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Agriculture and Automation: Potential Benefits, Difficulties and Economic Impacts

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Abstract

In contemporary agriculture, automation and robotics are the main players. They present viable answers to issues with the world's expanding population, changing demographics, and economic standing. This analysis examines the potential and difficulties of utilizing new technologies as well as the frequently overlooked connection between automation technology and agricultural economics. This study examines the potential of automation and robots in farming techniques, as well as their socio-economic impacts, through a methodical analysis of the literature. It also offers practical advice for those involved. For this reason, a variety of robot types used in diverse agricultural fields have been examined, along with the difficulties and technical viability of adopting automation. Additional significant aspects have been examined, such as changes in the labour market, economic conditions, and demographic trends. This study also looks into the social effects of automation, specifically with regard to worker adaption and employment. It discovers that although automation increases sustainability and efficiency, it also results in labour displacement and necessitates significant technological investment. This in-depth analysis closes a significant gap by evaluating precision agriculture's future, labour market change, and economic viability. Along with outlining a future roadmap for research and policy, it also plots a course for future studies and policy-making at the nexus of agricultural technology and socioeconomic domains.

1. Introduction

The world's rapidly expanding population is causing a severe scarcity of food resources. The population of the world is expected to rise from its current 7.6 billion in 2023 to approximately 9.8 billion by 2050. The swift increase in population poses a significant challenge in light of the escalating need for food. The ancient farming practices that have been in use for thousands of years are currently unable to meet the increasing demand for food. As the world's food supply cannot keep up with the growing demand, the agriculture industry needs to change its methods fast. For food production to be sufficient, effective, and sustainable, it must implement cutting-edge technologies [1-3]. However, the young population is dwindling and the share of the old is rising, which raises severe concerns about the labour force of the future, especially for agriculture. The labour-intensive duties may prove to be too much for the agricultural crew to handle. A larger knowledge-based workforce, including jobs in technology development, data analysis, precision agriculture, and automated system management, may result from this demographic shift [4–8]. Given the pressing worldwide issues surrounding this subject and its existing constraints, the incorporation of automation technologies into every facet of agriculture appears to be a practical and efficient resolution, heralding in a new age for this sector.

The development of automation from conventional to contemporary techniques, such as precision farming, will have a significant impact on food production in the future [5,9,10]. Several revolutionary revolutions in agriculture have occurred throughout history, all of which have been linked to advances in technology that have had a major impact on productivity and efficiency. The shift to the next generation of agriculture, which gives the chance to boost productivity and realise our full potential in the field, is made possible by the introduction of automation. Automation-driven precision farming is an illustration of how cutting-edge technologies and conventional farming methods may coexist peacefully. It provides data-driven decision making, accurate resource allocation, and input utilisation optimization—a set of characteristics vital in a time characterized by growing environmental concerns and a growing world population [9–12]. A closer examination of the field of agricultural robotics helps us see just how far-reaching the effects of automation can reach. Precision farming and efficiency could be revolutionised by agricultural robots that can carry out a variety of duties, from exact crop yield estimation to soil preparation prior to planting.

The economic implications of automation in agriculture, however, present a different aspect of the story. It is important to weigh the possible financial gains—like significant cost savings and increased labour efficiency—against the drawbacks and difficulties of automation, such as the high upfront costs of the infrastructure and the need for specialised technical knowledge to maintain it [3-5,13–17].

This essay offers a thorough analysis of the many ramifications of this technical advancement, with an emphasis on its viability, advantages, and difficulties from an economic standpoint. The goal is to give a comprehensive understanding of how automation affects and changes the economics of agriculture, which will be helpful to a wider range of scientists, policymakers, and stakeholders in addition to agriculture experts [2,3,5,10–13,18,19].

2. Material and Method

A thorough assessment of the literature was done in order to investigate the financial implications of agricultural automation. A wide range of databases and search engines were used in the thorough search for pertinent publications, ensuring a diverse collection of viewpoints and information. The databases that were utilised were Web of Science and Scopus, which are well-known for their comprehensive coverage of academic articles that have undergone peer review in a variety of fields, including technology, economics, and agriculture. Due to its extensive indexing of academic books, theses, conference papers, and reliable reports that offer a wide variety of viewpoints on the topic, Google Scholar was used. Specialised library catalogues were also searched in order to include research that might not be easily found in larger databases. Although papers and other materials published after 2005 were included in the search approach, we focused on more recent years because they represented notable advancements in agricultural technology.

This time frame is relevant to our research since it is seen as the start of a new age in agricultural automation. A wide range of pertinent research was covered by the use of keywords and phrases such "agricultural automation," "economic impact of farm technology," "environment impact," "precision agriculture," and "agricultural robotics." Boolean operators were used to combine terms in the search, and filters for publication date, document type, and full text accessibility were applied.

Studies that addressed the economic effects of agricultural automation, either directly or indirectly, were the focus of the inclusion criteria, while those that only addressed the technical elements without corresponding economic analysis were excluded. Duplicates were removed after the first search, and the remaining articles were evaluated for relevancy based on their titles and abstracts. The complete texts of the chosen articles underwent a comprehensive vetting process. Relevant data about the economic aspects of agricultural automation were extracted, such as research on the effects of new technology and productivity changes, the labour market and ecological effects, and larger economic implications.

3. Agriculture's Evolutionary Path

This timeline illustrates major changes from Agriculture 1.0, which was defined by antiquated farming practices based on human labor and animal power, to Agriculture 4.0, where digital technology are revolutionizing the agricultural sector. Agriculture 2.0 represented a significant turning point in which agricultural machinery was used to boost food output and decrease manual labour. Following this, developments in computing and electronics gave rise to Agriculture 3.0, also referred to as precision farming, which enhanced the efficiency of resources and the operational performance of agricultural systems. Precision agriculture, or PA, has been instrumental in starting the agricultural sector's digital transition. In the same way that Industry 4.0 has impacted many industries, Agriculture 4.0 offers a new revolution in which digital robotics 2024, 13, 33, 5 of 24 technologies are seamlessly incorporated into farming methods.

The parallel development of agriculture and industrial revolutions highlights the role that agricultural automation will play in determining crop yield in the future and resolving issues with contemporary farming methods [10,12-20]. But the prosperity of farmers will be greatly impacted by Agriculture 5.0, especially in the post-pandemic period. Using alternate energy sources and cutting-edge technologies into farming methods is known as "agriculture 5.0." When green energy sources are combined with these technologies, smart farms can benefit from affordable financial access, real-time weather updates, remote monitoring capabilities, and future energy options. Green energy sources can be added to Agriculture 5.0 to reduce costs, boost energy efficiency, and create sustainable, energy-smart farms [11, 21–25]. The potential for greater operational efficiency, improved precision, and the capacity to handle particular agricultural difficulties demonstrate the scientific and technological significance of robots in agriculture.

By utilising renewable energy sources to power autonomous robots, agriculture can operate continuously, decreasing the need for human intervention and raising total production. Furthermore, the integration of sophisticated sensing technologies, like photoelectric and capacitive sensors, enables enhanced intra-row weeding skills for robots. With the development of flying microrobots, new avenues for focused interventions—like controlling weeds and insects—are made possible by the robotic systems' special ability to fly and land. It is significant to remember that additional robotics research and development will spur innovation and increase the scope of robots' use in agriculture. These developments have a lot of potential to enhance farming methods, maximize resource use, and support effective and sustainable farming systems [22, 24–26].

4. Various Agricultural Robot Models

For plant detection and monitoring in precision agriculture, a variety of platforms are frequently utilised, including satellites, aerial vehicles (like unmanned aerial vehicles, or UAVs), and ground-based vehicles (like field robots or commercial off-highway vehicles).

Large-scale field monitoring, like variable-rate herbicide spraying, usually makes use of satellite and aerial sensing. These platforms do, however, have several limitations, including their reliance on weather and air quality and their geographic resolution. Higher spatial resolution is provided by low-altitude aerial sensing and ground vehicle-based sensing, making them appropriate for applications like in-row weed management in real time. Spectral reflectance and biological morphological features are the foundation of weed plant perception techniques, which are used to identify and examine the existence of weeds. When using ground vehicle-based techniques, factors to take into account are field travelability in different soil conditions, matching crop spacing, and clearance over the crop.[27–33]

4.1 Before planting, prepare the land

Ploughing and fertilizing are two tasks involved in land preparation for agriculture. While ploughing can have an impact on soil carbon reserves, it also aids in oxygen penetration and carbon dioxide release. Contrarily, fertilization is vital in replenishing the vital nutrients required for crop growth. In order to facilitate and enhance these duties, robots have been created to offer significant support. Notable examples include the DJIUAV, which specializes in aerials agricultural activities, the Casar [35], which is dedicated to soil fertilization and pest management, and the Greenbot robot [35], which is made for fertilizing, ploughing, and sowing. Modern technologies such as RTK/GNSS are used by these robots to precisely position themselves, greatly enhancing their control and navigational abilities. Furthermore, improved safety during their operations is ensured by the incorporation of collision sensors and obstacle detection systems. Research is still being done to produce more affordable embedded systems and enhance weed-detecting techniques to further expand robot control capabilities [33, 35–37].

Despite the adoption of protective measures, farmers' exposure to the potentially damaging effects of pesticides and liquid fertilizers must be reduced by the introduction of spraying robots. Owing to developments in computer vision and artificial intelligence, these robotic sprayers are outfitted with highly developed intelligence systems. These robots can selectively target areas for spraying, in contrast to traditional systems that administer a homogeneous spray over crops. This targeted strategy not only lessens the environmental impact of agriculture but also lowers consumer exposure to pesticides and helps keep pests from becoming resistant to these substances [37, 38].

4.2 Planting and Seeding

Agriculture-related activities such as planting and sowing are typically completed with tractor-mounted equipment. Heavy machinery and continuous tractor movement, however, can cause soil compaction and the detrimental impacts that follow on soil qualities and crop development. Robotics has emerged as a viable way to automate and improve the precision of sowing and planting procedures in order to address these issues. The goal of current research is to create low-cost, modular robots that can efficiently service small farms.

For tasks like precision seeding, spraying, and weeding, prototypes are being developed. The primary goals are to increase farmer accessibility, decrease soil compaction, and improve efficiency. Numerous robotic systems have been created, such as wheeled robots that can plant various crops at a rapid speed, robots that are specialized to particular crops, like wheat, and robots with straightforward designs that are simple to carry and assemble. These robots include closed-loop control mechanisms and sensors to keep an eye on their pressure, speed, and tilt [36, 34, 35, 38, 39].

A small-sized prototype seed drill robot with a 17 kg payload capacity in its reservoir has been unveiled by Indian researchers. It minimises soil compaction by navigating uneven soils effectively with a tracked drive system. The robot's estimation of its position and movement across the field is powered by a photovoltaic panel, which is part of its environmentally conscious design [27].

4.3 Plant Therapy

Innovative plant treatment techniques have been made possible by robotic applications in agriculture. These approaches involve using robots with a variety of sensors, cameras (including thermal and high-spectral cameras), and mechanical instruments to control weeds in crops, diagnose diseases, manage pests, and irrigate. Critical elements include plant disease detection and treatment, weed control, targeted herbicide application, and specialised crop monitoring have been the focus of recent research initiatives, all of which are essential to maintaining agricultural fields [40].

Strategic integration of AI-powered predictive analytics is employed in the project to mitigate potential data gaps and inconsistencies. These analytics combine gathered statistics with openly accessible data sources to refine models for application in particular scenarios. When sensor data experiences prolonged unavailability or inconsistencies, our customized data resource works as an efficient backup plan. Tests of actual irrigation systems in Slovenia and Cyprus provided clear evidence of the platform's practical effectiveness. For instance, the QUHOMA platform demonstrated its effectiveness throughout a strawberry crop cycle in Cyprus by significantly reducing water use by 10.88% when compared to traditional empirical irrigation techniques. This reduces the cost of human resources as well as water supplies [41, 42].

4.4 Determine Yield, Phenotyping, and Spatial Information

In this regard, money has recently been awarded to the extensive NaLamKI project by the German Federal Ministry for Economic Affairs and Energy, which aims to create a cloud-based Software as a Service (SaaS) platform with open APIs. These interfaces are intended to serve industry and service providers specializing in particular crop production applications and entities within the agricultural sector's downstream and upstream segments. The project aims to create a dataset by integrating sensor data from machinery, satellite and drone aerial surveillance, soil, meteorological conditions, and other pre-existing data sources. This project aimed to improve agricultural operations by utilizing advanced artificial intelligence techniques for pest management, fertilization, and irrigation. [43, 44].

Furthermore, the digital twin (DT) concept in the industrial area offers options for maintenance strategies, ongoing monitoring, and simulation testing. Despite the differences between factory production and agriculture, this approach aims to match Industry 4.0 requirements. The agricultural department plays a crucial role in improving crop prediction precision, cost control, and plantation data by acting as a trustworthy repository. Using a virtual replica, the DT facilitates the investigation of intricate situations impacted by multiple interconnected elements. It finds use in a variety of sectors, such as monitoring asset evolution, producing precise weed control maps, and quantifying phenotypic traits [45, 46]. The Simultaneous Localization and Mapping (SLAM) technique allows robots to navigate and map their surroundings. Agricultural robot autonomy is essential, particularly in complicated and unpredictable farm contexts. SLAM creates a map by combining information from multiple sensors and tracks the position of the robot on it. This technology increases the productivity of robots and decreases the need for manual labour by supporting tasks like crop monitoring, precision agriculture, and autonomous crop navigation. It's a part of a larger trend in agriculture towards automation to boost sustainability and production [47].

Even while technological improvements have been happening quickly, we still don't fully comprehend how they affect our relationship with the natural world. Let us introduce the notion of the "new ecology of automation," which combines the study of digital landscapes with the application of robots in environmental management. With a focus on how robots can be employed in fields like precision farming, conservation, and environmental monitoring to promote sustainability and increase our understanding of ecological systems, this approach intends to study how automation can affect the way humans interact with the natural world [48]. This technical evolution offers a critical chance to reevaluate and increase the economic value gained from this sector, especially in the context of agriculture. The vanguard of developing a more productive, sustainable, and financially successful agricultural economy is the integration of modern robotics and automation technologies into agricultural processes. These technologies aim to transform conventional farming practices, resulting in higher output, less environmental impact, and improved crop management and monitoring capabilities [49].

5. An Economic Assessment of Automation in Agriculture

With a substantial $1.420 trillion, or 5.5% of the GDP, given by the agricultural industry and related businesses to the U.S. economy in 2022. Agriculture produced $223.5 billion in direct value, or 0.9% of the GDP. Due to its fundamental role in a number of other sectors, including food and beverage manufacturing, food and beverage stores, food services, textiles, apparel, leather products, forestry, and fishing, all of which depend on agricultural outputs to add further value to the economy, this shows how the agriculture sector's influence extends beyond this number [50]. The convergence of agricultural automation and economic analysis arises as a catalyst between changing demographics and technological advancement.

5.1 Technological Automation's Feasibility

In the future, there will be more convergence and clarity at the nexus of economic analysis, technology adoption, and agriculture. Though they might not entirely replace much employment shortly, automation will alter most jobs in some way. The type of employment determines how much they alter it. These days, machines can perform a wide range of occupations that previously required a high level of competence, such as healthcare, banking, and agriculture [51]. The possibility that particular tasks can be performed by machines using the current technologies is evaluated in this automation analysis. In essence, it's questioning whether automating these duties is technically feasible. Each profession involves a wide range of tasks, each with a unique potential for automation; Figure 7 lists the seven main work types that were examined. Since every function has a distinct potential for automation, an overall estimate for the industry is obtained by analyzing the amount of time employees devote to each activity throughout a workweek [51].

5.2 Economic Shifts Caused by Automation

When analyzing the financial implications of implementing labor-saving technologies, decision-timing-based classification becomes crucial. Labor-saving technologies can be categorized as ex-ante (before to adoption) or ex-post (after adoption). This classification helps us understand the variables driving the adoption of these technologies [52].

The emphasis in ex-ante research is on expected profit maximization models with risk and uncertainty concerns as well as net present value (NPV) analysis. An essential method for evaluating investments is NPV analysis, which counts all financial activities up until the present by applying a discount factor. An investment may be lucrative if the net present value is greater than zero. Nevertheless, the NPV is constrained because it ignores the uncertainty surrounding investment decisions and decision-makers [52].
According to estimates, smart crop monitoring may unleash a value of between USD 130 billion and USD 175 billion globally by 2030. This is because improved connectivity would enable accurate crop, equipment, and oil monitoring. Drone farming is another rising technological development that has the potential to be worth USD 85 billion to USD 115 billion. Drones are useful for precise interventions, efficient crop surveillance, and even potential seeding in remote regions.

Smart livestock monitoring, which prioritizes better animal living conditions and early disease identification, may yield a value of $75 billion to $90 billion. The development of autonomous farming machinery, which makes use of sophisticated GPS controls, computer vision, and sensors, has the potential to generate an additional value of USD 50–60 billion. Furthermore, it is anticipated that by the end of the decade, building and equipment management using chip and sensor technologies, which can optimize storage conditions and minimize energy usage, would save between USD 40 billion and USD 60 billion. When taken as a whole, these developments demonstrate the revolutionary potential of digital technologies in transforming the agricultural environment and raising the world's GDP [53].

6. The Pros and Cons of Agricultural Automation

Because of its many capacities, robotics offers several scientific and technological advantages when applied to agriculture. Robotics integration in agriculture could replace human operators, leading to increased production, improved efficiency, and profitable returns on investment. Furthermore, the intrinsic benefits of robots—such as their speed, accuracy, and industriousness—also help to enhance agricultural processes [19, 40]. The use of automation and robotic technologies in agriculture has the possibility of lower labour costs, increased productivity, and cost savings. The requirement for human labour in agricultural chores can be decreased by implementing robotics and automation. Work-intensive tasks such as weeding, harvesting, and planting might be mechanized, therefore decreasing the need for physical labour. In addition to addressing issues with labor availability and pricing, this may increase efficiency by enabling continuous functioning without the constraints of humans [3,5,8].

The use of robots in agriculture is not without its obvious disadvantages, nevertheless, even with its scientific and technological advantages. Below is a summary of the drawbacks of automation and robotics in agriculture:

1. **High Initial Investment:** There is a large upfront cost associated with implementing robotics in agriculture. For farmers, particularly small-scale ones, the cost of buying, maintaining, and integrating robots into current farming systems might be high. The use of robotics in certain agricultural processes may be constrained by this financial burden [29, 54, 55].
2. **Restricted Flexibility:** Since agricultural robots are made to do certain jobs, they might not be able to adjust to a wide range of farming techniques. They frequently function best in regulated settings with standardized crops. It may be difficult for farmers with diverse or specialized farming operations to locate robots that meet their unique requirements [55].
3. **Technical Complexity and Maintenance:** The operation, programming, and maintenance of agricultural robots require sophisticated technical knowledge. To complete these responsibilities, farmers might need to recruit specialized staff or pick up new skills. In addition to being time-consuming, routine maintenance, software upgrades, and troubleshooting can cause farming operations to be disrupted if not handled correctly [56].
4. **Absence of Human Intuition:** Agricultural robots are effective at doing repetitive jobs, but they are not capable of making decisions or utilizing human intuition. When faced with difficult or uncertain circumstances that call for human judgment, they could struggle. This limitation may make it more difficult for them to perform activities requiring careful handling, disease or pest identification, or making complex judgments in the face of changing circumstances [57].
5. **Needs for Specialised Training:** Farmers and other agricultural personnel frequently need specialised training to successfully install and operate agricultural robots. There can be a learning curve and additional time and resource requirements to run and program this complex equipment [56].
6. **Employment:** The use of robotics in agriculture may result in a decrease in the demand for human

labour. Although this might result in higher production and efficiency, it might also cause agricultural workers—especially those who perform manual labor—to lose their jobs. This may have social and economic repercussions, particularly in areas where agriculture employs a sizable portion of the labour force [55-56].

7. Conclusion

This paper highlights the complexity of integrating robotic technology into agricultural operations, taking into account the thorough analysis of the relationship between demographic changes and the economic effects of automation in agriculture provided in the previous sections. Although robotic automation in agriculture offers significant benefits like lower costs, less reliance on manual labour, and more operational efficiency, it also comes with significant problems. The results of this investigation corroborate earlier studies that have repeatedly shown how automation can improve sustainability and productivity in agricultural settings. Furthermore, market alignment and economic viability highlight how crucial it is to keep funding research and development in this area.

Automation has the potential to revolutionize agriculture, especially when it comes to solving important problems like resource optimization and labour shortages. But it's important to understand the societal ramifications, especially as they pertain to labour, relocation as well as the need for particular skill sets. Furthermore, as the share of the working-age population declines, automation may be essential in reducing labour shortages, according to the demographic analysis included in this research.

In conclusion, even if the agricultural industry has a lot of potential for the integration of robotic technologies, careful analysis of the advantages and disadvantages is required to fully realize this potential. To ensure the equitable and sustainable application of automation in agriculture, it is imperative to conduct ongoing research and engage in strategic policymaking.

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