance
	[27]	Path-planning precision/recall Mission-success rate	(C) Equipment safety performance
Substitution of hazardous/strenuous manual labor	[28]	Simulation-only structural/weight-capacity validation	(D) Inferred potential benefit
	[29]	Harvesting time and labor-count reduction (83% time reduction)	(D) Inferred potential benefit
	[30]	Productivity and cost figures Fatigue reduction stated qualitatively (not measured)	(D) Inferred potential benefit
	[31]	Seedlings-per-minute comparison, semi-automated vs. manual	(D) Inferred potential benefit
	[32]	RULA ergonomic risk score (from 7 to 3) Productivity gain	(B) Ergonomic proxy (validated risk-assessment tool)
	[33]	Qualitative statement of improved “ergonomic safety” vs. ladder-picking (not quantified)	(D) Inferred potential benefit
Ergonomic machine design and workload evaluation	[34]	Whole-body vibration (m/s^2) benchmarked against the ISO 2631-1 exposure action value	(B) Exposure-related indicator
	[35]	Heart rate Oxygen-consumption rate Discomfort score Noise level (dB)	(B) Ergonomic/exposure proxy
	[36]	Heart rate Oxygen-consumption rate Energy-expenditure rate (across operator groups)	(B) Ergonomic proxy
	[37]	EMG muscle activation Seat pressure Infrared thermography	(B) Ergonomic proxy

This distribution indicates that the benefits attributed to Agriculture 4.0 technologies in the literature are, in most cases, inferred rather than directly demonstrated, as high detection accuracy or fast task-completion times are compatible with, but cannot yet substantially confirm, reduced pesticide exposure, fewer MSDs, or fewer fatal accidents. This fact reinforces the Risk of Bias and Certainty assessments reported in Sections 3.1.3 and 3.1.4 (79.8% Moderate RoB, 72.5% Moderate Certainty): the field’s laboratory evidence base is technically credible but largely proxy-based and prospective, yet very optimistic.

Despite these encouraging findings, there are many challenges regarding practical implementation, since most of the aforementioned technologies remain at TRL 3–6, with low external validity and a limited number of trials. The performance of many of the evaluated robotic solutions and obstacle avoidance systems has been demonstrated in a controlled environment or in a simulated setting, leaving questions about their reliability in real-world conditions, such as varying lighting conditions and weather extremes. Moreover, although autonomous systems reduce chemical and physical hazards, they are also accompanied by new technical and operational risks which require a stricter regulatory framework and comprehensive training for the users. From an ergonomics perspective, exoskeletons and smart machinery often face adoption problems related to field usability, cost, and infrastructure

constraints. The main research gap lies in the need for a more widespread transition from functional prototypes (TRL 3–6) to reliable commercial products (TRL 7–9) that will deliver proven, holistic safety across a wide range of real-world agricultural scenarios.

- Precision Agriculture and Field Operations

Table 5 presents a structured overview of the primary findings derived from the most significant research conducted in this domain.

Table 5. Structured overview of primary insights and studies focused on Precision Agriculture and Field Operations.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Autonomous harvesting and robotic manipulation	Robotic arms UAVs and UGVs Optimized mechanical grippers	Robotic systems ensure precise, non-destructive fruit and vegetable harvesting, drastically reducing harvesting times (<7 s/fruit) and crop loss (down to 14.5% from >30% manually). Aerial multirotor systems enable the remote harvesting of high-altitude crops (e.g., palm dates), eliminating climbing and the risks of falling.	[38–45]
Navigation, path planning and obstacle avoidance	UAVs and UGVs Radar perception Stereo vision Kinematic modeling	Advanced trajectory planning and covering-circle methods reduce back-end computation by more than 90%, slowing for smooth, collision-free headland operations in orchards. Stereo cameras provide a good solution for 3D trellis mapping of steep slope vineyards, especially if laser sensors are considered expensive.	[46–51]
Vision-based detection and Human–Machine Interaction (HMI)	Deep Learning (YOLOv5/v8, CycleGAN) Hand gesture recognition	AI-driven computer vision can accurately identify specific crops despite leaf occlusions. Moreover, by using hand gesture recognition frameworks (with KNN and SVM models), seamless, real-time collaboration between human workers and autonomous mobile robots can be achieved.	[52–56]
Smart irrigation and resource management	IoT networks Precision models Compound weather shock analysis	Smart, IoT-enabled watering systems optimize irrigation parameters (timing and volume) based on real-time data. With this precision management, water consumption can be reduced by approx. 25%, thereby protecting the crops against extreme heat-drought shocks and promoting long-term environmental sustainability.	[57–60]
System architecture, planning and cybersecurity	LLMs Symbolic reasoning Threat landscapes analysis	By combining Large Language Models (LLMs) with automated planning, high-level robot task specification is made possible, achieving 85–88% accuracy, while also reducing hallucinations. At the same time, research reports critical cybersecurity threats for intelligent harvesting robots (network/hardware/AI hacks).	[61,62]

The articles in the “Precision Agriculture and Field Operations” category highlight that the shift from traditional towards highly automated, data-driven agriculture is rapid. The main aim of these technological interventions is to make optimal use of resources to maximize crop yields and quality. Robotic manipulators and intelligent harvesting robots, equipped with deep learning vision models like YOLOv8 and CycleGAN, present unprecedented capabilities in detecting and picking crops quickly, with minimal mechanical damage and post-harvest losses. At the same time, navigation architectures based on stereo vision and optimized trajectory planners allow for safe navigation of UGVs and UAVs in structurally complex environments, such as steep vineyards or cluttered orchards, without damaging their surroundings. Additionally, the use of IoT-enabled irrigation systems marks a significant transformation in how the sector utilizes water resources, minimizing waste and promoting environmental sustainability and resilience to drought shocks [59].

However, there are major practical and socio-technical challenges preventing the widespread adoption of these technologies. There is a significant disparity between the theoretical algorithmic performance and its successful implementation in real-world scenarios. Although the literature reports outstanding accuracy of vision models in controlled lighting conditions, their performance drops significantly when operating in the field, due

to extreme weather conditions or occlusion by dense foliage. Nevertheless, commercial solutions already exist. In fact, as these agricultural systems become increasingly interconnected through IoT and remote-control networks, complex cybersecurity threats are becoming more prevalent, potentially compromising equipment functions or data security [62]. Economically, while precision agriculture substantially reduces manual labor and water costs, these savings can be counterbalanced by high initial capital depreciation, and the increased energy demands of operating autonomous machinery [57]. To achieve a viable and sustainable transition to Agriculture 4.0, future research needs to bridge these gaps by developing affordable, cyber-safe hardware and intuitive interfaces (e.g., gesture control or LLM-based task planning) that require minimal technical expertise from the end-user.

- **Pest, Weed, and Crop Disease Detection**

The key findings and technological approaches of the most prominent studies within this category are summarized in Table 6 below.

Table 6. Structured overview of primary insights and studies focused on Pest, Weed, and Crop Disease Detection.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Real-time pathogen and pest identification	Deep Learning (YOLOv9/v10, DenseNet) IoT Sound Analysis	Advanced computer vision and CNN models can detect pest, diseased leaves and plant abnormalities with remarkable accuracy (95–97%). The pest sound detection accuracy of the IoT audio analysis models (e.g., DConvNet) reaches 99.72%, significantly improving early-stage intervention.	[63–67]
Autonomous ground-based weed eradication	AI-equipped UGVs and robotic platforms Vision-guided collection	AI-equipped UGVs present high accuracy in distinguishing between crops and weeds, enabling precise mechanical weeding or collection (e.g., slug collection with 95.83% success). These systems achieve higher than 95% weed control rates, replacing “blind” mass spraying.	[68–72]
Targeted aerial spraying and precision application	UAVs Fuzzy priority scheduling Path optimization	UAVs enable highly targeted, high-speed pesticide applications. Compared to manual backpack sprayers, aerial spraying applies pesticides up to 5 times faster, increases coverage area from 30–60× times, and cuts pesticide volume by 30–50% and water use by 90%.	[73–75]
Disease forecasting and epidemiological modeling	Predictive analytics SEIR models Climatic indexing	Algorithms that are based on meteorological data (e.g., rainfall indices and temporal lags) can better predict the transmission rate of the disease, as well as determine critical epidemic thresholds for timely agricultural management.	[76]

Building on the last category’s insights, the literature addressing “Pest, Weed, and Crop Disease Detection” reports the shift from the traditional, hazardous approach of “blind” mass spraying to highly targeted and data-driven interventions. The heart of this transformation lies in cutting-edge DL architectures, notably the new versions of the YOLO (v9 and v10) networks and DenseNet, which offer high accuracy in weed and pest classification. The visual diagnostic capability of those models can sometimes be augmented by more innovative methods such as IoT-based acoustic pest detection, allowing both UGVs and UAVs to carry out precision spraying or mechanical weeding [66]. These technologies have a significant environmental benefit, as they enable a shift from broadcast application to spot-spraying, cutting down on pesticide usage by 30–50% and water usage by up to 90% [73]. Consequently, these robotic interventions not only reduce worker exposure to toxic chemicals but also directly promote long-term environmental sustainability by preventing soil degradation and agrochemical runoff.

Despite the impressive precision recorded in controlled environments, the challenge of transitioning TRL 7–9 is present in those technologies as well. Given that these AI models are data-driven, the quality and diversity of training data critically determine their performance and generalizability, which tend to drop significantly when faced with

unexpected field conditions like variable lighting, leaf occlusion, and similar crop and weed morphologies. In addition, variable weather conditions and payload constraints (SWaP—Size, Weight and Power) can affect UAVs' ability to operate in the optimal speed to achieve maximum coverage area, which makes the use of sophisticated path optimization essential to ensure battery longevity [75].

- **Animal Welfare and Wildlife Management**

The fundamental insights and core technological applications of the key studies examined in this section are outlined in Table 7.

Table 7. Structured overview of primary insights and studies focused on Animal Welfare and Wildlife Management.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Livestock health and reproductive monitoring	Sound cameras Infrared imaging (U-Net) ML algorithms	Advanced sensors enable non-invasive health tracking. For example, U-Net combined with infrared imaging significantly improves vulva segmentation accuracy for reproductive monitoring, while AI models reduce drug discovery time and detect antimicrobial resistance, enhancing farm biosecurity.	[77–79]
Behavioral tracking and anomaly detection	YOLOv7-tiny Embedded computer vision	Embedded vision systems can be used to continuously monitor large flocks (e.g., dispersion tracking of 20,000 chickens). Automatic warning systems are able to identify abnormal activity in real time, reducing the need for manual surveillance (which is labor-intensive) and lowering the risk of disease outbreaks.	[80]
Automated routine and veterinary interventions	Robotic arms (Digital Twins) Mecanum UGVs Automatic syringes	Automating stressful or labor-intensive physical tasks—such as cage-free egg harvesting, cattle feeder cleaning, and robotic vaccinations—minimizes human–animal friction and veterinary labor demands, while also ensuring the farm's hygiene.	[81–84]
Wildlife intrusion management	Multi-shift spatio-temporal features Deep Neural Networks (DNNs)	Spatio-temporal DNNs can be used in surveillance cameras to detect wild animals and track their movements. This provides real-time positional data to proactively deal with human–wildlife conflict and protect crops or livestock from predation attacks.	[85]

The research in the “Animal Welfare and Wildlife Management” category notes a critical shift in husbandry towards more data-driven and non-invasive approaches that aim to improve animal welfare and address the significant labor shortages. Technologies for sensor fusion or acoustic tracking allow for continuous, non-invasive observation of animals without causing them stress [77,78]. At the same time, automating standard and veterinary operations (such as feeder cleaning, egg collection and vaccinations) minimizes physical contact between humans and animals. These AI-driven systems promote efficiency, enabling the early detection of anomalies and reducing the need for reactive veterinary interventions, thus fostering sustainable livestock management. Moreover, DNNs applied to improve the perimeter security help in the detection of wild animal intrusions, reducing human–wildlife conflicts.

However, despite the high potential they present, these solutions also come with numerous technological limitations where complex, dynamic farm settings are concerned. The previously mentioned problems that the environmental “noise” and unpredictability of real-world settings can create for computer vision systems and UGVs are present in this category's technological solutions as well. Furthermore, acoustic monitoring systems are novel, and as a result, they tend to have low detection sensitivities in the high-noise environment of a typical, real-world barn, failing to detect critical events (e.g., piglet crushing). In order for these solutions to be considered scalable into sustainable commercial

products, they must be more algorithmically resilient and able to operate amidst the “noise” of modern livestock facilities, while also being economically viable for farmers.

- Socio-Technical Adoption and Stakeholder Perceptions

Table 8 presents a structured overview of the primary outcomes and methodologies derived from the most significant research conducted in this domain.

Table 8. Structured overview of primary insights and studies focused on Socio-Technical Adoption and Stakeholder Perceptions.

Thematic Focus/Subject	Approach/Method	Primary Findings and Insights	Relevant Studies
Technology acceptance models and psychological drivers	Structural Equation Modeling (SEM) Multinomial regression Technology Acceptance Model (TAM)	Perceived usefulness (PU) and attitude are the two main factors that determine adoption intention, overshadowing the perceived ease of use. Positive public attitude toward automation, especially when shaped by information on the potential environmental benefits, greatly increases acceptance (by up to 13%).	[86–90]
Farmers’ expectations vs. adoption barriers	Surveys Qualitative assessments Focus groups	Farmers view robotics as the primary solution to labor shortages and chemical exposure. Nonetheless, some of the biggest obstacles to adoption include high investment costs (mentioned by 77% of the survey participants), unreliability in field conditions due to limited training data, and infrastructural shortcomings in small farms.	[8,91–93]
Labor dynamics and worker–robot comparisons	Comparative field studies Economic modeling	Although autonomous robots may exhibit lower output rates per hour compared to skilled workers in some cases, their 24/7 continuous operation results in 20% higher daily net productivity, eliminating fatigue and seasonal labor shortages.	[94,95]
Time-to-adoption and technology typologies	Survival/Duration analysis Demographic profiling	“Embodied-knowledge” technologies (e.g., auto-steer systems) are generally adopted approximately 7.7 years sooner than “information-intensive” ones. Millennial farmers, along with large-scale agricultural operators, exhibit a significantly higher likelihood of participating in the sector’s digital transformation.	[9]
Policy, data ownership and societal concerns	Stakeholder interviews Legal/Regulatory frameworks	While farmers are mostly worried about the operational costs, both them and non-farmer stakeholders are also deeply concerned about issues such as data protection, cybersecurity, and job polarization.	[2]

The studies comprising the “Sociotechnical Adoption and Stakeholder Perception” category pivot the focus from technical feasibility to socio-economic factors related to the implementation of Agriculture 4.0. The severe seasonal labor shortages and the need to minimize physical stress and the use of dangerous chemicals are the primary catalysts driving technology adoption by farmers. Through approaches such as TAM and SEM, it was discovered that a farmer’s intention to adopt a technology is significantly influenced by factors like the “attitude” and “perceived usefulness”, which outweigh any initial concerns about ease of use. Additionally, a surprising yet positive finding is that public and stakeholder acceptance is strongly connected to environmental sustainability. Providing targeted information about the ecological benefits of agricultural solutions, as presented

in the previous categories, has been proven to greatly increase societal acceptance of automation technologies [89].

Nevertheless, the transition from intention to actual commercialization of such technologies faces considerable challenges beyond engineering. Firstly, the main issue remains the high investment cost, which makes the adoption unaffordable for small-to-medium-sized producers, creating a technological divide and raising concerns about potential job polarization. Beyond these internal labor and economic impacts, external market dynamics are equally important, with society's willingness to consume Agriculture 4.0 products being a critical factor to consider and investigate in the future. Although robotic targeted fertilization, for instance, can drastically reduce environmental pollution, it may affect the chemical balance of individual plants compared to traditional methods, potentially influencing consumer trust.

Apart from these obstacles, both farmers and other stakeholders are concerned about data security and the lack of sufficient regulatory frameworks regarding autonomous operations in the field [91]. A critical discrepancy also lies in adoption timelines; “embodied knowledge” systems, such as auto-steering tractors, are adopted much faster than “information intensive” data management platforms, which is an excellent indicator of the unwillingness of farmers to learn new technologies [9].

3.2.2. Dimension 2—Technology Application Domain

- Perception and Data Acquisition Systems

The key findings and technological approaches of the most prominent studies within this category are summarized in Table 9 below.

The literature discussing “Perception and Data Acquisition Systems” essentially establishes these technologies as the “sensory organs” of Agriculture 4.0. The technologies of this category aim to extract measurable data from complex physical agricultural environments. Machine vision technologies, integrating optical cameras and radar technology, are essential for the spatial awareness of autonomous machinery, while IoT technologies and WT extend this perception to the human operator, turning subjective fatigue and heat stress into objective measurements. This multi-level data acquisition becomes a prerequisite for any kind of precision operation and sustainable practice.

Table 9. Structured overview of primary insights and studies focused on Perception and Data Acquisition Systems.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Environmental and climatic monitoring	IoT sensor networks Weather tracking GHG/Heat sensors	Through continuous data acquisition, microclimates (e.g., greenhouse WBGT peaks) and dynamic weather anomalies (e.g., rainfall indices/heat shocks) can be mapped. This allows for precise epidemiological modeling and localized climate adaptation.	[58,59,76,96]
Machine vision and spatial perception	Optical cameras, LiDAR Radar (MIMO, micro-Doppler)	While optical cameras (paired with YOLO/DL) have demonstrated excellent results in object detection (e.g., crops, pests), radar systems ensure reliable spatial perception and obstacle avoidance under poor weather or dense foliage conditions.	[46,48,64]
Wearables and biometric tracking	BLE/RFID Smartwatches, IoT accelerometers	These technologies serve as an interface between the human body and the machine. They collect real-time biometric data (heart rate, posture, muscle activation) to quantify physical fatigue and strain, to automatically trigger safety alerts or modify the machine's behavior.	[20,34,35,37,97]
Industrial and equipment safety sensing	RFID layouts Smart actuators Vibration sensors	Wireless Sensor and Actuator Networks (WSAN) as well as passive RFID tags create digital “safety zones”. Within these zones, the machinery will be able to detect human presence, preventing collisions without requiring manual intervention.	[47,98,99]

However, the data quality and the reliability of the sensors under extreme agricultural conditions, is still unstable. Optical sensors are particularly vulnerable to interference from mud, dust, and variable lighting, whereas connectivity problems in isolated rural regions present IoT networks with a significant challenge. Moreover, with the exponentially increasing amount of data collected, interoperability between different sensor types (e.g., the use of LiDAR alongside RFID wearables) continues to pose an important technical barrier, which, however, does not significantly diminish their current marketability. To ensure uninterrupted and high-quality data collection in real-world unstructured environments, research should focus on developing durable, biomimetic sensors and standardized communication protocols.

- **Computational Intelligence and Decision Support Systems**

The fundamental insights and core technological applications of the key studies examined in this section are outlined in Table 10.

Table 10. Structured overview of primary insights and studies focused on Computational Intelligence and Decision Support Systems.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Computer vision and crop detection models	YOLO variations (v8/v9/v10) S1DCNet DenseNet CycleGAN	DL systems are optimized for real-time edge computing. Advanced models (e.g., CR-YOLOv9, CycleGAN) are used for high-resolution image processing and accurate weed segmentation, and pathogenic bacteria classification. When crop maturity stages are also detected, automated actions are enabled.	[54,63,65,67,100,101]
Predictive modeling and behavioral analysis	Multi-shift Spatio-temporal DNNs U-Net Audio tracking	AI algorithms go beyond simple image recognition. They are able to identify dynamic patterns over time, by monitoring livestock (e.g., farrowing sows via IoT sound data, tracking of dispersion anomalies, reproductive organ segmentation via infrared). Furthermore, wildlife intrusions can be detected and based on IoT sound data, overall biosecurity can be achieved, by predicting pest outbreaks.	[66,77,78,80,85,102]
Ergonomic evaluation and safety intelligence	ML classifiers (KNN, HTM) REDECA framework Warning logic	Biometric and kinematic data are analyzed to predict worker fatigue and ergonomic risks. By combining Time-To-Collision (TTC) logic and DNNs, AI systems detect hazards (e.g., impeding machinery–human collisions) and preventive safety protocols are triggered.	[24,25,36,103,104]
Spatial mapping and multi-modal fusion	DeepLabV3+ Focal Voxel R-CNN Radar micro-Doppler	Computational intelligence models process multi-modal data (merging LiDAR point clouds and camera data) to create 3D maps and detect obstacles with high accuracy, for effective path planning and navigation in unstructured environments.	[46,105–107]

While perception systems represent the “sensory organs” of Agriculture 4.0, “Computational Intelligence and Decision Support Systems” are essentially its “brain”. These systems are mainly designed to analyze big audiovisual data, aiming to transform them into operational commands and practical instructions. What is important to note regarding this category is that it extends across many categories from the first dimension, from weed detection to livestock and wildlife management, and occupational safety and ergonomics.

A recurrent challenge across these studies is the trade-off between the accuracy and the efficiency of the utilized algorithms. Although very complex models report almost perfect classification results in laboratory settings, the SWaP and cost constraints that accompany them need to be considered for real-world implementation. The algorithms need to be able to work on lightweight edge devices with limited processing power and battery capacity. This reality has rapidly shifted research interest toward model compression (pruning and quantization), aiming to develop “lighter” models (such as YOLOv8n) that will operate at high speed (more than 50 FPS) without draining the machinery’s energy [25].

- **Robotic Action and Physical Intervention**

The key findings and technological approaches of the most prominent studies within this category are summarized in Table 11 below.

Table 11. Structured overview of primary insights and studies focused on Robotic Action and Physical Intervention.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
End-effector kinematics and crop manipulation	Robotic arms Soft-robotic grippers Multirotor flying vehicles (MRFV)	The research focuses on the mechanical dexterity required for harvesting. Autonomous manipulators perform precision cuts and fruit detachment, without causing deformation with cycle times that last less than 7 s. Advanced systems, like tree-climbing robots and MRFVs, mechanically access high-altitude crops without requiring human intervention.	[28,38,40,42,44]
Targeted agrochemical spraying	UAVs and UGVs Variable-rate nozzles	Spatial data are translated into fluid mechanics. Autonomous platforms adjust nozzle pressure and spraying distance in real time, cutting down the amount of pesticide used by 30–50% with zero drift.	[11,12,70,73,74]
Mechanical and thermal weed eradication	Autonomous weeders Laser treatment Vision-guided collection	Instead of applying chemicals to the crops, UGVs execute targeted mechanical weeding or thermal laser treatments, managing to eliminate weeds and pests (e.g., slugs) with over 95% control rates.	[68,69,92]
Automated livestock physical interventions	Digital twins (Simulated arms) Mecanum UGVs	These technologies are about applying mechanical precision to delicate biological interactions. Mechatronic systems autonomously navigate within the facilities to perform physical tasks, such as harvesting cage-free eggs or cattle vaccination (still in simulation stage).	[81,82,84]

The studies regarding “Robotic Action and Physical Intervention” conclude the technological pipeline of Agriculture 4.0, examining the implementation of computational decisions into action. The research on physical intervention focuses on mechatronics, actuators, and applied kinematics, aiming to design robots and vehicles that replicate and outperform the human dexterity in the field. To achieve this, advanced end-effectors and soft-robotic grippers for the non-destructive handling of fragile biological objects are either under development or being tested, alongside autonomous locomotion systems for mechanical weeding or precision spraying.

At this point, it is clear that the aforementioned technological solutions are driven by the pursuit of operational efficiency and sustainability. However, these interventions currently lack mechanical robustness in unstructured environments, highlighting the need for deeper research on adaptive robotics and mechanical design that meets the real-world operational requirements.

3.2.3. Dimension 3—Degree of Human Involvement and Technological Autonomy

- **Technological Augmentation and Empowerment**

Table 12 presents a structured overview of the primary outcomes and methodologies derived from the most significant research conducted in this domain.

The studies categorized under “Technological Augmentation and Empowerment”, are completely human-centric and focused on how technology can enhance a worker’s physical abilities, instead of removing humans altogether from the process. The research aims to turn agriculture into a physically sustainable and socially inclusive profession by developing ergonomic interventions that reduce the high physical demands of traditional machinery, facilitating the integration of women in the process, while also allowing lower-limb disabled operators and aging farmers to remain productive and independent [36].

Table 12. Structured overview of primary insights and studies focused on Technological Augmentation and Empowerment.

Thematic Focus/Subject	Technological Approach/Method	Primary Findings and Insights	Relevant Studies
Physical augmentation and fatigue mitigation	Active/Passive Exoskeletons (Back/Arm support)	Exoskeletons absorb biomechanical forces during repetitive agricultural tasks, reducing lumbar and spinal stress, and extending the worker's stamina, thus boosting productivity. This way, long-term MSDs are prevented.	[14,15,17,18,108]
Inclusivity and empowerment	Wireless Hand Controls (HCs) Redesigned tractor cabins	By redesigning the interfaces through which human workers interact with the machines, vulnerable demographics are enabled to perform agricultural tasks safely. For instance, replacing traditional foot pedals with ergonomic Wireless HCs allows lower-limb disabled individuals and female workers to control heavy machinery without experiencing physiological distress.	[35–37]
Biometric monitoring and health preservation	Wearable sensors Mobile alert applications	Wearable IoT technologies convert previously invisible health risks into quantifiable data. By continuously monitoring the worker during task execution, these systems provide real-time alerts against overexertion or heat stress, promoting proactive self-care in demanding environments.	[19,20,103]

Despite the undeniable benefits that these solutions can offer regarding the well-being of agricultural workers, there are some practical barriers, mainly concerning their usability. In the case of current versions of passive and active exoskeletons, some farmers are often reluctant to use them because they are uncomfortable, restrictive, or not breathable enough in high temperatures. At the same time, transitioning from a conventional tractor to one with highly digitized cabins and interfaces requires significant unlearning and retraining, potentially turning a solution designed to reduce fatigue into one causing cognitive exhaustion. The future developments in this field must include lightweight designs made of breathable materials, as well as highly intuitive interfaces, to ensure that the workers perceive technology as a natural extension of their capabilities.

- Human–Robot Collaboration (Cobotics)

The fundamental insights and core technological applications of the key studies examined in this section are outlined in Table 13.

“Human–Robot Collaboration (Cobotics)” turns automation into a synergistic partnership, as the workers remain deeply integrated into the processes, guiding task execution at a more cognitive level, while cobots perform the physically demanding aspects of the tasks. The main requirement for successful HRC is the establishment of fluidity in communication and task execution, following real-time commands detected by the cobots through real-time hand gestures and markerless posture detection, allowing them to act as intuitive digital assistants.

Table 13. Structured overview of primary insights and studies focused on Human–Robot Collaboration (Cobotics).

Thematic Focus/Subject	Approach/Method	Primary Findings and Insights	Relevant Studies
Intuitive communication and intent recognition	Real-time gesture recognition Vision-based activity tracking	This approach allows for seamless, non-verbal communication between workers and robots. Cobots are able to predict user needs, through hand gestures or tracking of human picking activities, and adjust their functionality without requiring complex, physical control interfaces.	[38,52]
Spatial synchronization and adaptive movement	Markerless posture detection Collaborative mobile platforms	The main focus of these solutions is on matching robotic action to the human's ergonomic needs. Collaborative platforms autonomously adjust their speed and vertical positioning to match the worker's picking pace, while robotic arms adapt their movements to make the task execution more convenient for the operator.	[33,109,110]
Shared workspace safety and psychological trust	Probabilistic model-checking (PRISM) Qualitative expert perspectives	Evaluations of the socio-technical dynamics between humans and cobots that operate in the same confined space (e.g., polytunnels or greenhouses), highlight that guaranteeing physical safety during HRC, must be examined alongside building the worker's trust in the automated systems.	[111,112]

However, the use of heavy, moving machinery in close proximity to workers poses a series of serious safety and psychological concerns. Probabilistic injury models report that sharing confined agricultural spaces harbors collision risks, which vary in severity depending on the worker's level of training and the reliability of the robot's perception systems [111]. Ensuring successful HRC goes beyond physical safety, relying heavily upon trust. Overcoming workers' initial hesitation toward cobots requires fail-safe hardware (physical assurance in case of malfunction), as well as transparent communication protocols that clarify the robot's intended actions [112].

- Full Automation and Labor Substitution

Table 14 presents a structured overview of the primary outcomes and approaches derived from the most significant research conducted in this domain.

Table 14. Structured overview of primary insights and studies focused on Full Automation and Labor Substitution.

Thematic Focus/Subject	Approach/Method	Primary Findings and Insights	Relevant Studies
Macro-economic shifts and labor substitution	Economic impact assessment Grower perspective surveys	Full automation fundamentally restructures farm economics. According to relevant studies, agricultural labor costs can be reduced by up to 75%, by being completely turned from variable expenses to capital depreciation. Although full autonomy is considered a future certainty from growers, infrastructure and technical reliability remain a barrier for widespread adoption.	[7,55,57]
Unmanned fleet orchestration and remote supervision	UAV-UGV coordination LLM task planners Seamless network switching	The role of the agricultural worker shifts from driver to remote supervisor of autonomous systems. LLMs translate natural human language into complex autonomous field operations, enabling centralized systems to orchestrate multi-robot fleets with great accuracy.	[26,27,61]
Autonomy in hazardous and extreme terrains	RTK-GNSS navigation Modular steep-slope architectures	Automation intends to replace humans in dangerous and ergonomically challenging environments. On that note, unmanned vehicles achieve high-precision navigation (centimeter-level) in steep vineyards or dense orchards without any human intervention.	[21,49,113]
Unmanned operational risks and cybersecurity	Threat landscape analysis OSH framework reviews	Removing humans from the site might eliminate physical injuries, but it also poses serious cyber-physical threats. For instance, fully autonomous harvesters are exposed to various risks, such as sensor spoofing or hacking, which can lead to unpredictable machinery behavior as well as heavy economic losses.	[62,114]

In this final category, “Full Automation and Labor Substitution”, the technology transitions from being a collaborative partner to being the sole executor in the field. The relevant studies (in Table 14 as well as all the aforementioned ones in the context of previous categories) note a fundamental restructuring of the agricultural reality, as the labor-intensive nature of the sector is transforming into a technology-driven, remotely orchestrated operation, completely removing the worker from demanding and risky field operations.

It is undeniable that automation can resolve historical challenges associated with the agricultural sector [49]. However, as previously mentioned, it also generates new threats, namely cyber-physical risks from network hacking and sensor spoofing, which can result in severe crop and financial losses [62]. To successfully transition to full automation, continuous 5G connectivity is essential, alongside the development of impenetrable security protocols, the reskilling of the existing agricultural workforce, and the emergence of new

technologically skilled individuals who are interested in working in agriculture and able to manage digital threats.

4. Discussion

4.1. Interpretation of Findings

Through the synthesis of the 109 included studies, the multidimensional nature of the transition to Agriculture 4.0 is highlighted, alongside the factors that determine its success and the rate of progress. More specifically, this transition is currently at a stage where technological innovation and research on improving the agricultural working conditions and promoting overall sustainability are abundant, reporting impressive laboratory performance, yet failing in real-world environments due to the lack of extensive field testing.

The above-identified gap between laboratory performance and actual adoption is addressed in this review, since it is clearly reflected in the evaluation of the research data, as 87 of the 109 studies were rated at a “Moderate Risk of Bias” and 79 were characterized as having “Moderate Certainty”. This fact clearly demonstrates that the generalization of experimental findings to real agricultural scenarios is not possible for the majority of the solutions. However, certain solutions do achieve TRL 9, and those are mainly innovations that aim to execute simple tasks that do not require sensitive handling, such as UAV-based spraying and autonomous tractor navigation. These implementations fill the technical void by using already mature technologies (e.g., RTK-GNSS) which result in tangible and immediate improvements, such as a 90% reduction in exposure to chemicals. Solutions that attempt more complex physical interactions, like robotic fruit harvesting in unstructured agricultural environments, usually require longer testing periods and alterations, and therefore, they remain at TRL 3–6 because of the limitations such as lacking mechanical robustness and algorithmic generalization.

Another valuable observation lies in the lack of a deep understanding and practical technological focus of the current research on the human-centric needs of the sector. This is already very noticeable from the thematic classification of the selected studies, where while 40.4% of the research falls under the theme of “Occupational Safety, Health, and Ergonomics”, the third dimension of the analysis (“Degree of Human Involvement”) reveals that 80 out of the 109 studies focus on the development of fully automated systems, while only 13 specifically address technological augmentation and human empowerment. This means that despite the scientific community confirming the human-centric nature of the problem, contemporary research seems to lack focus on solutions that empower workers instead of replacing them. This “paradox” directly impacts the overall progression and social sustainability of Agriculture 4.0, since, according to the socio-technical studies included in this review, the willingness to adopt augmentation technologies is recorded as significantly higher compared to those meant to completely replace the worker in the field, even though the available solutions for the first category fall disproportionately short.

Apart from the aforementioned, the geographical distribution of the research offers another interesting dimension to the interpretation of the results. Given that the majority of the studies originate from the USA and Asia, the technological solutions are mostly designed to meet the needs of large-scale farming. Consequently, they may not be applicable in a European context, which is dominated by small and medium-sized producers that require more adaptable solutions that adhere to the existing regulatory framework. Therefore, the potential need for the proposed technologies to adapt to European standards raises an issue that is barely acknowledged or examined in the literature, thereby slowing down sustainable agricultural development and creating technological divides around the world.

Finally, it is important to note that the dimensions of the developed analytical framework are not isolated. In fact, through their dynamic interaction, they form a functional technological pipeline. For instance, interventions targeting “Occupational Safety, Health, and Ergonomics” (addressed through Dimension 1) frequently rely on “Perception and Data Acquisition Systems” (analyzed in Dimension 2), such as wearable biometric sensors, to enable “Technological Augmentation and Empowerment” (fully explored in Dimension 3). Conversely, “Precision Agriculture and Pest/Weed Detection” (Dimension 1) heavily utilizes “Computational Intelligence and Robotic Action” (Dimension 2) to completely remove the worker from hazardous environments, thereby achieving “Full Automation and Labor Substitution” (Dimension 3).

However, depending on the dimensional intersections of each proposed solution, the socio-economic issues and adoption barriers differ significantly. When a technology leans heavily toward “Full Automation and Labor Substitution” (Dimension 3), the primary socio-economic hurdles are prohibitive initial costs, a lack of necessary rural infrastructure, and workers’ fear of job displacement. In contrast, solutions focusing on “Technological Augmentation” (Dimension 3), such as active exoskeletons, do not trigger fears of job replacement, since concerns such as ergonomic discomfort, poor usability in real-world conditions, and steep learning curves are raised instead. Finally, across all operational fields (Dimension 1), whenever a solution relies heavily on “Perception and Data Acquisition Systems” (Dimension 2), concerns regarding data ownership, privacy, and cyber-physical security form a completely different spectrum of adoption challenges. Finally, it should be noted that the current review cannot assess for systematic differences in project funding or team composition between the TRL 9 studies and the TRL 3–6 studies due to inconsistent reporting across the included studies and the pre-defined parameters used to extract data for the review (Section 2.3).

4.2. Limitations of the Review Findings and Research Process

This systematic literature review followed the PRISMA 2020 guidelines. However, there are certain limitations that should be mentioned regarding the findings and the research process.

The first potential concern is the use of a single database (Scopus) for the literature search. Despite its benefits, restricting the search exclusively to this platform means this study is presented not as a fully comprehensive systematic review, but rather as a focused synthesis of the most important Scopus results. Consequently, equally relevant and impactful studies indexed exclusively in other databases—such as Web of Science, PubMed (with a great number of publications on occupational health and ergonomics), or IEEE Xplore (which focuses on technical robotics)—may have been excluded. Furthermore, grey literature and region-specific publications outside of Scopus were not captured. The final corpus of the 109 highly relevant studies, however, serves as a compensating factor for this limitation. Given that many high-impact journals are cross-indexed across multiple databases, the final corpus for this study remains sufficiently robust and representative to accurately map the current state of the art and address the review’s SRQs. Therefore, it provides a solid foundation for future research to expand upon by employing multi-database search strategies to provide an even more exhaustive synthesis.

Another point of attention is the heterogeneity of the selected studies, as previously mentioned, since the review comprises both technical and theoretical studies. Consequently, statistical formulas cannot be applied either to the entire corpus or solely to the technical papers, as the reported quantitative data do not derive from homogeneous experimental setups. Therefore, qualitative conclusions inevitably dominate this review.

Regarding the limitations of the research findings, the overwhelming majority of the examined studies present technological solutions at TRL 3–6 (functional prototypes), intended for very specific agricultural scenarios. This practically means that these studies exhibit low external validity and comparability. This fact, combined with the publication bias identified in the 8 studies classified as having a “High Risk of Bias”, suggests that the actual performance of the developed technologies under adverse, real-world conditions may be somewhat overestimated by the existing literature.

4.3. Answering SRQ 1

Regarding SRQ 1, “What are the primary operational challenges, ergonomic constraints, and safety risks currently faced by agricultural workers?”, the review has sufficiently established the connection between the current agricultural crisis, the human element, and the overall social sustainability of the sector. The findings from the 109 selected studies, alongside those from the publications from organizations such as the ILO and FAO, confirm that agricultural workers are exposed to risks on a daily basis during the execution of their tasks, while receiving little to no recognition, but rather experiencing the daily social devaluation of their profession.

One of the main challenges of agricultural labor concerning the worker’s health is musculoskeletal problems, which constitute a primary cause of disability and prolonged absence from work, and can evolve into chronic MSDs. They are directly linked to the demanding and repetitive nature of most agricultural tasks, given that their execution requires movements in awkward, non-ergonomic postures (such as bending of the lower back and continuous extension of the upper limbs), as well as the regular manual lifting of heavy loads.

The aforementioned tasks, however, are not the only ones threatening human health. Manual pesticide spraying frequently causes both short-term health issues (e.g., acute poisoning) and chronic respiratory diseases, due to the prolonged exposure of farmers to chemicals, either through dermal contact or via the inhalation of toxic substances.

Equally significant is the rate of injuries recorded from farmers’ interactions with machinery. Despite the efficiency and practicality that equipment offers during task execution, it poses critical risks for the operator’s safety. More specifically, tractor rollovers on sloping terrains and entanglements in moving mechanical parts are among the primary causes of fatal accidents, with the agricultural sector reporting, as analyzed, disproportionately high rates of injury and mortality compared to other industries.

Finally, demographic and psychosocial factors further influence the current agricultural reality. As noted, there is a significant aging of the workforce, which, combined with the reluctance of young individuals to pursue agriculture professionally, has resulted in a severe labor shortage crisis. In other words, the prospect of daily engagement in exhausting “3D” (Dirty, Dull, Dangerous) tasks, without receiving the appropriate societal recognition, acts as a deterrent for the younger generation, exacerbating the aforementioned spectrum of risks.

These findings indicate that technological intervention alone is not enough to address the operational challenges shaping the current landscape of the agricultural crisis. It requires the simultaneous development of national and European occupational safety policies that establish strict evaluation criteria for newly proposed solutions based on ergonomics and user safety. Moreover, it mandates the organization of informational and awareness campaigns regarding the challenges and the overall contribution of the agricultural sector to social well-being, as well as the research activity driving its digital and sustainable transformation.

4.4. Answering SRQ 2

Answering SRQ 2, “Which modern technological solutions aim to mitigate or replace hazardous, harmful, and unattractive agricultural tasks?”, the literature presents an exceptionally broad and rapidly evolving spectrum of technological solutions. The most fundamental ones are grouped by application in Table 15 below.

Table 15. Grouped presentation of key technological solutions identified from the selected studies.

Field of Application/Focus	Key Technological Solutions	Technology Readiness Level (TRL)	Primary Benefits
Full Automation of tasks	Spraying UAVs Autonomous tractors Autonomous harvesting robots	6–9 (Advanced prototyping and case-specific commercial availability)	Replacement of the worker in dangerous environments and highly demanding tasks (complete substitution).
Collaborative Robotics (Cobotics)	Robotic transport platforms Cobots for weeding, harvesting, seeding, and spraying Human gesture recognition systems	3–4 and 8–9 (Initial prototyping stage and existence of certain commercial solutions)	Reduction of physical strain during the execution of basic agricultural tasks.
Technological Augmentation	Passive/active exoskeletons Wearable sensors (WT)	5–9 (Optimization efforts, and broad commercial availability of passive exoskeletons)	Augmentation of the worker’s abilities and stamina and real-time health monitoring during task execution.
Intelligent Monitoring	IoT networks AI/ML algorithms LiDAR DNNs	1–3 and 5–8 (Theoretical development and algorithm training, with partial integration into commercial systems)	Early detection of pests or abnormal livestock behavior, less manual inspections in hazardous environments required, addressing labor shortages and worker safety.

The most mature technologies in terms of market readiness and availability are UAVs, and more specifically spraying drones. They can reduce farmers’ chemical exposure by more than 90%, allowing for full field supervision and remote control, while promoting the sustainable and efficient use of resources and pesticides, in the context of Precision Agriculture.

Another leading technological trend in agriculture is autonomous vehicles. There is plenty of room for innovative design in this domain, as the factors that must be considered are numerous and highly variable. Their widespread adoption is still at an early stage, especially in countries dominated by small and medium-scale farming, with vineyards and orchards being the main areas of interest. Smaller-sized UGVs and specialized robots are increasingly gaining ground; however, there are important constraints to full adoption, which are examined through SRQ 3.

One of the few solutions that require zero infrastructure and, therefore, can be easily integrated into daily agricultural life are exoskeletons, both passive (mainly) and certain active ones, provided they are adapted to the specific needs of agricultural labor and the intended end-user characteristics. As long as their design can support use under real-world conditions by vulnerable demographics, they are considered a highly critical means of facilitating and augmenting farmers, ultimately ensuring long-term occupational sustainability.

Furthermore, the literature highlighted the structural basis of all the aforementioned technologies, namely intelligent recognition and monitoring systems (DNNs, AI cameras, etc.). Beyond crops, they are frequently applied in livestock management, where the innovation aims to offer solutions that combat the labor shortages and relieve humans from demanding, unattractive barn tasks, therefore contributing to the improvement of ergonomics and overall biosecurity.

4.5. Answering SRQ 3

The answer to the final research question, “What are the technical limitations and factors influencing technology acceptance among agricultural workers, particularly regarding ergonomic integration and operational drawbacks of automated solutions?”, constitutes a combination of a critical analysis of the selected technical research and findings from socio-technical studies. Table 16 below summarizes the fundamental barriers identified regarding the acceptance and use of agricultural technologies.

Table 16. Limitations of technology acceptance in the agricultural sector.

Barrier Type	Identified Limitations	Impacts (1-to-1 Mapping)
Technical/Operational	- Limited battery autonomy, SWaP constraints in UAVs - Lack of interoperability among IoT systems - Generalization gap in AI algorithms - Reduced hardware performance in real-world conditions (mud, dust, fog) due to insufficient field testing	- Inability to achieve continuous 24-h operation and (potentially) insufficient payload capacity for spray liquids and sensors - Data silos, complicating the information extraction - Lack of adaptability and efficiency of the solutions across crops and geographies that differ from those of the training - Unreliability in real agricultural scenarios (sensor “blindness”, accidents, breakdowns, and idle times)
Ergonomic	- Use of limited/unsuitable demographics as testing samples (e.g., testing exoskeletons exclusively on young volunteers) - Increased weight and steep learning curve of active exoskeletons (often featuring rigid frames)	- Uncertain effectiveness and adaptability of the solutions for elderly farmers - Poor user experience and induction of additional discomfort, causing technology rejection
Economic	High acquisition costs (mainly for autonomous systems)	Exclusion of small and medium-sized producers, technological divide and inequalities
Regarding Infrastructure	- Inadequate telecommunications coverage (lack of or unstable 4G/5G signals) - Lack of local RTK-GPS stations - Insufficient charging capacity of the equipment - Absence of robust Edge Computing capabilities in agricultural equipment	- Inability to control equipment and transmit data to the cloud in real time - Loss of the required centimeter-level accuracy, overlaps and errors during spraying, seeding, etc. - Inability to fast-charge and support the operation of electric autonomous fleets - High latency during local (offline) data processing, heavy dependence on Internet connectivity
Socio-psychological	Fear of replacement, distrust towards automation (technophobia)	Resistance and low willingness to adopt, particularly among older farmers
Regarding Data	Concerns regarding the ownership, privacy, and security of agricultural data	Avoidance of digital interconnection, resulting in exclusion from advanced data-driven insights
Institutional	Regulatory gaps, absence of a comprehensive legal framework for new technologies	Legal uncertainty and investments’ “freezing”, hindering innovation

In addition to adoption barriers, some challenges are yet to be addressed on the technical side despite funding and infrastructure. These include mechanical robustness of robots operating in unstructured field settings [47,49,113], reliability of acoustic and vision-based monitoring systems in high-noise or high-occlusion environments [38,77,106], and the ability of AI/ML models to be trained for specific crops/crop-climates and then applied to vastly different field situations [67,69]. These represent genuine technical frontiers rather than adoption or cost barriers.

At this point, three distinct gaps can be identified at the technical, ergonomic, and social levels. For a successful transition in Agriculture 4.0, it is necessary to undertake combinatory initiatives to ensure that market-ready solutions can truly be utilized, benefiting

producers, the sector, and its overall sustainability across all levels. These initiatives are extensively analyzed in Section 4.6.

4.6. Future Directions and Outlook in Agriculture 4.0

This literature review maps and analyzes the operational challenges, the contemporary technological solutions, and the research gaps that lie within Agriculture 4.0, providing the ideal context for reflection and proposals for future research. Given that economic and social development globally is not uniform, it is evident that a “one-size-fits-all” solution is not applicable, meaning that regional contexts should be considered, and tailored strategies should be implemented.

As analyzed, one of the primary adoption barriers is the high initial cost of the technological solutions, which constitutes a severe constraint for small and medium-sized producers. In this context, and especially in developed regions, such as the EU, ensuring producers’ access to favorable financing tools, such as “green” loans, and providing targeted subsidies for the sustainable technological transformation of their farms (e.g., establishing dedicated “Agriculture 4.0 Transition Funds”), can substantially and widely support those wishing to gain permanent access to new digitalized equipment. Furthermore, a modern trend currently entering the agricultural sector is a subscription-based business model, known as Farming as a Service (FaaS). This model can serve as an excellent alternative for small and medium-sized producers in technologically mature markets, as it allows them to rent autonomous machinery strictly for as long as required, effectively turning the prohibitive acquisition cost into a manageable operational expense. A way of possibly extending this concept in developing regions as well could be the establishment of community-owned machinery initiatives, creating a culturally appropriate and financially viable pathway.

Economic accessibility, however, does not mean much without technological reliability. Therefore, the research community must focus on determining how to securely accelerate the transition from TRL 6 to TRL 8–9. This requires the systematic execution of extensive field trials under real-world, heterogeneous conditions, aiming to cover scenarios that reflect the immense diversity of agricultural activity across different climates, terrains, and crop types. To facilitate this, establishing co-creation practices and regional “living labs” that allow the active participation of local farmers in the design and testing process can prove very insightful for technology developers, since this way the specific regional needs and microclimates can be addressed more effectively. For this to be possible, collaboration and co-investment between the government and research institutes are required. In the European context, for instance, steep-slope terrains require particular attention, as they are characteristic of a large portion of the continent’s agricultural land, and UGVs’ stability in these environments has not been adequately examined yet.

At the software level, the generalization gap identified in the operation of AI and ML algorithms is considered one of the greatest barriers to the development of broadly applicable technological solutions. To address this issue, institutional partnerships must be fostered for the creation of universal, yet regionally categorized, open-source datasets (concerning crop diseases, pest types and characteristics, livestock behavior, etc.). Such initiatives will guarantee the reliability of real-time feedback provided by machine vision technologies across different climate zones.

Moreover, the use of Digital Twin technology in more applications is anticipated to be critical in the optimization and more precise control of technological systems, especially for algorithm and robotic systems’ training within high-fidelity virtual simulation environments. This method allows for the evaluation of failure scenarios without causing actual damage to equipment or livestock, while drastically reducing testing costs. Addi-

tionally, for a smoother integration of automation into agricultural labor, the development of Explainable AI (XAI) algorithms is deemed essential. Their main functionality will be to provide transparent justifications for every automated decision made. This will ultimately transform the farmer from a resistant operator into a collaborative partner during the decision-making process.

Beyond performance optimization, the new technologies being developed must be ergonomically designed to be usable by older individuals and others with reduced cognitive capacity, muscle mass and mobility, and they must be tested on these specific groups (rather than solely on young, healthy volunteers, as frequently observed in exoskeleton studies). This should be formalized by policymakers through the introduction of a “safety and ergonomic certification framework” for agricultural technological solutions that mandates age- and capability-inclusive testing prior to commercialization. The socio-technical gap can also be bridged by establishing and integrating localized educational hubs into rural communities, providing digital literacy training and support, and practically enabling farmers to interpret data and operate complex interfaces.

Regarding the human element, it is equally important to address the distrust surrounding the ownership of data collected automatically in the field. It is, therefore, necessary to institutionally and legally establish a clear regulatory framework both at the national and European levels, to strictly define who owns, manages, and capitalizes on agricultural data. A practical step towards that path, can be the formation of “Data Trusts” dedicated to agricultural data, allowing farmers to securely concentrate, keep and potentially negotiate the use of their field data with large technology providers.

Finally, bridging the digital divide on a broader geographical scale is urgent. Beyond the solutions intended for use in large-scale farming, the unique conditions prevailing in more isolated rural areas and developing countries must redirect the research interest toward designing simpler and low-cost alternative solutions. These systems must be able to operate without requiring continuous internet connectivity and highly specialized technical support. However, such capabilities do not negate the need for specific interventions regarding the installation of stable telecommunications and energy-efficient infrastructures to support the universal and sustainable transition to Agriculture 4.0.

5. Conclusions

This systematic literature review clearly demonstrates that Agriculture 4.0 is an evolving reality, rather than a futuristic concept. Despite the already intense research interest, the transition from traditional agriculture to a fully technologically integrated environment is still significantly far from a broad and effective implementation, as its success does not rely on a single technological innovation. In reality, the systematic effort to bridge the three critical gaps identified in this study—the technological gap (from TRL 6 to TRL 9), the ergonomic gap (from idealized laboratory conditions to real agricultural settings), and the social gap (from skepticism and distrust to the active participation of the producer in the shift)—will prove critical for a successful transition to Agriculture 4.0 and the assurance of the agricultural sector’s long-term sustainability.

Unlike existing reviews, which typically assess Agriculture 4.0 through a purely technical or economic lens, this review’s originality lies in its human-centric, three-dimensional classification framework, which exposed a clear imbalance between full automation (80 studies) and worker-augmenting solutions (only 13 studies), despite the fact that this sector’s crisis is clearly labor-driven. Conducting a formal Risk of Bias and Certainty appraisal, along with the evidence-type classification of hazard-reduction claims used in this review for a more accurate analysis and presentation of specific findings, further revealed that most reported benefits regarding occupational safety are inferred from accuracy

and efficiency metrics of the proposed technological solutions rather than demonstrated through direct injury, exposure, or MSD outcome data—a distinction hardly mentioned in any previous literature in this field.

Based on these findings, this review recommends: (i) dedicated financing mechanisms (e.g., transition funds, FaaS models) to lower financial barriers to technology adoption for small and medium-sized producers; (ii) mandatory age- and capability-inclusive ergonomic testing prior to commercialization; (iii) a shift in future research on occupational safety in agriculture toward prospective, outcome-level evidence rather than accuracy-only reporting; and (iv) stronger research emphasis on augmentation technologies, given their higher acceptance among farmers compared to full-substitution solutions.

Finally, since this review's search was conducted solely in the Scopus database, its findings should be interpreted as a focused synthesis of the Scopus-indexed literature rather than an exhaustive, multi-database systematic review. Future work that incorporates additional databases is encouraged to extend these conclusions to specific contexts.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18168358/s1>. Table S1: PRISMA 2020 Checklist [6]; Table S2: Paper Classification and Appraisal.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AR	Augmented Reality
AUEQ	Agricultural Exoskeleton Usefulness Questionnaire
BLE	Bluetooth Low Energy
CNN	Convolutional Neural Network
CycleGAN	Cycle-Consistent Generative Adversarial Network
DL	Deep Learning
DNN(s)	Deep Neural Network(s)
FAO	Food and Agriculture Organization
FaaS	Farming as a Service
FPS	Frames Per Second
GHG	Greenhouse Gas
HCS	Hand Controls
HMI	Human–Machine Interaction
HRC	Human–Robot Collaboration
HTM	Hierarchical Temporal Memory

ILO	International Labour Organization
IoT	Internet of Things
KNN	K-Nearest Neighbors
LiDAR	Light Detection and Ranging
LLMs	Large Language Models
ML	Machine Learning
MRQ	Main Research Question
MRFV	Multi-Rotor Flying Vehicle
MSDs	Musculoskeletal Disorders
OSH	Occupational Safety and Health
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PU	Perceived Usefulness
R-CNN	Region-based Convolutional Neural Network
RFID	Radio Frequency Identification
RoB	Risk of Bias
RTK-GNSS	Real-Time Kinematic—Global Navigation Satellite System
RTK-GPS	Real-Time Kinematic—Global Positioning System
SIDCNet	Sugarcane Internode Detection Convolutional Network
SLR	Systematic Literature Review
SRQ	Specific Research Question
SVM	Support Vector Machine
TAM	Technology Acceptance Model
TRL	Technology Readiness Levels
TTC	Time-To-Collision
U-Net	U-shaped Convolutional Neural Network
UAV(s)	Unmanned Aerial Vehicle(s)
UGV(s)	Unmanned Ground Vehicle(s)
WBG	Wet Bulb Globe Temperature
WSAN	Wireless Sensor and Actuator Network
WT	Wearable Technology
XAI	Explainable Artificial Intelligence
YOLO	You Only Look Once

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