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Review

Automation's Impact on Agriculture: Opportunities, Challenges, and Economic Effects

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Abstract: Automation and robotics are the key players in modern agriculture. They offer potential solutions for challenges related to the growing global population, demographic shifts, and economic status. This review paper evaluates the challenges and opportunities of using new technologies and the often-missed link between automation technology and agricultural economics. Through a systematic analysis of the literature, this study explores the potential of automation and robotics in farming practices, as well as their socio-economic effects, and provides strategic recommendations for those involved. For this purpose, various types of robots in different fields of agriculture and the technical feasibility and challenges of using automation have been discussed. Other important factors, including demographic shifts, labor market effects, and economic considerations, have been analyzed. Furthermore, this study investigates the social effects of automation, particularly in terms of employment and workforce adaptation. It finds that, while automation boosts productivity and sustainability, it also causes labor displacement and demands considerable technological investment. This thorough investigation fills a crucial gap by assessing economic sustainability, labor market evolution, and the future of precision agriculture. It also charts a course for further research and policy-making at the intersection of agricultural technology and socio-economic fields and outlines a future roadmap for further research and policy.

Keywords: agricultural automation; precision farming; data-driven farming; demographic shifts; economic feasibility; agricultural productivity; environmental impact

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1. Introduction

The world is facing a serious food resource shortage due to a rapidly growing population. It is predicted the global population will reach around 9.8 billion people by 2050, a substantial increase from the current 7.6 billion in 2023. This rapid population growth leads to a major problem concerning the growing demand for food. Traditional farming methods, which have been used for thousands of years, now struggle to keep up with this growing need for sustenance. As the gap between food production and global demand continues to widen, the agricultural sector must quickly transform its practices. It needs to adopt advanced technologies to ensure sustainable, efficient, and enough food production [1–3].

On the other hand, the changing demographics, characterized by a declining youth population and an increasing proportion of the elderly, make for a serious concern about the future labor force, particularly for agriculture. The agricultural workforce might struggle to meet the demands of labor-intensive tasks. This transition in demographics could lead to a shift toward a more knowledge-based workforce, encompassing roles related to technology development, data analysis, precision agriculture, and the management of automated systems [4–8].

Based on the global urgency of this topic and its current limitations, the integration of automation technologies into all aspects of agriculture seems an effective and feasible solution and promises a new era in this field. Automation, as it has evolved from traditional to modern methods like precision farming, will substantially influence the future of food production [5,9,10].

Throughout history, agriculture has been affected by various transformative revolutions, each tied to technological advancements that have significantly influenced productivity and efficiency. The advent of automation has provided a basis for the transition to the next generation of agriculture, which offers the possibility of increasing productivity and reaching our maximum potential in the field of agriculture. Precision farming, powered by automation, is an example of the harmonious integration of state-of-the-art technologies with traditional farming practices. It offers data-driven decision making, precise resource allocation, and the optimization of input utilization—a set of capabilities crucial in an era defined by an expanding global population and escalating environmental concerns [9–12].

A deeper look into the realm of agricultural robots gives us a clear vision of the expanse of automation's influence. Agricultural robots designed to perform a collection of tasks, ranging from land preparation before planting to the precise estimation of crop yields, have the potential to revolutionize efficiency and perform precision farming. However, the other side of using automation in agriculture is related to its economic effects. The potential economic benefits, such as substantial cost savings and enhanced labor efficiency, must be carefully compared to its consequences and challenges, including the substantial initial investments required for automation infrastructure and the demand for specialized technical expertise for its maintenance [3–5,13–17].

This paper provides a comprehensive exploration of the multifaceted implications of this technological evolution, with a specific focus on its economic feasibility, benefits, and challenges. The objective is to provide a holistic understanding of how automation intersects with and reshapes the economics of agriculture, beneficial not only for experts within the field but also to a broader audience of scientists, policymakers, and stakeholders [2,3,5,10–13,18,19].

Central to this discussion, this paper's contributions are mapped out across the following fundamental concepts:

- The technical feasibility and adaptability of automation in various fields;
- The socioeconomic impacts of agricultural automation;
- The economic impact analysis of agricultural automation;
- The ecological considerations of agricultural automation.

2. Materials and Methods

To explore the economic effects of agricultural automation, a systematic literature review was conducted. The search for relevant publications was comprehensive, utilizing various databases and search engines to ensure a wide-ranging collection of perspectives and data. The databases used included Scopus and Web of Science, renowned for their extensive coverage of peer-reviewed scholarly articles across multiple disciplines such as economics, technology, and agriculture. Google Scholar was employed for its broad indexing of scholarly articles, theses, books, conference papers, and credible reports, offering a comprehensive range of perspectives on the subject. Additionally, specialized library catalogs were searched to encompass research that might not be readily available in larger databases.

The search strategy was designed to include articles and materials published after the year 2005, but our emphasis was on more recent years, marking significant advancements in agricultural technology from this period onward. This period is recognized as the beginning of a new era in agricultural automation, making it pertinent to our study. Keywords and phrases such as "agricultural automation", "economic impact of farm technology", "environment impact", "precision agriculture", and "agricultural robotics" were utilized, capturing a broad spectrum of relevant research. The search was refined using Boolean operators to combine terms and by applying filters for publication date, document type, and access to full texts. Inclusion criteria were centered on studies that directly or indirectly addressed the economic impacts of agricultural automation, while exclusion criteria ruled out articles focusing solely on the technological aspects without accompanying economic analysis.

Following the initial search, duplicates were eliminated, and the remaining articles were screened for relevance based on their titles and abstracts. The full texts of the selected articles were then thoroughly reviewed. Data pertinent to the economic aspects of agricultural automation were extracted, including studies on the labor market and ecological effects, new technology and productivity changes, and broader economic implications.

The data extracted from these sources underwent both qualitative and quantitative critical analysis. This included thematic analysis to identify key themes and trends in the economic discourse surrounding agricultural automation. This information was synthesized by comparing and contrasting empirical findings, theoretical perspectives, and case studies, providing a coherent narrative on the economic effects of agricultural automation. This approach ensured a balanced review that reflects the diverse range of available literature on the topic. However, it is important to note the limitations of this study. Our reliance on English-language sources may have excluded significant research published in other languages, potentially limiting the scope of our global perspective.

In this study, various publication sources were utilized to gain access to all the relevant journal articles needed for the literature review. The lists of journal publishers and the number of articles included from each publisher are presented in Table 1.

Table 1. Database showing the number of papers based on publishers.

Publisher	**No. of Papers**
ELSEVIER	23
MDPI	19
Springer	9
IEEE	9
Taylor & Francis	3
SSRN	3
frontiers	3
Annual Reviewers	3
world bank	2
McKinsy &company	2
arXiv	2
Goldmansachs	2
Taylor & Francis Group	1
Korea Information Processing Society	1
USDA ERS	1
American economy association	1
IVES	1
CABI	1
US Department of Agriculture	1
Population Pyramids	1
Wageningen Academic	1
Pointcloudtechnology	1
ASABE	1
Fortune	1
Cambridge Core	1
European Association of Geoscientists & Engineers	1
MITSLoan	1
Grand Total	95

Table 1 displays the distribution of cited papers by publisher. The majority of papers cited in this study were published by Elsevier, MDPI, Springer, and IEEE. While Figure 1 analyzes the publication years, indicating that the majority of publications used in the study are from recent years.

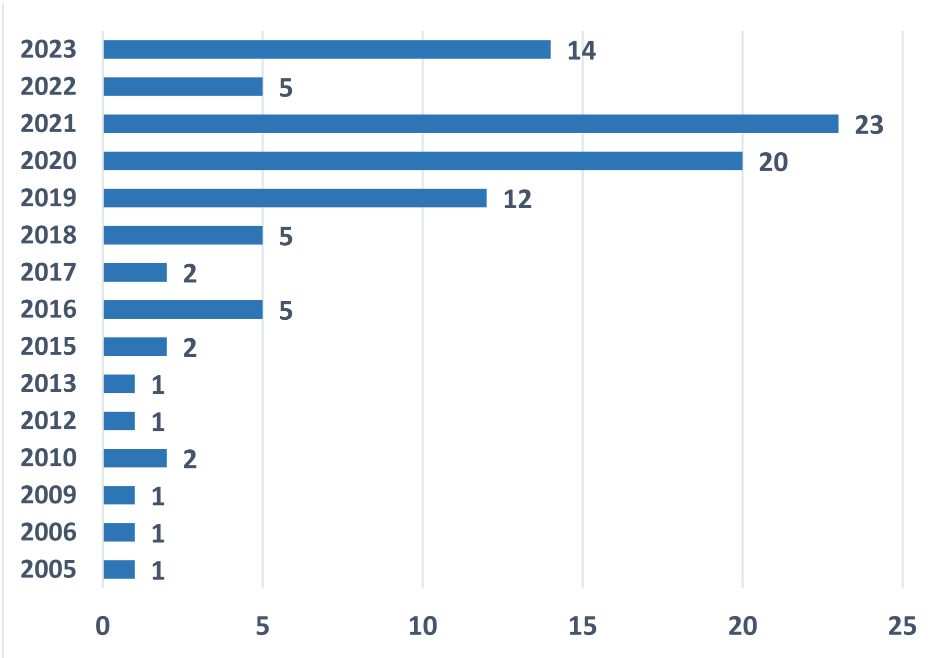

Figure 1. Distribution of cited papers based on publication year.

3. Path of Evolution in Agriculture

The concept of agricultural automation aligns with the broader context of industrial revolutions. Industry 4.0, the term coined for the fourth industrial revolution, signifies the latest wave of technological advancements. Similarly, the evolution of agriculture has progressed gradually over time, and its milestones can be correlated with the different industrial revolutions [9–12,20] (Figure 2).

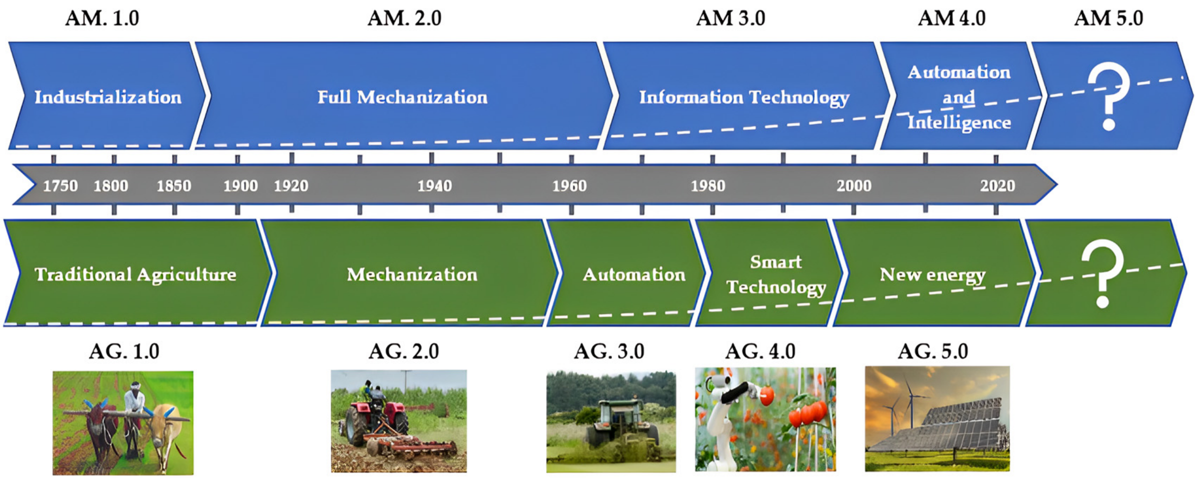

Figure 2. The trends in agricultural development [9,20].

From Agriculture 1.0, characterized by primitive farming methods relying on manual labor and animal power, to Agriculture 4.0, where digital technologies are revolutionizing the agricultural sector, this timeline showcases significant transformations. Agriculture 2.0 marked a crucial phase during which agricultural machinery was introduced to increase food production and reduce manual labor. Subsequently, Agriculture 3.0, also known as precision farming, emerged with advancements in computing and electronics, leading to improved resource efficiency and operational performance in agricultural systems. Precision agriculture (PA) has played a pivotal role in initiating the digital transformation of the agricultural sector. Today, Agriculture 4.0 represents a new revolution, where digital technologies are seamlessly integrated into farming practices, just like the influence of Industry 4.0 in various industries. This alignment between industrial revolutions and agricultural advancements underscores the significance of agricultural automation in shaping the future of crop production and addressing the challenges faced in modern farming practices [10–12,20].

However, Agriculture 5.0 will have a significant impact on farmers' prosperity, particularly in the post-pandemic era. Agriculture 5.0 involves the integration of emerging technologies and alternative energy sources into farming practices. Combining these technologies with green energy sources provides cost-effective financial access, real-time weather updates, remote monitoring capabilities, and future energy solutions for smart farms. Implementing Agriculture 5.0 with green energy sources can lead to cost reduction, increased energy efficiency, and the establishment of sustainable energy-smart farms [11,21–25].

In terms of the future, there is a projected substantial increase in the utilization of robotics within the agricultural sector. Autonomous robots powered by solar energy exhibit the capability to operate continuously for extended periods without the need for breaks. This advancement opens up new possibilities for increased efficiency and productivity in agricultural operations, potentially preserving ecosystems by reducing fuel and energy consumption. Advancements in robotics have also led to the development of flying microrobots, inspired by the mechanics of insects. These microrobots have been specifically designed to fulfill various tasks such as reconnaissance on battlefields, search and rescue operations in disaster scenarios, and image capture in agricultural fields. They are equipped with propellers that enable their precise flight and landing, and show potential for applications in agriculture, particularly for tasks such as insect and weed control [10,20,21,24].

The scientific and technical significance of robotics in agriculture is evident in the potential for increased operational efficiency, enhanced precision, and the ability to address specific agricultural challenges. The integration of autonomous robots, powered by renewable energy sources, allows for continuous agricultural operation, reducing the need for human intervention and increasing overall productivity. Additionally, the incorporation of advanced sensing technologies, such as photoelectric and capacitive sensors, facilitates robots' improved intra-row weeding capabilities. The development of flying microrobots introduces new possibilities for targeted interventions, such as insect and weed control, utilizing the unique flight and landing capabilities of these robotic systems.

It is important to note that further research and development in robotics will continue to drive innovation and broaden the range of their applications in agriculture. These advancements hold great promise for improving agricultural practices, optimizing resource utilization, and contributing to sustainable and efficient farming systems [22,24–26].

The digital transformation in agriculture is incremental and depends on digital technology adoption throughout the value chain. A clear digital strategy and robust human capital are essential for this transformation [3,14,15,26].

Agricultural automation, employing robotic systems, is redefining traditional farming tasks. These systems, equipped with sensors, gather data on environmental conditions and crop health, assisting in tasks like planting, harvesting, and pruning [3,4,14,26].

Precision farming uses data-driven tools like satellite imagery and GPS-guided machinery to optimize resource allocation and crop monitoring, aiming to increase income, improve production quality, and reduce environmental impacts [3,5,9,24,27–32].

4. Different Types of Agricultural Robots

In precision agriculture, diverse platforms including satellites, aerial vehicles (such as unmanned aerial vehicles (UAVs)), and ground-based vehicles (like field robots or commercially off-highway vehicles) are commonly used for plant detection and monitoring. Satellite and aerial sensing are typically employed for large-scale field monitoring, such as variable-rate herbicide spraying. However, these platforms have limitations in terms of their spatial resolution and dependency on weather and air conditions. Ground vehicle-based sensing and low-altitude aerial sensing offer higher spatial resolution and are suitable for tasks like real-time, in-row weed control. Weed plant perception methods rely on spectral reflectance and biological morphology characteristics, which are utilized to detect and analyze weed presence. For ground vehicle-based methods, considerations include clearance over the crop, matching crop row spacing, and field travel ability under various soil conditions [33–39].

Robotic platforms have lots of applications in agriculture, particularly in land preparation before planting, plant treatment, sowing and planting, estimating yield, and phenotyping.

4.1. Land Preparation before Planting

Land preparation in agriculture involves activities like plowing and fertilization. Plowing helps with oxygen penetration and carbon dioxide release, but it can also impact soil carbon stocks. Fertilization, on the other hand, plays a crucial role in replacing the essential nutrients necessary for crop growth. To streamline and optimize these tasks, robots have been developed to provide valuable assistance. Notable examples include the Cäsar robot (Figure 3a) [40], dedicated to soil fertilization and pest control, the Greenbot robot (Figure 3b) [40], designed for fertilizing, plowing, and seeding, and the DJI UAV, which specializes in aerial agricultural activities. These robots utilize cutting-edge technologies like RTK/GNSS for precise positioning, significantly improving their control and navigation capabilities. Moreover, the integration of obstacle detection systems and collision sensors ensures enhanced safety during their operations. Ongoing research efforts are focused on further improving weed detection methods and developing cost-effective embedded systems to advance robot control capabilities even further [37,40–42].

Figure 3. Land preparation robots: (**a**) Cäsar robot [40] (**b**) Greenbot robot [40] (**c**) Spraying robot [42].

The introduction of spraying robots is essential for minimizing farmers' exposure to the potentially harmful effects of pesticides and liquid fertilizers, despite any protective measures used. Due to advancements in artificial intelligence and computer vision, these robotic sprayers are equipped with sophisticated intelligence systems. Unlike traditional methods that apply a uniform spray over crops, these robots can selectively target areas for spraying. This selective approach not only reduces the environmental footprint of agriculture but also lowers the risk of pesticide exposure to consumers and helps prevent pests from developing resistance to these chemicals (Figure 3c) [42,43].

4.2. Sowing and Planting

Sowing and planting tasks in agriculture are traditionally carried out using tractor-mounted equipment. However, heavy machinery and constant tractor movement can lead to soil compaction and its associated negative effects on soil properties and crop development. To address these challenges, robotics has emerged as a potential solution to automate and enhance the precision of sowing and planting processes. The focus of ongoing research is on developing low-cost and modular robots that can effectively serve small farms. Prototypes are being created for tasks like precision seeding, spraying, and weeding. The main objectives are to improve efficiency, reduce soil compaction, and increase accessibility for farmers. Various robotic systems have been developed, including wheeled robots capable of the high-speed planting of different crops, robots tailored to specific crops like wheat, and robots with simplified designs for easy transport and assembly. These robots incorporate closed-loop control systems and sensors for monitoring their speed, angle, and pressure [36,40,41,44,45].

Among the innovative robotic systems developed, several stand out for their unique technologies and applications.

The Lumai-5 Robot (Figure 4a), developed by Haibo et al., is specifically designed for wheat sowing on Chinese farms. It utilizes a four-wheel steering (4WS) system, a closed-loop control system, and is equipped with speed, angle, and pressure sensors to ensure a consistent sowing quality across different speeds. The robot's design focuses on small size, high precision, and agility, making it highly effective in precision sowing tasks. The main factors affecting its seeding quality include the size of the planting tray, vacuum chamber pressure, and planting speed [40].

Figure 4. Sowing and planting robots: (**a**) Lumai 5 [40], (**b**) Di Weel [40], (**c**) Sowing robot [40].

The Di-Wheel Robot (Figure 4b) is part of the Digital Farmhand project by the Australian Center for Field Robotics (ACFR) at the University of Sydney. The Di-Wheel robot introduces a novel approach with its two-wheel drive (2WD) system. This design significantly reduces the robot's size, weight, and mechanical complexity, facilitating its easy transport and assembly. The Di-Wheel is capable of precision seeding, spraying, and weeding, with all its electronic devices centrally located. It supports smartphone integration to utilize built-in sensors for temperature, light, humidity, and more, alongside RGB cameras and motion sensors. The use of open-source machine learning algorithms enhances its capability for crop management and control [40].

The 4WD Seeding Robot, designed in Pakistan, is a four-wheel drive (4WD) seeding robot that has been developed for efficient corn sowing. It features an individual seed selector, capable of distributing a precise number of seeds for planting. This robot demonstrates a significant increase in sowing speed compared to traditional methods, achieving a rate of 90 seeds per minute and covering 0.66 acres per hour. Its design aims to optimize the weight-to-soil compaction ratio, making it suitable for small-scale farming operations.

Indian researchers have introduced a prototype seed drill robot, small in size but capable of carrying a payload of up to 17 kg in its reservoir. It uses a tracked drive system to navigate non-uniform soils efficiently while minimizing soil compaction. The robot is designed with sustainability in mind, featuring a photovoltaic panel for recharging its electrical system. Additionally, the implementation of a Kalman Filter improves the robot's estimation of its position and its movement across the field [40] (Figure 4).

4.3. Plant Treatment

Robotic applications in agriculture have paved the way for innovative plant treatment methods, utilizing robots equipped with an array of sensors, cameras (such as high-spectral and thermal cameras), and mechanical tools to irrigate, detect diseases, manage pests, and control weeds in crops. Recent research endeavors have focused on critical aspects like plant disease identification and treatment, weed management, precise herbicide application, and specialized crop monitoring, all playing pivotal roles in safeguarding agricultural fields [34–38,40,46].

For this purpose, the IoF 2020 project in Europe is at the forefront of harnessing IoT technologies to revolutionize precision farming across the European food and agriculture sector. By leveraging IoT-driven precision agriculture (PA), the project aims to optimize farming operations, fostering amplified crop yields and decreasing the input costs of water, fertilizers, insecticides, and herbicides. Introducing the innovative QUHOMA platform

(Figure 5), a smart irrigation solution developed using FIWARE technology, this initiative seamlessly merges AI capabilities with complex event processing (CEP), crafting irrigation schedules grounded in real-time sensor data [47–49].

Figure 5. Sensors and components of the QUHOMA platform [47].

To reduce potential data gaps and inaccuracies, the project strategically integrates AI-fueled predictive analytics. Combining accumulated datasets with publicly available data sources, these analytics fine-tune models to utilize them in specific contexts. This customized data resource serves as an effective contingency for instances where sensor data faces extended unavailability or discrepancies. The practical efficacy of this platform was demonstrated through tangible irrigation experiments conducted in real-world settings in Cyprus and Slovenia. For example, within a strawberry crop cycle in Cyprus, the QUHOMA platform showcased its potency by remarkably curbing water consumption by 10.88% compared to conventional empirical irrigation practices. This saves not only water supply costs but also human resources [48,49].

4.4. Estimating Yield, Phenotyping, and Geospatial Insights

Efficient crop management develops on accurate farming data. Yield estimation involves assessing the total crop output, factoring in variables like the climate and soil quality. Bridging plant traits (phenotype) with their genetic composition (genotype) is key to establishing optimal growth conditions. This fusion of geospatial data, AI algorithms, and digital twin technologies equips us with a holistic understanding of crops, paving the way for more intelligent and well-informed agricultural decisions [35,36,40,50].

In this context, the German Federal Ministry for Economic Affairs and Energy has recently allocated funding to the expansive NaLamKI project, which seeks to develop a cloud-based Software as a Service (SaaS) platform featuring open interfaces. These interfaces are designed to cater to entities within the agricultural sector's upstream and downstream segments, as well as industry and service providers specializing in specific crop production applications. The project's objective revolves around creating a dataset through the integration of sensor data derived from machinery, aerial surveillance (via satellites and drones), soil, climatic conditions, and other pre-existing data sources. This initiative is poised to refine agricultural practices such as irrigation, fertilization, and pest management by leveraging sophisticated AI techniques [46,51].

In addition, in the manufacturing domain, the concept of the digital twin (DT) presents opportunities for simulation testing, continuous monitoring, and maintenance strategies. Although agriculture differs from factory production, this concept extends to meet the expectations of Industry 4.0. The agricultural DT plays a pivotal role by serving as a reliable repository for plantation data, enhancing crop prediction precision and cost containment. Operating as a virtual replica, the DT enables the exploration of complex scenarios influenced by numerous interwoven factors. It finds application in diverse domains, including measuring phenotype traits, generating precise weed control maps, and overseeing the evolution of assets [47,52–54].

An interesting aspect of the agricultural DT lies in its spatiotemporal breadth, encompassing everything from individual plants to land parcels, farms, and entire regions. The establishment of meaningful feature spaces for geospatial entities is a critical consideration. Spatial digital twins tied to 3D point clouds provide universal 3D representations, yet their meaningful interpretation requires the use of AI algorithms. The German DEAL project showcases this through its application of geospatial AI, underpinned by ML and DL, to autonomously extract vegetation insights from 3D point clouds. This innovation facilitates the creation of an agricultural DT, revolutionizing the way we understand and manage agricultural landscapes [47,51,55,56] (Figure 6).

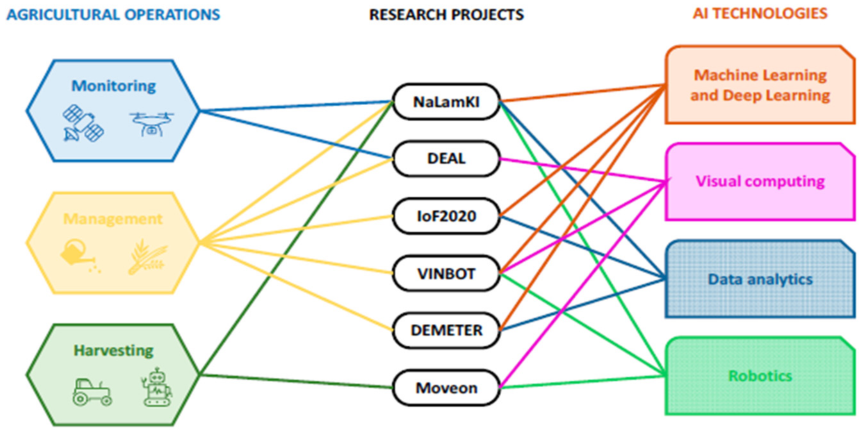

Figure 6. Agricultural operations and the AI-related technologies of European research projects [47].

Recent trends in robotics have shifted focus from traditional factory settings to more service-oriented and field-based roles, showing that robots are becoming an integral part of our everyday lives and that they can operate in complex, unpredictable environments. This shift is not just about robots moving around in the physical world; it also represents a leap in how they interact with digital information, enhancing their ability to navigate, perceive, and manipulate their surroundings [57]. The SLAM (Simultaneous Localization and Mapping) method enables robots to navigate and map their environment in real time. It is crucial for agricultural robots to operate autonomously, especially in complex and unpredictable farm environments. SLAM combines data from various sensors to create a map while tracking the robot's location within it. This technology supports tasks like crop monitoring, precision agriculture, and autonomous navigation among crops, enhancing robots' efficiency and reducing the need for manual labor. It is part of a broader move towards automation in agriculture, aiming to increase productivity and sustainability [58].

However, while these technological advancements have been rapidly evolving, there is a gap in our understanding of how they affect our relationship with nature. Enter the idea of the "new ecologies of automation", a concept that merges the study of digital landscapes with the use of robots in environmental management. This approach aims to examine how automation can change the way we interact with the natural world, focusing on how robots can be used in areas like precision farming, conservation, and environmental monitoring to promote sustainability and deepen our understanding of ecological systems [57].

This technological evolution, particularly in the context of agriculture, presents a pivotal opportunity to reassess and enhance the economic value derived from this sector. The integration of advanced robotics and automation technologies into agricultural practices stands at the forefront of creating a more efficient, sustainable, and economically viable agricultural industry. These innovations promise to revolutionize traditional farming methods, leading to increased productivity, reduced environmental impact, and enhanced crop monitoring and management capabilities [59].

As we focus on the economic implications of these technological advancements, critical questions emerge regarding their tangible value and investment justification. What specific areas within agriculture can expect a significant impact from these investments? How do the cost savings from improved efficiency and productivity balance with the initial investment in these technologies?

5. Economic Analysis of Agricultural Automation

In 2022, the agricultural sector and related industries significantly contributed to the U.S. GDP, amounting to approximately $1.420 trillion, or 5.5% of the total GDP. The direct output from farms was about $223.5 billion, representing 0.9% of the GDP. This illustrates that the agriculture sector's influence extends beyond this figure due to its foundational role for various other sectors like food and beverage manufacturing, food and beverage stores, food services, textiles, apparel, leather products, forestry, and fishing, all of which rely on agricultural outputs to add further value to the economy [60]. Between evolving demographics and technological progress, the fusion of economic analysis and agricultural automation emerges as a catalytic force.

5.1. Technical Feasibility of Automation

Looking to the future, the intersection of economic analysis, technology adoption, and agriculture will come into sharper focus and greater alignment. However, even though machines might not replace many jobs completely in the near future, they will change parts of most jobs. How much they change a job depends on the type of job. At present, machines are not just used for basic factory work; they can also change jobs in many areas like healthcare, finance, and agriculture, which need a lot of expertise [61].

A comprehensive study, which analyzed over 2000 tasks across more than 800 professions, provides valuable insights into this trend. Drawing on data from the US Bureau of Labor Statistics and O*Net, this research revealed that current technologies have the potential to automate about 45% of tasks for which individuals are compensated. Moreover, approximately 60% of all professions could see the automation of at least 30% of their tasks by leveraging existing technological advancements. It is crucial to recognize that the potential for task automation does not automatically imply its adoption (Figure 7).

Decisions to implement automation are influenced by a range of factors, including technical feasibility, the costs associated with developing and deploying automation solutions, labor expenses, and broader economic considerations [61].

In this examination of automation, the likelihood that specific tasks can be executed by machines using the presently available technologies is assessed. Essentially, it is determining the technical feasibility of automating these tasks. Every profession encompasses a variety of tasks, each with its own distinct potential for automation, Figure 7 delineates the seven primary categories of tasks analyzed. Given that each activity possesses a unique automation potential, an aggregate estimate for the sector is derived by evaluating the duration workers allocate to each activity throughout their work week [61].

The heat map highlights the large variation in how automation could play out, both in individual sectors and for different types of activities within them. In the U.S. workforce, a significant portion of time is dedicated to data collection and processing, activities with over 60% automation potential. While sectors like finance and insurance heavily rely on expertise, they still spend about half their time on data-related tasks, suggesting a high automation potential. For instance, the financial sector could technically automate 43% of its tasks, allowing professionals, like mortgage brokers, to focus more on advisory roles. Activities in sectors like construction, farming, and forestry, which involve physical work in unpredictable environments, currently have a 25% automation potential. However, with advancements that allow technology to handle unpredictability, this potential could rise significantly [61].

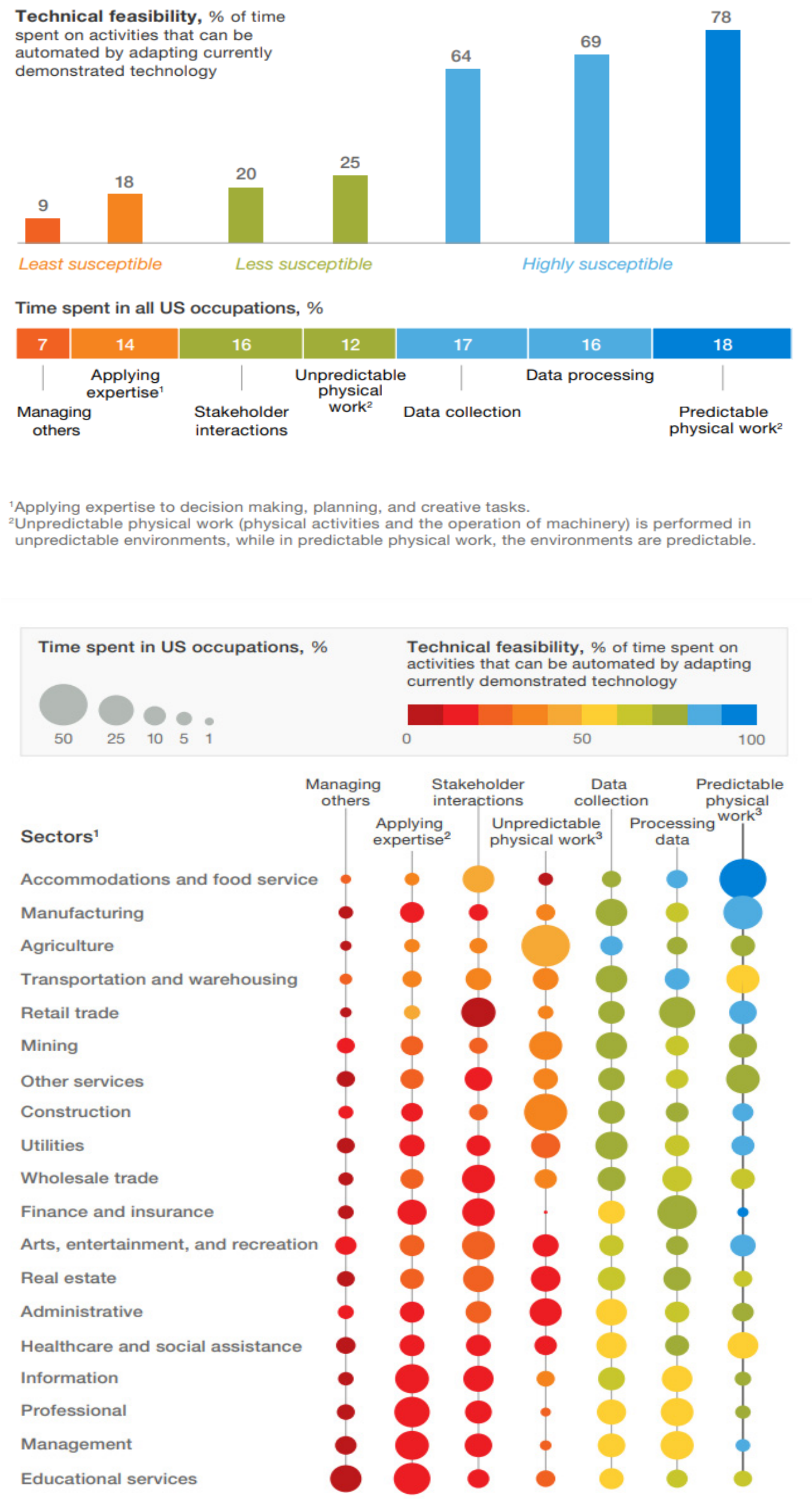

Figure 7. *Cont.*

[1]**Agriculture** includes forestry, fishing, and hunting; **other services** excludes federal-, state-, and local-government services; **real estate** includes rental and leasing; **administrative** includes administrative support and government administration; **healthcare and social assistance** includes private, state-government, and local-government hospitals; **professional** includes scientific and technical services; **educational services** includes private, state-government, and local-government schools.
[2]Applying expertise to decision making, planning, and creative tasks.
[3]Unpredictable physical work (physical activities and the operation of machinery) is performed in unpredictable environments, while in predictable physical work, the environments are predictable.

Figure 7. Automation potential across U.S. professions by task category [61].

5.2. Dynamics of Demographic Shifts

The world population can be broadly categorized into three age groups: ages 0–14 (youth), ages 15–64 (working-age adults), and ages 65 and above (elderly adults) (Figure 8). These data rely on comprehensive demographic data collection and analysis, including the use of statistical models to project population trends based on historical data.

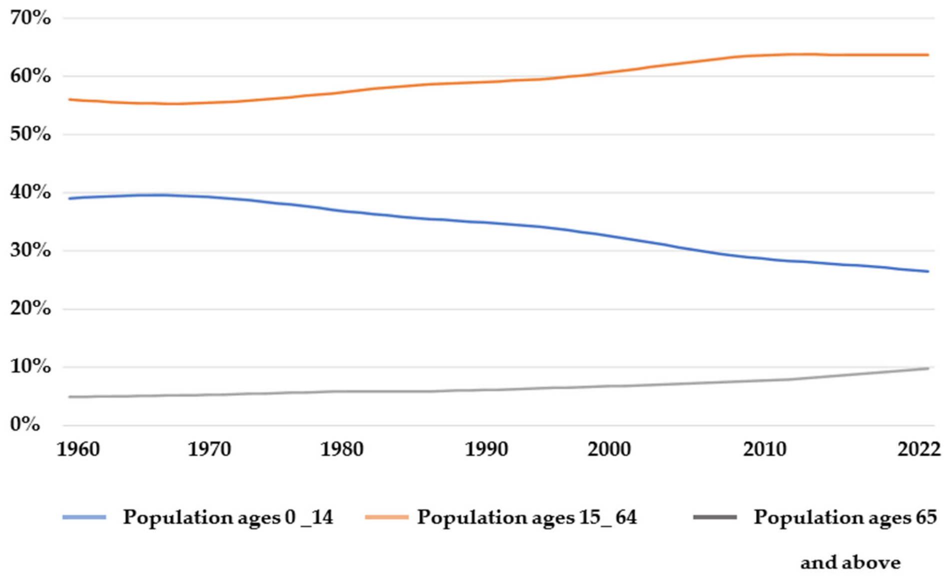

Figure 8. World Population Prospects: 2022 Revision [2].

These categories are often referred to as "population age cohorts". The distribution of the population across these age cohorts has important implications for various sectors, especially for industries. The proportion of the global population in the 0–14 age group has been gradually decreasing in many regions, resulting in a decline known as the "youth dependency ratio". Moreover, the working-age population, ages 15–64, has historically been a driving force behind labor participation across sectors, including agriculture, serving as the main column of industrial labor. Additionally, due to improved healthcare and increased life expectancy, the proportion of elderly individuals (65 and above) within the global population has been steadily increasing [2–4].

As we consider the dynamics of population demographics and their potential impacts on the labor force, it is evident that, in the coming years, numerous regions are projected to undergo shifts in their age distribution. These shifts could have deep consequences for the labor force and various industrial sectors. One potential scenario envisions a higher proportion of working-age adults replacing both the decreasing youth population and the increasing elderly population. While this scenario offers certain advantages, it also raises significant concerns that demand careful consideration [2,3].

One notable example that supports this demographic trend is the Population Pyramids figure for the United States in 2023 (Figure 9), which exhibits a similar trajectory as the global trends discussed above. This figure showcases the age distribution within the U.S. population, highlighting the diminishing youth segment and the increasing elderly segment [2,3].

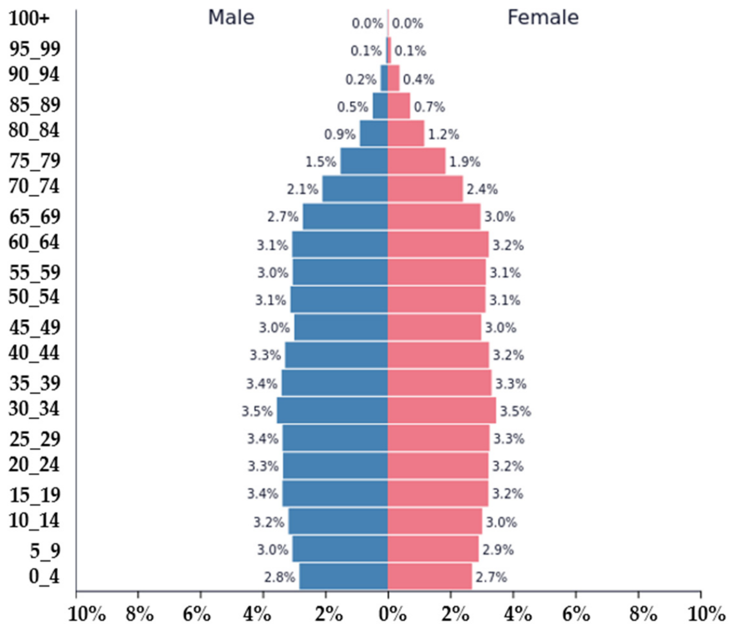

Figure 9. United States of America Population Prospects: 2023 Revision [3].

This potential demographic trend can be analyzed in the following manner and yield the corresponding impacts:

i. Elderly Dominance: The proportion of elderly individuals (ages 65 and above) is expected to experience substantial growth, contributing to the emergence of an aging society. This phenomenon can be attributed to factors such as improved healthcare, increased life expectancy, and declining birth rates.
ii. Shrinking Working-Age Population: Projections indicate a decline in the working-age population (ages 15–64) relative to the elderly population. This reduction may result from declining birth rates and a smaller youth population, leading to a reduced entrance of individuals into the workforce.

These shifts in population demographics are likely to reshape various sectors, including agriculture, as the labor force undergoes a transformative phase. Policymakers, industries, and societies need to anticipate and effectively address the potential challenges and opportunities that might arise from these demographic changes.

This trend has some consequences for labor and agriculture:

i. Labor Shortages in Agriculture: With a declining working-age population, labor shortages in various sectors, including agriculture, could become more obvious. The agricultural workforce might struggle to meet the demands of planting, cultivating, harvesting, and other labor-intensive tasks [3–6].

Figure 10 illustrates the trajectory of labor surpluses and shortages in the US manufacturing sector from 2002 to 2030. Over the years, there have been fluctuations between periods of labor surplus and shortage, with the surplus peaking around 2004 with a surplus of 0.47 million people. However, post-2018, a steep labor shortage is evident, culminating in a sharp projection, indicating a significant deficit by 2030. This figure emphasizes the increasing demand for robotic intervention in the manufacturing domain, especially with the advent of advanced humanoid robots. These robots could potentially address a notable portion of the projected US manufacturing labor gap by 2030, further emphasizing the importance of technological advancements in bridging the labor divide [62].

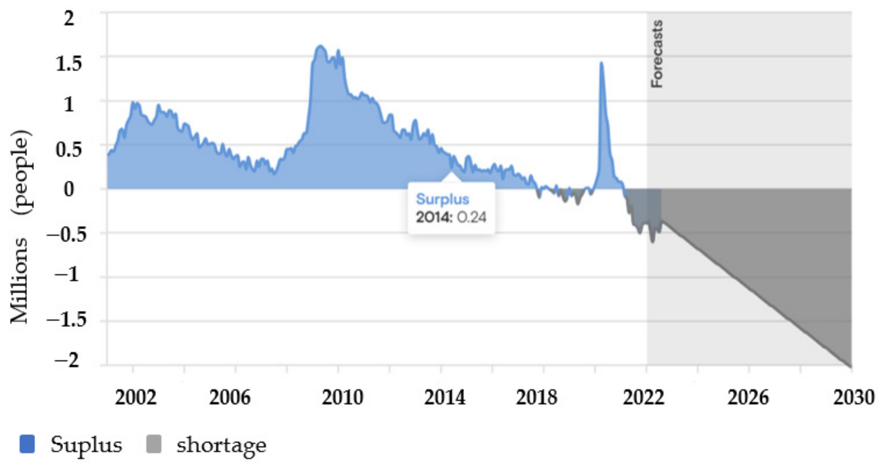

Figure 10. U.S. manufacturing labor surplus/shortage [62].

ii. Increased Reliance on Technology: The decreasing availability of traditional manual labor might drive the adoption of technology and automation in agriculture. Robots, drones, and AI-driven systems could fill the gap by performing tasks that require physical strength and endurance, allowing for continued productivity [3–6,22].

iii. Transition to a Knowledge-Based Workforce: With a lower number of individuals entering the workforce, there could be a shift toward more knowledge-based roles. This includes roles related to technology development, data analysis, precision agriculture, and the management of automated systems.

The blending of careful economic analysis, the rise of agricultural automation, and changing demographics weave together to create the roadmap of this sector. By assessing the cost-effectiveness of automation, understanding the insights from NPV analysis, and grasping how it all aligns with shifting demographic trends, those involved will be in a strong position to move toward agriculture that is resilient, efficient, and full of growth [3–6,22].

5.3. Economic Shifts Caused by Automation

When examining the economics of adopting labor-saving technologies, classification based on decision timing becomes essential. Technologies that save labor can be classified as ex-ante (before adoption) or ex-post (after adoption). This categorization aids in our understanding of the factors influencing the adoption of such technologies [63].

Within ex-ante studies, the priority lies in net present value (NPV) analysis and expected profit maximization models with risk and uncertainty considerations. NPV analysis, a fundamental approach to investment evaluation, involves discounting all financial activities until the present using a discount factor. An NPV greater than zero indicates a potentially profitable investment. However, the NPV has limitations due to its disregard for the uncertainties associated with investment decisions and decision-makers [63].

Expected profit maximization models, incorporating risk and uncertainty, dig into the investment decisions involving productivity efficiencies, technology reliability, and input/output prices. These models address the investment choices characterized by uncertainty, considering adoption decisions at specific moments or over time, based on the critical values of key variables [45,60,64].

It is estimated that by 2030, smart crop monitoring could unlock a value between USD 130 billion and USD 175 billion globally, with the use of enhanced connectivity allowing for accurate soil, equipment, and crop surveillance (Figure 11). Farming by drone, another emerging technological trend, could bring a value ranging from USD 85 billion to USD 115 billion, as drones offer efficient crop surveying, precise interventions, and even potential seeding in remote locations. Smart livestock monitoring, which emphasizes the early detection of diseases and improved animal living conditions, might produce a value of

USD 70 billion to USD 90 billion. Meanwhile, the advent of autonomous farming machinery, leveraging advanced GPS controls, computer vision, and sensors, could add another USD 50 billion to USD 60 billion in value. Additionally, building and equipment management through chip and sensor technologies, which can optimize storage conditions and reduce energy consumption, is expected to save between USD 40 billion and USD 60 billion by the end of the decade. Collectively, these advancements highlight the transformative potential of digital technologies in reshaping the agricultural landscape and boosting global GDP [64].

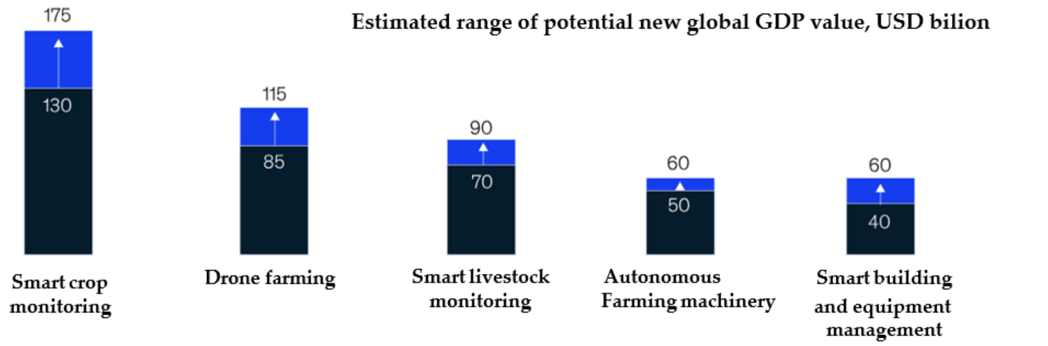

Figure 11. Projected impact of technology on global GDP growth in agriculture and building management [64].

The technological innovations depicted in Figure 11 enable precision farming methods. As these technologies and methods become increasingly prevalent, agricultural efficiency and yields rise. Higher yields mean more products to sell, both domestically and internationally, directly boosting the GDP. It also reduces waste, lowers operational costs, and creates more efficient resource use, like that of water, pesticides, and fertilizers, which means that agricultural operations become more profitable. This profitability not only benefits individual farmers but also has a positive ripple effect on related industries and the economy as a whole, contributing to GDP growth. Furthermore, as these technologies and methods become standardized, they can lead to the emergence of new industries or boost existing ones, like tech companies specializing in agricultural drones or smart sensors, further influencing GDP [64].

The adoption of advanced technologies in agriculture marks a significant shift in the sector, promising to enhance efficiency and profitability. These innovations are not merely incremental; they represent a major leap forward in how we approach farming. The graph presented in Figure 12 offers an overview of the economic impact projected from integrating these technologies into global farming practices by 2050. It draws on comprehensive field research to estimate the potential financial benefits that such technological advancements could yield. The figures forecast an encouraging trend in value generation across various facets of agricultural technology, from precision planting to moisture sensing, indicating a robust potential for growth in the industry [65].

Overall Crop Yield Increase: By integrating emerging technologies into farming practices, there is a potential to uplift global crop yields by an astounding 70%. Considering the 2015 global annual crop production value of USD 1.2 trillion, this surge translates to an additional economic value of USD 800 billion by 2050 if these technologies are universally adopted [65].

Precision Fertilizer Application: This method alone can tap into an addressable market worth USD 65 billion by enhancing yields by 18%. The integration of tractor-mounted sensors, drones, satellites, and data analysis software will be pivotal in this regard [65].

Reduction in Soil Compaction: By employing a fleet of smaller, automated tractors, there is a potential to mitigate soil compaction, which has historically reduced yields by 15–20%. This approach alone presents a USD 45 billion market opportunity based on a projected 13% yield increment [65].

Precision Irrigation: Modern irrigation systems paired with real-time water sensors can not only enhance yields by 10% but also curtail water wastage by up to 50%. This method taps into a USD 35 billion market [65].
Precision Planting: With an expected 13% improvement in yields, the addressable market for this technology stands at USD 45 billion. The key here lies in the use of multi-hybrid planters and sophisticated data analysis tools [65].
Precision Spraying: By optimizing pesticide and herbicide applications, yields can be boosted by 4%. This precise approach carves out an addressable market of USD 15 billion [65].

These figures emphasize the vast economic potential awaiting the full-scale integration of these technologies. Also, with a 70% increase in crop production, it will have a humanitarian impact and can sustainably feed a projected 35% growth in the global population by 2050. In the grand scheme of things, while these technologies promise heightened crop yields, they also signal a significant reduction in resource wastage, thereby amplifying the economic viability of modern farming.

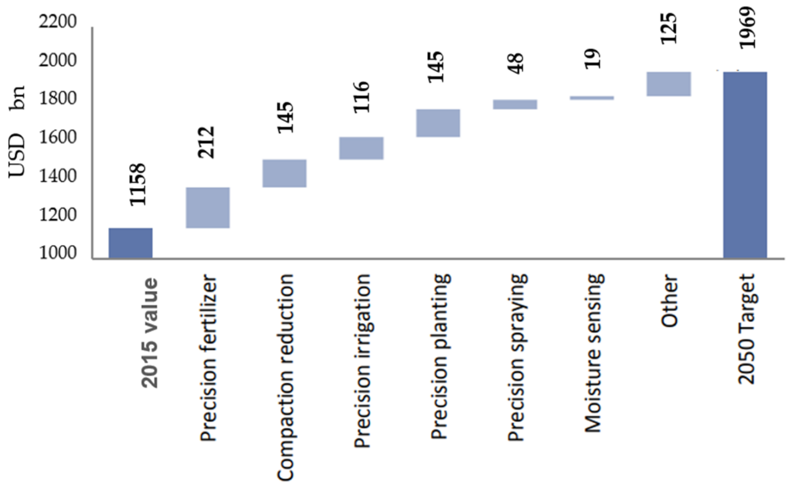

Figure 12. Projected increase in the contribution of farming technologies to the global crop production value by 2050 [65].

6. Advantages and Disadvantages of Automation in Agriculture

The global market for automation and robotics systems in agricultural applications is expected to experience substantial growth, with estimates indicating a rise from USD 7.4 billion in 2020 to USD 20.6 billion by 2025. This growth can be attributed to several factors such as labor reduction, the increasing global population, and the demand for enhanced productivity within the agricultural sector [4,18,66,67].

Additionally, the COVID-19 pandemic has influenced our perspectives on automation. This health crisis has highlighted the vulnerability of numerous industries to disruptions caused by disease outbreaks and lockdowns. Consequently, some businesses, including agriculture, have sought to enhance their reliance on robotics and automation to mitigate such risks and ensure uninterrupted operation [3,8,68]. It should be noted that the proportion of mechanization varies significantly across different industries and fields. Some sectors, such as manufacturing and logistics, have been at the forefront of adopting automation technologies for decades. In contrast, other industries, such as healthcare and hospitality, have traditionally relied more heavily on human labor due to the unique skills and interactions required in these fields [8,67,69,70].

The application of robotics in agriculture presents numerous scientific and technical benefits due to their diverse capabilities. Integrating robotics into agriculture has the potential to substitute human operators, resulting in heightened efficiency, enhanced productivity, and favorable returns on investment. Moreover, robots' inherent advantages, including tirelessness, precise operation, and high speed, further contribute to improved agricultural processes [19,46].

The adoption of robotic technologies and automation systems in agriculture offers the promise of potential cost savings, reduced labor, and enhanced efficiency. Here are further details regarding each aspect:

i. Cost Savings: Utilizing robots and automation systems in field crop production has the potential to save costs through expense reduction. Robots can perform tasks like planting, weeding, and harvesting more efficiently, reducing the need for manual labor. This can result in lower labor costs and increased productivity. Furthermore, automation optimizes resource usage, including water and fertilizers, leading to reduced input costs [5,8,67].

ii. Labor Cost Reduction: In 2021, the agricultural and food sectors in the United States generated 21.1 million jobs, comprising 10.5 percent of total employment. Direct on-farm employment accounted for 2.6 million jobs (1.3 percent of total employment), while the rest were supported by industries related to agriculture, with food services leading at 11.8 million jobs, followed by food/beverage stores at 3.3 million jobs, and other agriculture-related industries adding 3.4 million jobs [70]. However, labor expenses in the U.S. agricultural sector are projected to reach USD 42.09 billion in 2023. This reflects a 4.4 percent increase from the 2022 level of USD 40.31 billion (adjusted for inflation).

Labor costs are a significant part of agricultural production expenses, accounting for nearly USD 10 out of every USD 100 spent. These expenses cover both contract and hired labor but exclude non-cash employee compensation (Figure 13) [71].

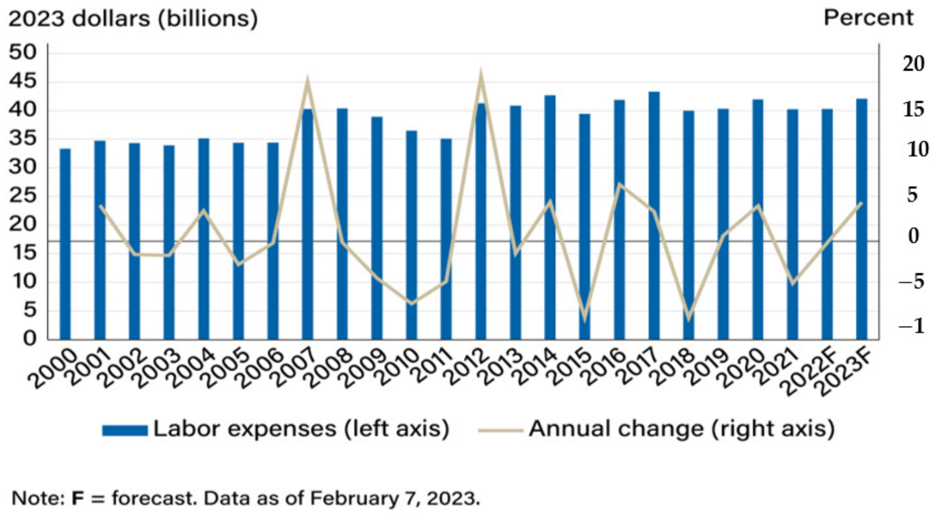

Figure 13. USA agricultural labor expenses forecast: 2023 revision [71].

By incorporating robotics and automation in agricultural tasks, the need for human labor can be reduced. Labor-intensive activities like planting, weeding, and harvesting can be automated, reducing the reliance on manual labor. This can address challenges related to labor availability, labor costs, and potentially improve efficiency by enabling continuous operation without human limitations [3,5,8].

iii. Efficiency Improvements: Robots and automation systems have the potential to improve the overall operational efficiency in field crop production. They can operate with precision and accuracy, resulting in optimized resource usage, reduced errors, and increased crop productivity. For instance, robots can precisely apply fertilizers or pesticides in specific quantities and to targeted areas, minimizing waste and improving effectiveness. Automation can also enable tasks to be performed at optimal times, considering factors such as weather conditions and crop growth stages [3,5,67].

iv. The utilization of robots in agriculture holds significant potential for promoting sustainable practices and preserving ecological systems. By leveraging the precision and efficiency of robotics, farming can transition towards methods that minimize environmental impact, optimize resource use, and enhance biodiversity. Such technologies not only aim to boost productivity but also support the regeneration of natural ecosystems, highlighting a path forward where agricultural innovation and ecological conservation go hand in hand. This approach underscores a vital research direction, emphasizing the need for solutions that are economically viable, socially equitable, and environmentally sustainable [57].

However, despite the scientific and technical benefits, there are also notable drawbacks associated with the adoption of robotics in agriculture. Here, an overview of the disadvantages of robotics and automation in agriculture is given:

i. High Initial Investment: Implementing robotics in agriculture requires significant upfront investment. The cost of purchasing and maintaining robots, as well as integrating them into existing farming systems, can be expensive for farmers, especially small-scale ones. This financial burden may limit the adoption of robotics in some agricultural operations [29,72–76].
ii. Limited Adaptability: Agricultural robots are designed for specific tasks and may lack the flexibility to adapt to diverse farming practices. They often operate optimally in controlled environments with standardized crops. Farmers who have varied or specialized farming operations may face challenges finding robots that suit their specific needs [72,73].
iii. Technical Complexity and Maintenance: Agricultural robots require advanced technical knowledge for their operation, programming, and maintenance. Farmers may need to acquire additional skills or hire specialized personnel to handle these tasks. Regular maintenance, software updates, and troubleshooting can also be time-consuming and may disrupt farming operations if not properly managed [26,74].
iv. Lack of Human Intuition: Agricultural robots, while efficient at performing repetitive tasks, lack human intuition and decision-making capabilities. They may struggle with complex or unpredictable situations that require human judgment. This limitation can hinder their effectiveness in tasks that involve delicate handling, the identification of pests or diseases, or making nuanced decisions based on real-time conditions [60,71,77].
v. Specialized Training Needs: The successful implementation and operation of agricultural robots often require specialized training for farmers and agricultural workers. Learning to operate and program these sophisticated machines may involve a learning curve and an additional investment of time and resources. Acquiring the necessary skills and knowledge to effectively utilize robotic technology may pose a challenge for some farmers, especially those who are less familiar with advanced technologies or have limited access to training resources [75,76,78].
vi. Impact on Employment: The adoption of robotics in agriculture has the potential to reduce the need for human labor. While this can lead to increased efficiency and productivity, it may also result in job displacement for agricultural workers, particularly those involved in manual labor. This can have social and economic implications, especially in regions where agriculture is a significant source of employment [72–74].
vii. Dependence on Technology: The upcoming “digital agricultural revolution” has sparked excitement as it promises to boost productivity and minimize environmental impacts. As a result, multinational corporations are investing more in agricultural data management. These companies, usually involved in various aspects of agricultural production, have been acquiring technology firms to strengthen their presence in this domain. For instance, Monsanto acquired Precision Planting in 2012 and Climate Corp the following year, while Dupont partnered with John Deere to offer a wireless data-transfer system and collaborated with DTN to provide market and weather information. John Deere has also expanded its machine-learning capabilities by purchasing Precision Planting from Monsanto and recently acquiring Blue River Technologies. Several entrepreneurs have followed suit and invested in digital services for the agricultural sector. However, despite their significant interest and investments, the

actual transformation of agricultural practices through this technological revolution has been relatively slow [24,63,79–81].

Introducing robotics into agriculture increases its dependence on technology. Any system failures, power outages, or technical issues can disrupt operations and have a significant impact on productivity. Farmers need to have contingency plans in place to mitigate such risks and ensure the continued functioning of their operations.

It is important to note that advancements in robotics technology and ongoing research may address some of these drawbacks over time. However, it is crucial to carefully consider these factors before implementing robotics in agriculture to ensure they align with specific farming requirements and circumstances [23,82–84].

One major concern in the context of robotic systems replacing human labor in agriculture is the potential unemployment, particularly for tasks traditionally performed by farm workers. Although digital agriculture often idealizes its image without considering agricultural workers, labor remains integral to the sector, playing a crucial role in rural economies, sustainable farming practices, and ensuring food supply. Unfortunately, discussions surrounding digital agriculture have largely overlooked its social impacts, particularly concerning labor. Studies suggest that while digital technologies may generate new skilled jobs, they may also displace low-skilled labor, potentially reinforcing existing inequities. To ensure a sustainable and equitable farming system alongside digitalization, it is necessary to carefully consider the implications of labor in agricultural practices [35,84–86].

The decision to replace human labor with automated machines in various industries and contexts is influenced by several factors. In the agricultural sector, common considerations include cost-effectiveness, labor availability, technological advancements, safety, scalability, production volume, and quality consistency. However, the implementation of robotic technology may give rise to liability issues due to complexities surrounding the responsibility for damages or accidents caused by robots. Additionally, limited access to advanced robotic technology poses challenges for smaller-scale or resource-constrained farmers in adopting and implementing such systems. Although robots can autonomously perform numerous tasks, periodic human intervention remains necessary for their supervision and maintenance, adding complexity to the overall system. To fully capitalize on the potential of agricultural automation, it is essential to address these challenges and invest in advancing technological maturity. Continued research efforts, investments in infrastructure and data platforms, and supportive policies from governments and private firms are crucial to ensuring the successful integration of automation technologies into agriculture. Moreover, considerations of the social and labor implications of automation should be taken seriously. While automation can enhance efficiency and productivity, it should be done in a way that ensures a sustainable and fair farming system. Policymakers, businesses, and societies as a whole must proactively address these challenges to create an ideal future for people around the world [85,87–95].

7. Discussion

Considering the comprehensive examination of the relationship between demographic shifts and the economic impacts of automation in agriculture outlined in the preceding sections, this paper emphasizes the complex nature of integrating robotic technologies into agricultural operations. While offering substantial advantages such as cost reductions, reduced dependency on manual labor, and improved operational efficiency, the introduction of robotic automation in agriculture also presents notable challenges.

The findings of this analysis support previous research, which has consistently highlighted automation's potential to enhance productivity and sustainability within agricultural settings. Moreover, economic feasibility and market alignment underscore the imperative need for continued investment and exploration in this domain.

The transformative potential of automation in agriculture is evident, particularly in addressing critical issues such as labor shortages and resource optimization. However, it is crucial to recognize the societal implications, particularly those relating to workforce displacement and the demand for specialized skill sets. Additionally, the demographic analysis presented in this review suggests that automation could play a crucial role in mitigating labor shortages as the proportion of the working-age population decreases.

In summary, while the integration of robotic technologies holds immense promise for the agricultural sector, careful consideration of both the benefits and challenges is necessary to realize its full potential. Continued research and strategic policymaking are essential to navigate the complex landscape of automation in agriculture and ensure its equitable and sustainable implementation.

8. Future Work

Future inquiries in the field of agricultural robotics should prioritize investigating the socio-economic consequences of increasing automation, emphasizing strategies for equitable integration and the creation of skilled employment opportunities. Further research trajectories must study the specific application of automation in diverse agricultural sectors, tailoring technological solutions to accommodate varied farming practices and crop types. Interdisciplinary research, integrating economic, social, and technological insights, will play a crucial role in establishing comprehensive frameworks for the responsible adoption of automation technologies. Collaboration between policymakers and industry stakeholders is essential to formulate policies that foster sustainable and equitable growth, considering changing demographic dynamics and the broader implications for global agriculture.

The challenges associated with utilizing robots in agriculture, including navigating through dynamic and unstructured environments, developing robust control systems, and addressing high costs, require comprehensive solutions. Our future work in this area will focus on harnessing artificial intelligence to analyze vast datasets, incorporating both traditional and modern agricultural practices to inform decision-making processes. This approach aims to identify innovative solutions to agricultural challenges through automation, enabling the development of robots capable of adapting to varying plant, soil, and weather conditions. By gathering reliable information, this research seeks to address the economic feasibility of robotic technologies in agriculture, aligning them with market needs and contributing to sustainable farming practices.

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