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The Role of AI in the Primary Sector

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ABSTRACT

Increased reliance on Artificial Intelligence (AI) has intensified patterns of sectoral dependency in the global economy, a trend that dates back to the Industrial Revolution. While the adoption of AI in the secondary and tertiary sectors has greatly expanded, its integration remains uneven for the primary sector. This paper assesses the advantages and disadvantages of AI in the agriculture, fishing and forestry industries. The current literature also adds to this, highlighting that smaller firms face particularly significant barriers, ethical and regulatory concerns surrounding inequality and job displacement, among other barriers. Overall, this paper suggests the need for stricter regulations, and tailored planning for each industry, through government initiatives that integrate Environmental Non-Governmental Organizations (NGOs) and AI developers. Moreover, it suggests that technological progress promotes efficiency, equity, and sustainability.

Keywords:
Artificial Intelligence, primary sector, working conditions, sustainability, inequality

SECTION 1: INTRODUCTION

The evolution of technology and its ever growing dependency, especially in recent years, with Artificial Intelligence (AI), has exacerbated the global economy's sectoral dependency, a trend seen since the Industrial Revolution. Since the 1760s, there has been an enormous drop in agricultural employment in major countries, going from being roughly 50% of their total employment to less than 10% nowadays.[1] Consequently, while investments in AI in other sectors have skyrocketed, those in the primary sector have decreased. This change has led to the relocation of investments and automation, primarily focusing on the secondary and tertiary sectors, which has left the primary sector limited in its potential. As a result, understanding how to efficiently implement AI and examine the challenges and benefits of this implementation has become increasingly significant.

[1] Sources: Our World In Data, "*Employment in Agriculture*", 2023; LSE, "Economic development in Africa and Europe: reciprocal comparisons", October 2015; Economic History Association, "Rural Agriculture Workforce By County, 1800 To 1900", n.d

Current literature explores both the promise and limitation of AI in the various economic sectors. Chan (2024) showcases that, in general, AI use has significantly increased in recent years, particularly in the tertiary sector. This is because the tertiary sector is currently the sector that relies the most on AI, while the primary sector is still in the early stages of adoption. The difficulties of implementing AI have also been discussed in various papers. For instance, Aliu and Sarumi (2026) suggest that Small and Medium-sized Enterprises (SMEs) would particularly struggle with the immense costs, lack of digital literacy and limited access to infrastructure. On the other hand, Bjola (2022) emphasizes ethical issues, especially in areas like healthcare distribution, poverty reduction, pollution curtailment. Overall, the literature stresses the need for a more universal regulation system, in the hope of not only reducing job displacement but also socioeconomic inequalities.

Building on this literature, this paper analyzes the process of AI integration within three industries, namely, the agricultural, fishing and forestry industries. The results reveal that, overall, AI in the primary sector offers significant efficiency gains and safety improvements. However its impact relies on the industry in which it is implemented. For instance, the agricultural industry faces the most obstacles in regard to accessibility and cost, while the fishing and forestry industries present a more lenient integration pathway. Yet, there are still common challenges that persist, such as the risk of workforce displacement, the need for training workers, and concerns regarding long-term sustainability and viability.

Moreover, this paper shows how the primary sector aligns with the current literature, it also highlights the importance of sector dynamics and the implications for policymakers and stakeholders. Within the three industries studied, the agricultural industry presented the most drawbacks, primarily due to its extent, while the other two did not present as many. Overall, the findings point to a need for stronger regulations concerning training, safety, and sustainability. These would be implemented through collaboration of the government alongside Environmental Non-Governmental Organizations (NGOs) and AI developers. Overcoming these challenges through collaboration would enable increased support for Small and Medium-sized Enterprises (SMEs), better investments in digital infrastructure and the development of more accessible, comprehensive training programs to facilitate workforce adaptation. Ultimately, stakeholder collaboration is essential to ensure that AI adoption promotes efficiency, sustainability and equity for all.

The rest of the paper is structured as follows. Section 2 provides an in-depth literature review on AI and the primary sector. Section 3 explains the criteria used for the selection of sources and perspectives explored. Section 4 provides the historical and economic context. Section 5 presents the analysis of AI implementation across agriculture, fishing, and forestry. Section 6 compares the feasibility of AI adoption between agriculture, fishing, and forestry. Section 7 discusses the findings and concludes the study.

SECTION 2: LITERATURE REVIEW

Many studies have been made to explore the impact of AI on our modern society, however, the literature covers a wide range of AI applications in different sectors. To maintain focus, this review will specifically focus on AI's role within the primary sector. This review will sit within two branches: one that explores what AI is and what its implications are, and another that describes the primary classification, the primary sector.

Section 2.1: AI

Researchers have examined how AI is used in various sectors. AI, as referred to by Chan (2024), refers to a machine-based system that is capable of influencing the environment by producing an output, such as predictions, recommendations, or decisions, from a given set of objectives. However, it is also seen as the technology that enables computers and machines to simulate human learning, comprehension, problem-solving and decision-making. Essentially, machines that are capable of understanding and corresponding to human language (Stryker, 2024). Ultimately, both papers highlight the most important aspect of AI in the primary sector: comprehension and data processing, which enable it to function with a reliability similar to human judgment. Chan (2024) shows that AI is being used in sectors that are in all three economic classifications, but the AI application differs by classification. In particular, the tertiary sector is the one that relies the most on AI, due to the added levels of social intelligence and analysis needed for most service jobs, while the primary sector is still in the implementation process of these technologies. It also shows that, in recent years, the use of AI in general has increased, thus making it evident that it is necessary for the further development of all industries. Rao (2025) focuses on its use in the financial sector, specifically in risk management. However, both papers emphasize the significance of AI in improving the efficiency of financial risk assessments. In particular, in recent years, with the implementation of AI, the financial sector has seen a major increase in efficiency, accuracy and profits (Mehta, 2024).

In terms of AI implementation, researchers also find it relevant to highlight its challenges and benefits. Bjola (2022) addresses the fact that AI implementation can only be achieved by analyzing which AI tools are the most beneficial for each task.[2] It also shows different challenges that come with AI implementation, in this case, development issues. Specifically, it emphasizes ethical issues, especially in areas like healthcare distribution, poverty reduction and pollution curtailment.[3] These strengths and weaknesses are also echoed in Aliu and Sarumi (2026). Nevertheless they also stress AI adoption struggles, specifically for SMEs, namely immense costs, lack of digital literacy and limited access to infrastructure.

When looking at these strengths and weaknesses, researchers find it important to highlight the impact that AI has on employment and job opportunities. Wu and Liu (2023) argued that the ongoing AI revolution

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[2] Specifically, Bjola (2022) mentioned the need to master “data integration”, “analytical modeling”, “ethical AI” and “pursuing an interdisciplinary approach” in order to fully utilize AI tools.

[3] For example, Bjola (2022), mentioned that “by ‘supporting the provision of food, health, water, and energy services to the population,’ AI may act as an enabler for all the targets on no poverty (SGG1), quality education (SDG 4), …”

has intensified the need for stronger regulations on AI tools, which are capable of evolving alongside technological progress, so as to not break the equilibrium between technological uncertainty and regulatory restrictions. In particular, the paper concludes that without a unified, international approach to this issue, the gap between innovation and regulation could widen, potentially cooling the job market and causing job displacement. These concerns are also echoed in Chan (2024) and Klyman *et al.* (2025), which also stress the need for a more universal regulation system, in the hope of not only reducing job displacement but also socioeconomic inequalities.

Knowing the potential threats of AI, researchers have come to discuss the current and potential regulations, or policies, laid to eschew possible hazards. Klyman *et al.* (2025) reviewed the wide range of potential risks posed by AI.[4] In particular, the paper comes to the conclusion that AI companies' policies of independent evaluation are inconsistent, opaque, and burdensome, thus stating the evaluation of AI systems to be of great importance, as this process is crucial to understanding the technology, ensuring public accountability, and reducing these risks. Similarly, Wu and Liu (2023) also emphasize the lack of the current regulations.

Section 2.2: Primary Sector

Riedinger (2025) offers a broad overview of the current economic structure by distinguishing three different classifications, the primary, secondary and tertiary sectors. The paper highlights the primary role of the primary sector, noting that although its influence has greatly decreased over time, mainly due to the advances in mechanization and technology implementation, it is still economically significant. The primary sector refers to the extraction of raw materials, such as agriculture, fisheries, forestry and mining, whereas the second sector consists of processing these materials into usable products, and the tertiary sector is focused on providing services to sustain the economic processes, such as healthcare, education, etc.. The paper further mentions the existence of a fourth sector[5], which goes beyond the tertiary sector, by emphasizing the role of information as a driver of economic development. It analyzes shifts in sectoral dependency across time and diverse countries, highlighting how the importance of different sectors changes over time. Similarly, Ionașcu *et al.* (2024) stress the historical significance of the primary sector and point out that only a small portion of countries that once depended on it as the cornerstone to their economic success and consolidation of regional power continue to depend on it nowadays.

Although fewer countries now rely on the primary sector as their main source of income, the sector still remains highly relevant to economic development. Researchers have explored both its benefits and drawbacks, particularly its contribution to the enhancement of economic efficiency and employment generation. Gupta and Kumar (2026) argue that reliance on the primary sector has shown a positive effect on the nations' economic efficiency within the context of sustainable development.[6] The paper also concludes that, for the more efficient use of the primary sector, an increase in technology implementation

[4] The paper gives light to risks from enabling the creation of nonconsensual intimate imagery to facilitating the development of malware.

[5] A sector described as the "information age", as economies go from being primary to tertiary sector economies.

[6] Although this reliance proves to be a benefit for many countries, it appears to be a challenge in African countries' sustainable development, in the context of sustainable development, as their biggest issue, poverty reduction, isn't always solved.

and a more skilled workforce are necessary. These ideas are also echoed in Riedinger (2025) and Ionașcu *et al.* (2024), which also stress that the future of the primary sector depends on constant adaptation and modernization of technology.

Despite its importance to economic development, the primary sector also presents drawbacks, especially in relation to its environmental impact and economic instability. Zarach and Parteka (2023) showed how dependence on natural resources can limit economic diversification, even in more developed countries. This paper also demonstrates that reliance, even on only a few primary products, can restrict technological and export development, causing economic instability. In addition, it is also important to highlight labor issues and hazards, particularly within the fishery and seafood industries, where severe abuse hotspots[7] and unsustainable practices are still to be thoroughly addressed (Lozano *et al.*, 2022).

Few studies examine problems within the primary sector, such as employment inequality, labor shortages and poor working conditions, yet it remains an important area of research. Fabry *et al.* (2022) explored Senegal's horticultural sector, focusing on its inclusiveness for wage employment.[8] The paper reveals the disparities in job quality between workers hired by small-scale farmers that supply the domestic market and those hired by agro-industrial companies that are connected to export supply chains. By assessing both wage and non-wage dimensions of a decent job, it concludes that job quality is better in the agro-industry. Similarly, Causa *et al.* (2025) assesses job quality in diverse sectors, though focusing more on causes of labor shortages, such as poor working conditions which cause workers to quit.

SECTION 3: METHODOLOGY

This paper adopts a literature-based approach, to evaluate the role and further potential of AI in the primary sector. The sources used, such as the OECD, MDPI, Research Gate, among other databases and websites, were selected for their extensive coverage of peer-reviewed publications, as well as their comprehensive study of the topic. The research covered the period from 2014 to 2026, reflecting the evolution of AI in the industry over recent years.

The selection of these sources followed three major steps: (1) an initial screening for titles and abstracts that included the two main subjects of this study, the primary sector and AI; (2) an in-depth review of each article and identification of their purpose and intended audience; and (3) a selection of the articles that seemed the most complete and relevant to this paper's objective, particularly, those which explored different sectorial and industrial perspectives.

Ultimately, this paper focuses on the agriculture, fishing, and forestry industries. These industries were selected not only because they are key industries in the primary sector, but because they allow for the

[7] Severe abuse hotspots - countries/industries where abuse is the most common, and which includes modern slavery, forced labor, human trafficking and more.

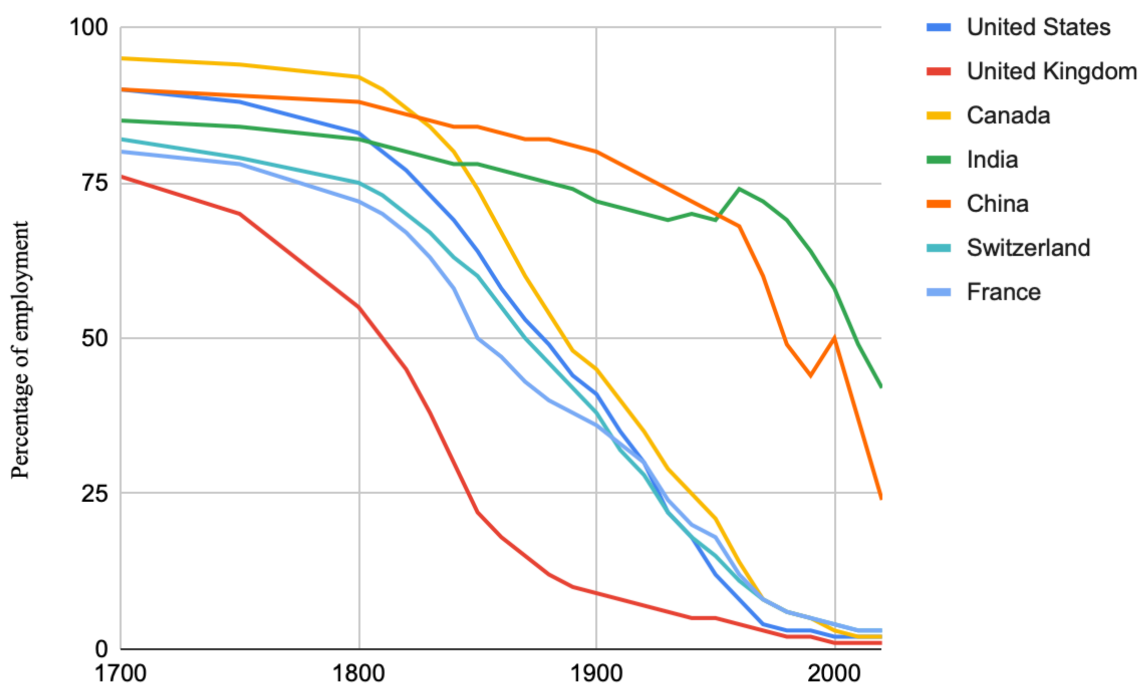
[8] Specifically, exploring if the sector is inclusive to women, younger workers and migrants. Furthering this study by comparing the quality of employment for each of these groups.

examination of the impacts of AI on the forestry and fishing industries, areas which are often overshadowed by the mining and oil extraction industries. Thus, the study highlights the issues faced by these more obscured industries, while still leaving room for agriculture, the most prominent industry in its sector.

SECTION 4: CONTEXT

Following the Industrial Revolution, between the 18th and 19th centuries, the use of machinery became ever more common. Manual labor and industries within the primary sector became less relied on, causing a shift in sector dependency. Countries like the US, the UK, among others, have turned to the secondary and tertiary sectors as their main source of income. The decreasing employment rates in the agriculture industry, as shown in Graph 1, reflect the sectoral shift pre and post Industrial Revolution. However, it should be noted that Graph 1 contains gaps in data for some countries, specifically between 1700 and 1990, thus limiting the precision of this cross-country comparison across time.

Graph 1: Employment in Agriculture Pre and Post Industrial Revolution (18th and 19th century)

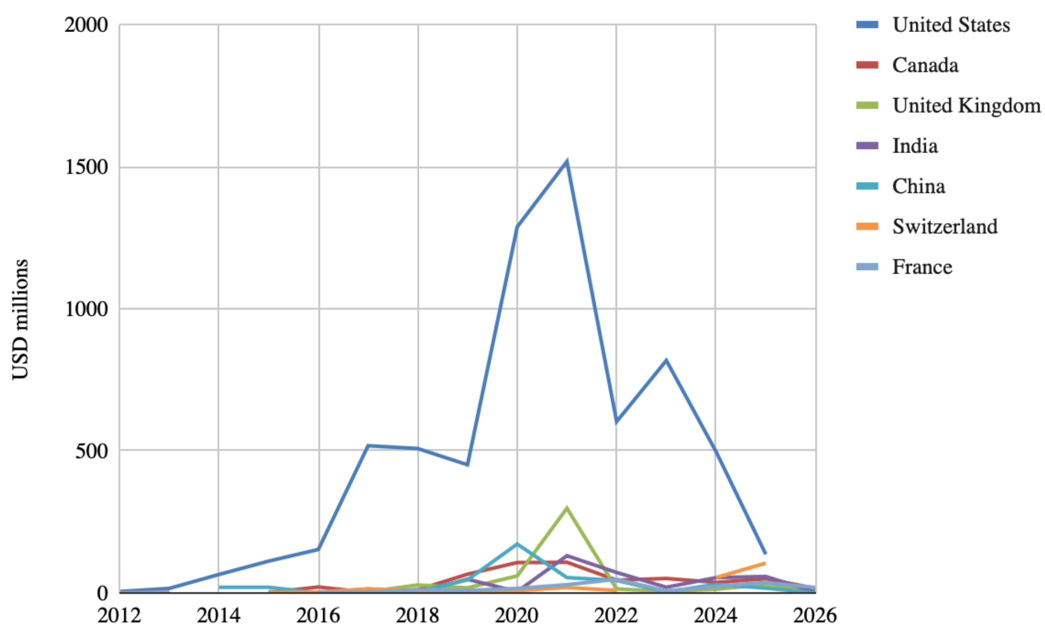


Sources: [LSE Research Online]; [Economic History Association]; [Our World In Data]; [International Labour Organization]

Following the Industrial Revolution, agricultural employment fell for most of the countries represented. For instance, the UK went from 76% in the 1700s to roughly 1% in 2020. This sharp fall reflects the structural changes in the economy that took place after the introduction to the first mechanized tools, as mechanization encouraged farmers to switch from farming to manufacturing and services jobs.[9] By the late 20th and early 21st century, most of the countries represented were not heavily dependent on agriculture. Curiously, this shift was driven by mechanization, as the other sectors adapted more readily; however, modern technology in agriculture may be what revitalizes the primary sector. Overall, Graph 1 reflects post-Post Industrial economic development which reduced dependency on the primary sector over time.

The countries selected for this study were chosen to represent both advanced economies and emerging markets, including G7 (The Group of Seven) members, like the United States, United Kingdom, Canada and France; a highly developed non-G7 member, Switzerland; and some of the fastest growing and biggest emerging markets such as China and India. This selection allows for meaningful comparison across different levels of economic and technological development. According to OECD Artificial Intelligence Policy Observatory data, the United States has led AI investments in agriculture for many years now, as seen in Graph 2, the highest annual investments and an overwhelming peak at 1.5 billion USD in 2021. Comparably, other countries such as the United Kingdom, India, France and others have also reached their peak investment in 2021. This trend is mostly due to the pandemic accelerated automation and increasing interest in AI tools at the time.[10]

Graph 2: Major countries' investments in AI in agriculture



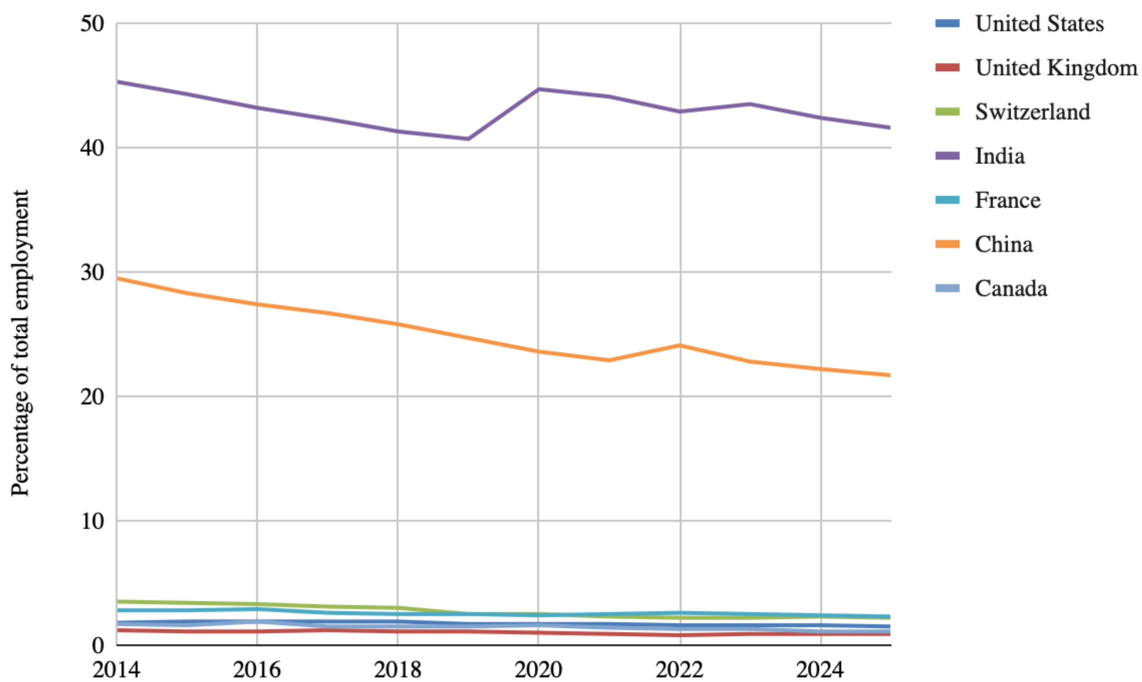
[9] Source: FILO, *"Historical Change in Primary, Secondary, and Tertiary Sectors"*, Aug 2025
[10] Even so, while COVID-19 significantly accelerated automation AI adoption, this was already underway as technological advancements, efficiency and long-term digitalization was needed. Source: OECD Science, Technology and Industry Working Papers, *"Digital adoption during COVID-19"*, April 2024.

Source: [OECD.ai]

After 2021, several countries like the UK, India and Canada show a tremendous decline in investments, the US' being the most remarkable one, having dropped from 1.5 billion USD, its peak, in 2021, to roughly 600 million USD in 2022. In particular, this decrease in investments resulted from several regulatory actions, such as the European Union Artificial Intelligence Act or EU AI Act[11], which created a lot of uncertainty around Agrotechnology. These new regulations brought unexpected fees and fines, and required costly safety certificates. Ultimately, these factors made agricultural profit margins lower, causing investors to slowly decrease their investments (Grimaud and Debono, 2025; Werner, 2024). This downward trend, however, has become even more apparent in recent years, which may indicate the beginning of a new era of even stricter regulations and caution around AI, a phase of development for agricultural AI.

As investments in agriculture continue to decrease, not only in regard to AI tools, the rate of employment in the agricultural industry also shows a downward trend. As a result, we turned to examining data from the World Bank, which is represented in Graph 3.

Graph 3: Employment in agriculture in major countries



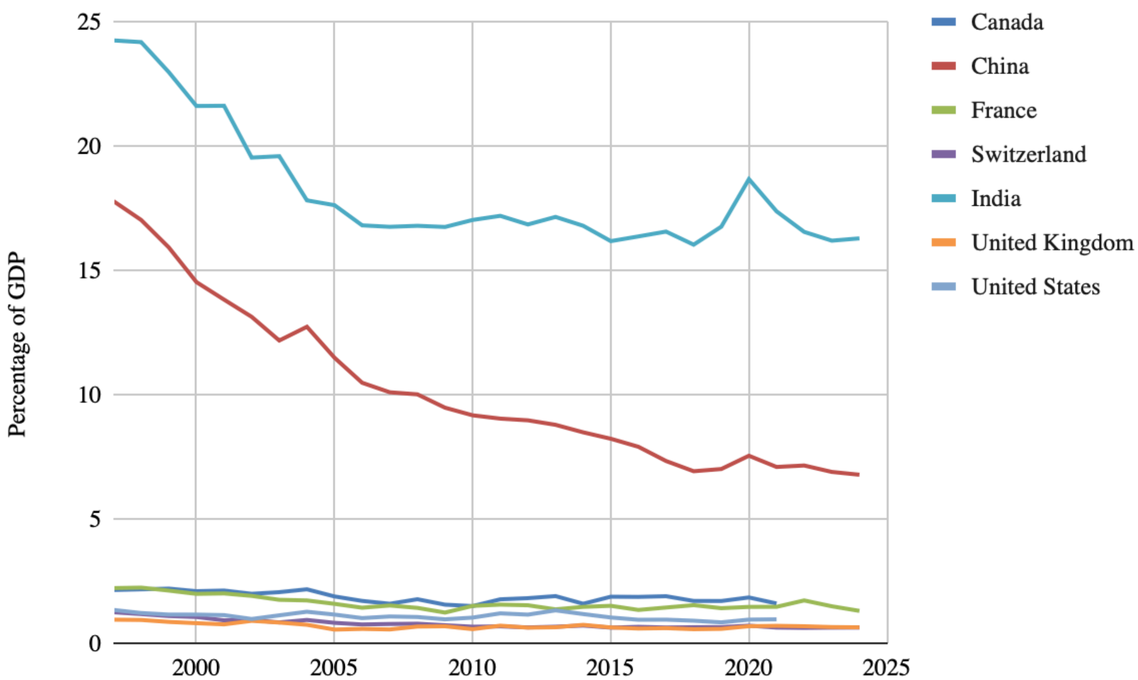
Source: Data World Bank

[11] This regulatory act, although started in the EU, has shown to have greatly influenced regulatory acts worldwide. Source: Information Technology & Innovation Foundation, *"How Much Will the Artificial Intelligence Act Cost Europe?"*, July 2021.

According to World Bank data, India and China present the highest average employment rates in agriculture, at an average of 43 and 25% of their total employment, respectively. Even so, these rates are not only due to their vast population but also their continued importance of farming in rural livelihoods. Graph 3 shows that the rates of agricultural employment decline, especially between 2019 and 2021, a pattern that can be traced to the economic and employment disruptions caused by the COVID-19 epidemic. Remarkably, despite being a major economic power, the US presents one of the lowest employment rates in agriculture, with its highest employment percentage being 1.5% in 2025. This indicates that the agricultural industry employs a relatively small portion of the labor force, reflecting high levels of productivity and technological development.

As a result of the smaller employment rates in agriculture, the GDP of the industry also decreased. Graph 4, showcases the ever diminishing impact of agriculture on the total percentage of GDP in the countries studied.

Graph 4: % of GDP in the agriculture, forestry and fishing industries, in major countries



Source: [Data World Bank]

Following the trend of Graph 2 and 3, Graph 4 also reveals a decline in the share of Gross Domestic Product (GDP) generated by agriculture, forestry and fishing across the countries studied. World Bank data shows that India presents the highest average share of GDP from the primary sector, at 18% average and a peak of 24% in 1997. Similarly, China also presents a significant share of GDP from the primary sector, which suggests that economic size can't completely erase the role of the primary sector in economic development. By contrast, the US shows a very low share of annual GDP in these industries, at an average of 1%, emphasizing its more industrialized and advanced economy. Taken together, it can be concluded that the primary sector still plays a relevant role in the economy of a few countries. Its importance, however, varies depending on the level of development and structural dependency of each country.

SECTION 5: RESULTS

The primary classification comprises three major industries, agriculture, fishery and forestry, which help define a foundation for understanding this classification. Although these industries appear to share various similarities in their automation and organizational systems, their use of AI differs significantly. These differences are mainly due to the extension, as well as the variety of tools that each industry needs to become automated. Accordingly, this analysis will go over the nature of AI in each industry, and its impact on employment and working conditions, sustainability and the economy, outside and inside the primary classification.

Section 5.1: Agriculture

Implementing AI in the agriculture industry offers significant efficiency gains and safety improvements, yet, its high costs and unbalanced accessibility raise concern about its long-term and sustainable impacts. Currently, in agriculture, AI tools are being used to help detect rotten produce, check soil fertility, monitor livestock health, analyze historical and real-time data to forecast yields, and further enhance the overall efficiency. AI tools have demonstrated to not only improve produce variety but, as a consequence, increase yields by up to 25% in diverse types of crops (OECD AI Policy Observatory, 2026). This increase in production and productivity highlights that AI isn't simply a tool for automation, but a tool for development of industries and ultimately the economy.

Despite these benefits, AI implementation in agriculture comes at a very high cost, especially for SMEs, which, according to Dieu (2025), may spend between $200,000 and $500,000 on implementation over five years. In agriculture, even more than in other industries, it is necessary to identify which tools are the most efficient for each task, in order to increase efficiency to the maximum. However as the agricultural industry presents many branches within it, it requires more tools compared to other sectors (Bjola, 2022). Given the various tools, there would also be a need for workers to acquire new skills (Aliu and Sarumi, 2026). As a result, although bigger agricultural corporations might benefit to the fullest from AI, smaller farms would be greatly affected by the investments required for adoption, thereby widening the already existing economic disparities. As AI continues to be implemented, this could further deepen inequalities within the sector by concentrating on productivity gains, innovation and market advantages among larger, more moneyed groups and risking leaving smaller farms out of business and competition (Cook and O'Neil, 2020).

The impact on agricultural labor is similarly two-sided. While AI tools greatly reduce the need for physically demanding and repetitive tasks, lowering injury or fatality rates, and improving working conditions. Job displacement, especially for low skilled and seasonal workers, is still a concern as the maintenance and work with these machines would require more skilled workers, leaving these aside. However, as many as 70% of agricultural workers in low-income countries and 20% in medium or highly developed countries are uneducated in their jobs and rely on experience only to work. Besides, many of these workers don't have access to the training needed to transition into new working positions (Augère-Granier, 2017). Even so, it is important to recognize the point made by Jain (2023) and Wu and Liu (2023), which state that AI is also creating new opportunities and roles, demanding skills that complement and collaborate with intelligent systems. Thus, striking a balance between the benefits of AI-driven efficiencies and potential challenges of job displacement remains a critical aspect of ensuring a smooth integration of technology into the workforce and maximizing profits.

Looking beyond the industry itself, AI implementation also has its benefits and drawbacks. As automation becomes the norm and more efficient systems appear, production of agricultural products is likely to increase, which could lower production costs and eventually lead to a decrease in consumer prices on these products. According to Cook and O'Neil (2020), this could be a major factor in ensuring global food security by enhancing the resilience of farming methods, reducing the cost of quality inputs and services to underserved farmers and improving market access to facilitate smallholder farmer integration into regional and global supply chains.

Within the scope of sustainable and long term practices, AI presents both promising opportunities and notable risks. AI system tools can optimize the use and minimize the waste of produce by 40% to 60% and create new varieties of agricultural products, thus aligning with the Sustainable Development Goals (SDGs) (Omotayo *et al*., 2025; Chen, 2025). However, the production, maintenance and energy consumption of the diverse AI-driven machines, needed to fully automate the agricultural industry, would prove to be a concern in terms of long term environmental and economic costs. Even though these machines bring fewer risks to the workers and increase productivity and produce variety, it is also important to address the practices that they may encourage, such as intensive agriculture, which nowadays creates 10% of global CO_2 emissions, and genetic modification of products. Taking Genetically Modified Produce (GMP) for example, this type of produce, although immensely cheaper than others, requires constant regulation so as not to become an ecological harm.

Ultimately, AI has the potential to transform modern agriculture; yet, its long-term success is dependent on overcoming and addressing structural challenges such as high implementation costs, sustainability, unequal accessibility and workforce adaptation. While it offers clear gains in productivity and safer working environments, its implementation should be carefully managed in order that technological development doesn't deepen already existing inequalities or imperil ecological progress. Overall, AI implementation in the agricultural industry doesn't only depend on innovation, but whether these tools are able to ensure a cost-effective, fair, sustainable development of the industry.

Section 5.2: Fishing

According to Strout (2025), although the fishing industry is widely considered old-fashioned and reliant on outdated technologies, it has quietly started incorporating advanced AI tools in recent years. From technologies created to better comprehend the global seafood industry and the ways they operate within it, to those responsible for automating aquaculture practices. Slowly, AI is revolutionizing the way fishers, regulators, and producers interact with the world's oceans. Nowadays, AI technologies have seen the most widespread adoption in aquaculture, where producers are using machine learning (ML) to monitor systems, sort animals and products and automate feedings (Mandal *et al.*, 2025). Additionally, technologies in the fishery industry have gone so far as warning systems and marine spatial planning, which have already decreased fatality rates by 50% and Maritime Traffic Safety Assessment related accidents by 17.41% (Jensen, 2014; Milt and Lecarte, 2022; Won *et al.*, 2024).

Moreover, while the fishing industry can still be further developed, AI adoption costs may not be as burdensome. This is because the industry doesn't require multiple new machines, but similar, more advanced and adapted tools for each task that will permit the enhancement of the already existing system. For example, one of the main reasons driving AI adoption in fish farming includes the need to reduce operational costs. Feed accounts for up to 70% of aquaculture costs, so minimizing waste has a direct impact on profitability, making further technology adoption optimal for increased efficiency and yields.

However, its impact on fishing labor proves to be a more complicated issue. While the adoption of new technologies opens a path to jobs related to data handling, maintenance and monitoring, it also reduces demand for less skilled workers. Even so, as found by UBC (2024) and Voorhees (2016), forced labor and other human rights abuses[12] such as debt bondage and in the fishing industry are a widespread and entrenched yet neglected issue that continue to affect crews across various regions. Similarly, ITF (2026) found that, from the more than 100 fishermen interviewed, as many as 35% of the interviewed fishermen reported experiencing regular physical violence[13] and as many as 60% reported working a minimum of 16 hours a shift. These studies help showcase the reality of work for fishers around the globe. Because of this, although jobs in the industry might change in nature with the adoption of AI, they would go from being heavily reliant on manual work, straining schedules and abusive environments to having safer, more ethical environments. Additionally, it is important to recognize what UBC (2024) examines. UBC (2024) explains that the cause for such neglect regarding the working conditions in the industry is mainly due to the lack of availability of directly observed data on what happens onboard fishing vessels, meaning that aside from automating the fishing industry, AI has the potential to bring a new sense of safety and ethics to fishers by serving also as a surveillance system.

In the long term, it is also important to look at the impact of AI on sustainability and the economy outside the primary sector. As argued by Mahajan (2025), in recent years, AI tools in the fishing industry have proven to strengthen the global economy by improving productivity, reducing operational costs and inefficiencies, and lowering mortality rates. These developments are reflected in the projected growth of the Global AI-Powered Fish Farming Market, which is projected to hit USD 1,837 million by 2034. This

[12] Other abuses mentioned in these papers included: deceptive recruitment practices, withholding of pay, excessive overtime, abusive living and working conditions, abuse of vulnerability, restriction of movement, isolation, intimidation and threats and retention of identity documents.

[13] Aside from physical violence, racial abuse and sexual violence were reported by the same fishermen. However, other workers also reported unethical practices such as "conditions comparable to forced labour", and

boost in output, especially for major aquaculture nations, has increased export revenues and strengthened domestic food security. Additionally, the adoption of AI-driven tools also enables the creation of highly skilled jobs in data analysis and maintenance in aquaculture. Ultimately, as fish farming shifts to smart systems, harvesting cycles are optimized and feed waste is reduced, showcasing improved resource efficiency, decreased environmental impact and long-term economic sustainability in the blue economy.

Section 5.3: Forestry

In the forestry industry, although not as common as in other industries, the implementation of AI has shown real results that have boosted efficiency, sustainability and profitability. Forestry has traditionally been a field where manual labor and human judgment are essential, where many tasks require expertise. However, although still under explored, AI technologies, including neural networks and ML, are transforming forestry by offering innovative solutions that make the process faster, more accurate, and more sustainable (Timbeter, 2024). At the moment, AI is being primarily used to monitor ecosystems in real-time, detect subtle changes in forest health and biodiversity, soil conditions and even prevent and detect wildfires. For example, FireCNN, a convolutional neural network (CNN) is one of these tools, which is not only estimated to reduce up to 76% of wildfires, but has already proven to detect these with 35.2% more accuracy than the traditional threshold method (Barker, 2023; Hong, 2022).

Even though this tool has yet to become more accurate on a bigger scale, its implementation in the industry has already proven to be the first step to ensuring safety and sustainability in the forestry industry. However, it is still important to recognize the benefits and drawbacks of such networks. While this big scale factor, the need for this network to cover such broad areas, requires much more than development, it requires investments; the implementation of these have also the potential to decrease long-term costs. According to Venâncio *et al.* (2022), by removing the less important convolutional filters in FireCNN, while preserving its original performance, computational costs can be reduced by up to 83.6% and the memory consumption by up to 83.86% without degrading the system's performance. Not only would this be a cost-efficient solution to the high upfront structural investments needed initially, it would mean a more sustainable system in the future, which presents greater availability to even small forestry firms.

Beyond its financial advantages, however, AI also has significant implications for employment in the forestry industry. Although AI presents opportunities to increase efficiency by allowing for precise monitoring of deforestation or assisting in making informed decisions related to spatial planning, for example, it still poses a threat to workers in the industry, as its implementation requires educational investments for workers to acquire technological competence (Ahmad, 2024; UNECE, 2019). As examined by Ross (2025), between 20 and 30% of manual labor jobs in the field could be replaced with AI-enabled automation due to human limitations like physical safety risks. Still, these technologies are of great relevance as they are also able to provide safer jobs. Eventually, this displacement of workers will depend solely on whether it will be assessed that full automation of the industry is required. Thus, while AI may lead to a decrease in the demand for manual tasks, it is likely to lead to transformation rather than a complete elimination of forestry jobs, towards higher skilled, supervisory roles (ILO, 2023).

This leads to the question of whether AI implementation is actually worthwhile in regard to its impact in the long term, both on the economy and on sustainability. With the EU alone covering 182 million hectares of forest, which receive 9% of the total GHGs (Greenhouse gases), AI technologies are increasingly necessary to monitor such vast areas efficiently and ensure the health of these forests (Bartoszek, 2021). Not only that, AI also plays a crucial role in optimizing supply chains and automated risk management by reducing manual labor, cutting fuel consumption by up to 22%, and boosting harvesting accuracy by 40% (Alam *et al.*, 2025). By harnessing remote sensing, CNNs, ML, blockchain, etc., the industry is pushed to address critical challenges and build a more resilient and sustainable future for our forests. As studied by UNECE (2019), the digitalization of the forestry industry is a transformative force, enhancing sustainability, transparency, and collaboration towards more efficient, sustainable, and data-driven management practices. However, this force, as it is still new, also faces some challenges such as high initial cost of adoption, resistance to change by organizations, and the need to develop specialized technical skills (Nunes, 2025).

SECTION 6: COMPARATIVE DISCUSSION

Taken together, the evidence suggests that AI adoption is not equally feasible across the primary sector. While all three industries stand to benefit from AI implementation in terms of efficiency, safety and increase in yields, the fishing industry appears to be the best placed to adopt AI, followed by the fishing industry, and then the agricultural industry, which faces more obstacles. This is because the fishing industry relies essentially on monitoring and data handling systems and machines, which are already mainstream and scalable, making further AI adoption more accessible. The forestry industry also presents great potential. Still, the need for surveillance of such great areas requires immense funds, as well as the need for cross-national collaboration in certain forestlands. These factors, although few, require extensive periods of time to arbitrate, making AI adoption in the forestry industry less feasible than in the fishing industry. By contrast, the agricultural industry faces even more impediments, as it requires a broad range of tools, higher investments and more extensive workforce adaptation, making it the most difficult to automate efficiently.

Beyond in-sector gains, AI also produces external benefits that should also be taken into consideration. For instance, AI in the fishing industry has the potential to create safer work environments for workers, going beyond usual approaches to AI, especially in these industries. In the forestry industry, AI can enhance safety in forestlands and surrounding areas, safeguarding both the population and the ecosystems present. The agricultural industry, however, appears to have the most far-reaching external benefit, as AI adoption can strengthen global food security. This reveals that the automation of the agricultural industry would have the broadest global impact, despite being the industry that faces the most obstacles, while the forestry and fishing industries would produce more localized, sustainable gains.

This comparison shows that the main issue is not whether AI can benefit the primary sector, but whether it can be efficiently implemented in each industry. Current literature and data indicate that the fishing and forestry industries are best placed to adopt AI, as they rely on already existing, more specialized tools.

Although the agricultural industry has the potential to produce more gains, it will most likely lead to more inequalities, displacement and accessibility issues. Therefore, AI implementation should not be limited to enhancing already existing machines, but should be tailored to the needs of each sector in a gradual way as to ensure maximum profit and efficiency.

SECTION 7: CONCLUSION

In modern society, AI has become the pinnacle of automation, a tool that enables industries to evolve beyond what was once thought to be the maximum. The current literature has examined the expansion and efficiency growth of AI in different industries, and it all points to how AI presents challenges such as high upfront costs and the need for higher skilled workers. This thus presents the question of whether it is actually worth implementing AI. This paper explores the agriculture, fishing and forestry sectors in order to more easily establish a comparison of how AI impacts different industries in the primary classification differently.

This paper shows how the primary sector aligns with the current literature; it identifies that while all three industries studied are expensive to automate, the agricultural industry appears to be the one that faces the most challenges. This is because it requires the widest variety of machines for each task and showcases the most uneven accessibility, especially for SMEs. Whereas the fishing and forestry industries do not have the extent nor the need for an immense number of different machines. In terms of efficiency, agriculture seems to benefit the most in the ambit of production yields, while fishing benefits in the ambit of reduction of production costs and increased safety for workers, and forestry benefits in area management and monitoring. In terms of sustainability, however, fishing and forestry showcase more benefits such as waste reduction and a lesser environmental footprint in the face of production, while agriculture shows a potential to intensify energy use and ecological issues such as the carbon footprint with further automation. Ultimately, AI shows the potential to increase the impact of the primary classification as a whole, nonetheless, it tends to benefit larger firms and higher skilled workers while excluding smaller firms and less skilled workers.

Overall, the findings point to a need for regulations concerning training, safety, and sustainability by the government in order for small firms and the primary sector to thrive under AI. Additionally, they point to the need for tailored planning regarding AI adoption in different industries. Similarly to government bodies and policymakers, Environmental NGOs would ensure that AI-driven tools support sustainability goals, minimize overexploitation, reduce production process pollution and maintain standards of safety. After them, AI developers have the responsibility to continue expanding the reach of AI in the industry as well as create new, more efficient, ways of production, data analysis and monitoring. At the same time, government bodies would ensure that AI developers work closer with sector-specific stakeholders such as SMEs farmers, small fishers and small forestry firms to obtain better feedback on regulation and implementation. This partnership would rely essentially on subsidies, which would somewhat bridge the existing wealth gap.

While this paper tries to give a complete analysis of the benefits and challenges that come with AI implementation in the primary sector, it might be missing nuances in other sectors as well as sub-sectors within the primary classification. Researchers could further this study by exploring the areas of the mining, oil and gas extraction and hunting industries. Moreover, the impacts of AI implementation in the primary sector on other industries and on the wider economy, can be further explored in order to create a more detailed study. Despite these limitations, this paper offers the necessary foundation to understand the balance needed to implement AI in the primary sector, as well as contributing to the growing literature on the practical AI debate. Consequently, it ensures there is more knowledge about the difficulties underdeveloped and developing countries face in implementing AI, so as to prevent more developed countries from undervaluing these, ensuring equality.

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