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Automation in Agriculture: Occupational Trends, Worker Outcomes, and Labor Market Implications

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Abstract
This paper investigates how automation technologies are reshaping agricultural labor, focusing on both labor market dynamics and changes in work organization. Drawing on a systematic literature review of 33 peer-reviewed studies and following the PRISMA protocol, the analysis adopts an inductive approach to extract empirical patterns. Findings reveal a dual transformation: while automation reduces the demand for low-skilled, repetitive labor, it simultaneously generates new opportunities for workers with technical and cognitive skills. The study identifies key risks—displacement, polarization, and digital exclusion for vulnerable groups—alongside potential benefits such as professional upskilling and improved working conditions. By introducing a dual-level thematic framework, Occupational and Worker level, the paper provides a granular understanding of labor impacts across macro and micro dimensions. It offers a critical and interdisciplinary contribution to ongoing debates on the social consequences of technological change, with implications for policy, workforce development, and equitable innovation in the agricultural sector.
Keywords: Agricultural Automation, Digital Transition, Employment, Labor Transformation, Systematic Review, Technological Change

Introduction

Agricultural automation, defined as the use of machinery and equipment to support the functions of diagnosis, decision-making, and execution in crop operations, represents a structural transformation within contemporary agricultural production systems (FAO, 2022). Its primary objectives are threefold: to reduce the physical strain associated with agricultural labor, improve the timeliness of operations, and enhance operational precision. This process of technological innovation aligns with a broader historical trajectory, wherein agricultural mechanization over the past two centuries has played a decisive role in increasing productivity and reshaping the agricultural labor force (Binswanger, 1986). The evolution of the agricultural sector in the United States serves as an emblematic case. In 1920, approximately 350 million acres were cultivated with the labor of 9.5 million workers, representing 26% of the total workforce. By 1995, despite a reduction in cultivated land to

320 million acres and a sharp decline in agricultural employment to 3.3 million workers (2.6% of the workforce), agricultural output had increased by a factor of 3.3 (Sunding & Zilberman, 2001). This trend has continued: in 2022, the number of agricultural workers in the U.S. had declined further to 2.6 million (1.2% of the total workforce), while the average farm size increased and employment grew in downstream sectors such as food services (USDA, 2024). The FAO (2022) report emphasizes that the impact of automation on agricultural employment is complex and heterogeneous. Technological transition is generally gradual and highly dependent on the type of crops, geographic location, and specific tasks involved. Between 1991 and 2019, the share of agricultural employment declined across all global regions, regardless of income level. This decrease was most pronounced in high-income countries, but also clearly observable in low- and middle-income nations. In Brazil, for example, the mechanization of sugarcane harvesting led to a 64% reduction in labor demand, disproportionately affecting low-skilled workers. In Zambia, the introduction of tractors doubled farmers' incomes and increased labor productivity by 25%, while simultaneously reducing the need for traditional agricultural labor. In California, where more than 90% of the agricultural workforce consists of immigrant laborers, a persistent labor shortage has driven the adoption of automated solutions such as strawberry-picking robots and automatic milking systems. In this context, agricultural automation has emerged as a strategic lever to enhance the efficiency and sustainability of production systems, although adoption dynamics among farmers remain fragmented and subject to ongoing debate (Apicella & Tarabella, 2024a; Apicella & Tarabella, 2024b). Its evolution—from basic mechanical tools to advanced precision agriculture technologies—has produced tangible benefits, including increased productivity, reduced physical labor for operators, greater resilience to climate change, and improved food quality and safety (Bazargani & Deemyad, 2024). However, these benefits are unevenly distributed, reflecting structural disparities in access to technology. Smallholder farmers, women, and youth, especially in capital-constrained environments, tend to be excluded from innovation processes, thereby risking a deepening of existing social and economic inequalities (FAO, 2022). However, as highlighted by Acemoglu and Restrepo (2019), the relationship between automation and employment cannot be reduced to a simple dynamic of labor substitution. Alongside the substitution effect, the introduction of new technologies can generate a reintegration effect, whereby new tasks emerge that capitalize on the comparative advantage of human labor, potentially resulting in positive impacts on both productivity and labor's share of national income. Agriculture, unlike the industrial sector, is characterized by a high degree of operational complexity due to environmental variability and the biological nature of its outputs. This inherent complexity demands the adoption of intelligent and adaptive technological solutions (Marinoudi et al., 2021).

In light of these ongoing transformations, a systematic decomposition of agricultural tasks becomes essential in order to distinguish between those activities that are amenable to automation and those that continue to require human intervention.

Within this context, the present study aims to analyze the state of the art in scientific literature concerning the application of automation technologies in agriculture, with a particular focus on their impacts on labor markets and the organization of work processes. To this end, a systematic review was conducted, encompassing 33 peer-reviewed contributions identified through leading international bibliographic databases (Scopus, Web of Science, Dimensions), using a combination of automated search and hand-searching techniques.

Following an inductive approach, a detailed information set was developed for each contribution, including bibliographic details, the types of automation and technologies investigated, the level of analysis adopted (micro, meso, or macro), the geographical scope, and the observed effects on labor markets and work activities. The objectives of this review are twofold: first, to contribute to a better understanding of the ongoing transformations within the agricultural sector, marked by high heterogeneity and structural specificity that demand a multilevel analytical lens; and second, to propose a research agenda capable of more effectively exploring how recent technological advancements are reshaping agricultural labor, thereby offering insights for policymakers, industry stakeholders, and the scientific community.

Methodology

This study employs a systematic literature review that integrates the conceptual framework proposed by Tranfield et al. (2003) with the procedural rigour of the PRISMA protocol (Moher et al., 2009). Tranfield's model informed the planning, execution, and reporting phases of the review, including the formulation of objectives, selection of databases, and development of inclusion and exclusion criteria. In parallel, PRISMA served as a practical guide for documenting the stages of identification, screening, eligibility, and inclusion in a transparent and replicable manner. The literature search was conducted on 11 March 2025. The primary database used was Scopus, chosen for its multidisciplinary coverage and indexing consistency. This was complemented by manual searching (snowballing) in other authoritative databases such as Web of Science and Dimensions. These sources were selected to increase coverage and mitigate potential bias, in line with previous comparative studies (Chadegani et al., 2013; Singh et al., 2021b; Zhu and Liu, 2020). The inclusion of multiple databases was intended to leverage their complementary strengths and enhance the representativeness of the final corpus (Singh et al., 2021b). A Boolean query was formulated to capture literature at the intersection between agricultural automation technologies and labour dynamics: "Automation AND technology AND agriculture AND employment OR occupation OR job". Automation was chosen as a central concept due to its encompassing nature, including technologies such as robotics, artificial intelligence, and the Internet of Things. This approach enables a broad yet focused exploration of the digital transformation in the agricultural sector. The relevance of automation as a long-term driver of labour restructuring is also well documented in historical literature (Tauger, 2010). The initial search via Scopus returned 133 records. These were screened for format and language, with 33 documents removed due to being books, book chapters, or non-English publications. This resulted in 100 peer-reviewed journal articles. An additional 15 documents were identified through snowballing techniques, leading to a total of 115 records assessed at the title and abstract level. After this screening phase, 49 records were excluded, leaving 66 articles for full-text eligibility assessment. At this stage, 33 articles were excluded due to a lack of relevance to the research question—either focusing solely on technological development without considering labour implications, or being outdated or sectorally misaligned. This resulted in a final sample of 33 articles, which comprise the core analytical base of the review. The entire selection process is summarised in Figure 1, following PRISMA guidelines. For each article, structured data were extracted, including: bibliographic metadata (authors, title, year, journal, DOI), type of automation technology discussed, methodological approach, geographical scope, and reported impacts at two levels of analysis:

- Occupational level (e.g. task substitution, job creation, labour market polarisation);
- Worker level (e.g. changes in skills, risk of exclusion, wellbeing, and training needs).

To synthesise findings, an inductive thematic analysis was employed. This involved coding content iteratively to allow empirical patterns to emerge without imposing a priori theoretical categories, as recommended by Filippi et al. (2023), Fereday and Muir-Cochrane (2006), and Thomas (2006). Through multiple rounds of review, key themes were grouped and refined into a dual-level interpretive framework that captures both structural and individual dimensions of automation's impact on agricultural labour.

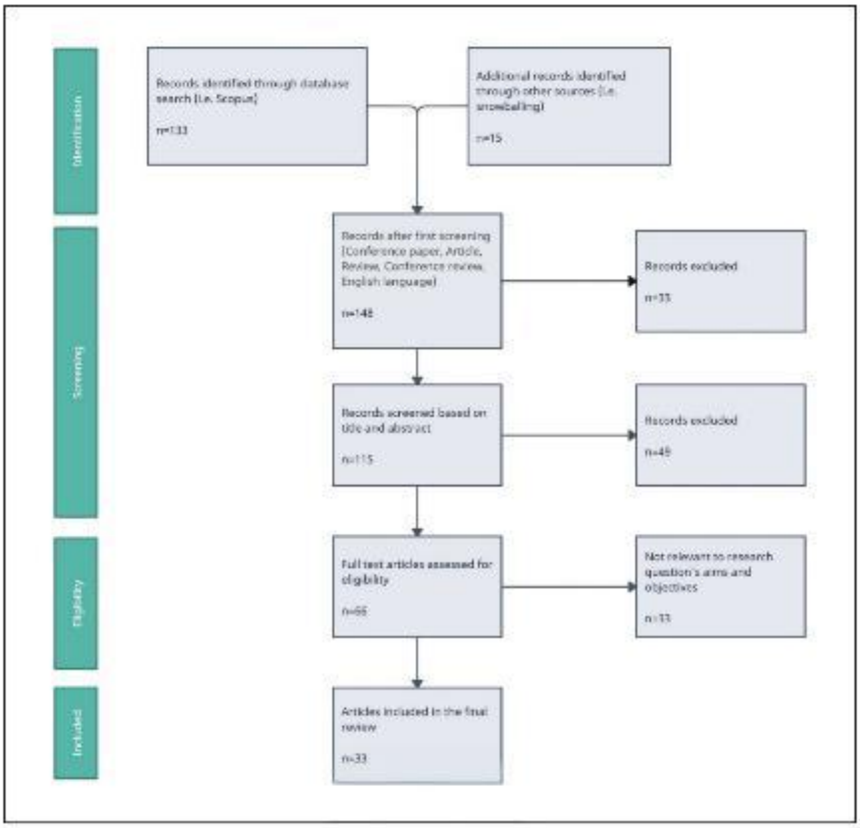

Figure 1. PRISMA Flow Diagram of the Study Selection Process. Source: Author's own elaboration.

Results

Methodological and Empirical Issues

Based on the inductive approach adopted, the categories Technological Domain and Technology Analyzed, Geography, and Level of Analysis (micro, meso, macro) were included within the section Methodological and Empirical Issues, as they represent cross-cutting dimensions essential for systematically framing and interpreting the reviewed contributions. These dimensions do not directly concern the effects of automation on labor but rather constitute key contextual and structural variables through which the empirical analyses are configured. The technological domain enables the mapping of specific technologies examined (e.g., robotics, IoT, AI); the geographical scope captures the spatial and socioeconomic distribution of the studies; while the level of analysis (micro, meso, macro) reflects the epistemological focus and the degree of theoretical abstraction of each contribution.

Technological Domain and Technology Analysed

Although this review focused on the impact of automation technologies and their implications for employment in agriculture, it is evident that emerging technological domains increasingly encompass a broader range of innovations aimed at automating agricultural processes (Tauger, 2010; Trivelli et al., 2019). The literature review shows that agricultural automation is a well-established area of research, with numerous studies examining its applications, impacts, and employment-related implications (Alarcón, 2021; Hansen & Stræte, 2020; Homrich et al., 2017; Kron et al., 2019; Perez-Silva & Campos, 2021; Schröder et al., 2022; Rijnks et al., 2022; Posadas, 2012). However, in most cases, automation is analyzed in close connection with agricultural robotics, which is applied to a variety of tasks such as harvesting, planting, milking, and environmental management (Barzagani & Deemyad, 2024; Bissadu et al., 2025; Cheein et al., 2015; Fassakhova et al., 2020; Marinoudi et al., 2019, 2021, 2024; Lowenberg-DeBoer et al., 2019; Christiaensen et al., 2020; Sparrow & Howard, 2021; Rotz et al., 2019; Grift et al., 2008; Carbonero et al., 2020; Campos-Gonzalez et al., 2025). An increasing number of studies focus on the integration of Internet of Things (IoT) technologies, highlighting their potential to optimize production processes and support real-time decision-making (Assante et al., 2018; Bissadu et al., 2025; Cho et al., 2010a, 2010b; Petcu et al., 2024). In parallel, the use of Artificial Intelligence (AI) is emerging as a key trend, with applications ranging from yield prediction and intelligent resource management to the cognitive automation of specific operational phases (Bissadu et al., 2025; Fuentes-Peñailillo et al., 2024; Ludwig-Ohm et al., 2022; Marinoudi et al., 2019, 2021; Petcu et al., 2024; Rotz et al., 2019; Gwagwa et al., 2021; Campos-Gonzalez et al., 2025). The reviewed literature also converges on the theme of technological integration within the framework of precision agriculture, defined as a coordinated set of digital technologies aimed at increasing efficiency, sustainability, and productivity (Trivelli et al., 2019; Singh et al., 2021a). Within this context, many contributions explore the use of advanced sensors for environmental and agronomic monitoring (Cheein et al., 2015; Cho, 2010a; Ludwig-Ohm et al., 2022; Quendler et al., 2017; Rotz et al., 2019; Grift et al., 2008), automated workflows for operational management (Cho, 2010a, 2010b), and data analytics systems based on Big Data and intelligent management platforms (Ludwig-Ohm et al., 2022; Petcu et al., 2024). Overall, the findings reveal a dynamic and rapidly evolving landscape in which automation is no longer a stand-alone technical component but rather part of an integrated technological ecosystem that blends physical and digital tools, progressively reshaping the production and labor structures within the agricultural sector.

Geography

The analysis of the selected publications reveals significant heterogeneity in terms of geographical focus, with studies ranging from local contexts to global perspectives. The contributions can be classified into four main categories: single-country studies, multi-country comparative analyses, macro-regional analyses, and global or non-specified approaches. The first group includes studies focused on individual countries, such as: Sweden, specifically the Uppsala region (Alarcón, 2021); Brazil, with reference to the Mantiqueira community (Homrich et al., 2017); Germany (Ludwig-Ohm et al., 2022; Schröder et al., 2022); Chile (Perez-Silva et al., 2021); Ireland (Rijnks et al., 2022); the United States (Posadas, 2012); Canada, with a focus on rural communities (Rotz et al., 2019); the United Kingdom (Campos-Gonzalez et al., 2025); and Russia (Fassakhova et al., 2020; Kron et al., 2019). Other studies adopt a comparative approach across two or more countries, such as the work by Cheein et al. (2015), which compares Chile and Argentina, offering an integrated perspective on similar dynamics across different regional contexts. In terms of macro-regional analyses, several contributions focus on Europe, emphasizing the role of EU policy frameworks and their interaction with the adoption of automation technologies (Assante et al., 2018; Petcu et al., 2024). Others explore the African context, analyzing both the opportunities and risks associated with the introduction of automation in agricultural systems (Gwagwa et al., 2021). A further set of studies is based on conceptual classifications, distinguishing between developed countries (Lowenberg-DeBoer et al., 2019), developing countries (Christiaensen et al., 2021), or comparative analyses across income groups (Christiaensen et al., 2020), contributing to the understanding of structural and contextual differences in the adoption of automation technologies. Finally, numerous studies adopt a global or non-geographically specified approach, often focusing on theoretical models, technological trends, or systemic implications without explicit territorial references (Bazargani & Deemyad, 2024; Cho et al., 2010a, 2010b; Fuentes-Peñailillo et al., 2024; Hansen & Stræte, 2020; Marinoudi et al., 2019, 2021, 2024; Quendler et al., 2017; Charlton et al., 2022; Sparrow & Howard, 2021; Grift et al., 2008; Carbonero et al., 2020). In some cases, these theoretical frameworks are applied to specific national contexts, such as Japan, which has been the subject of modeling and applied analysis (Bissadu et al., 2025).

Overall, the literature demonstrates that the geographical dimension is a critical variable for understanding the heterogeneity of the impacts of agricultural automation, reinforcing the need for a multilevel and context-specific analytical approach.

Table 1
Country of analysis considered in publications. Source: Author's own elaboration

Country of analysis	Number of publications
Publications focusing on global level	13
Publications focusing on global level from a single country perspective (*Japan)*	1
Publications focusing on developed and developing countries	3
Publications focusing on the continental level (*Europe*)	2
Publications focusing on the continental level (*Africa*)	1
Publications focusing on two countries	2
Publications focusing on one country	11
Germany	2
Russia	2
Brazil	1
Sweden	1
Chile	1
Ireland	1
USA	1
Canada	1
UK	1

Level of Analysis

Following the inductive approach, the level of analysis was categorized into three main contexts: Micro (e.g., individual farms, labor conditions, and worker well-being), Meso (e.g., specific structural contexts such as sectors or geographic areas), and Macro (e.g., global trends and systemic implications).

Table 2

Level of Analysis considered in publications. Source: Author's own elaboration

Level of analysis	Authors
Micro	Hansen and Stræte (2020); Lowenberg-DeBoer et al., (2019); Quendler et al., (2017); Schröder et al. (2022).
Meso	Alarcon et al. (2021); Assante et al. (2018); Campos-Gonzalez et al. (2025); Cheein et al. (2015); Cho et al. (2010a); Cho et al. (2010b); Fassakhov et al. (2020); Homrich et al. (2017); Ludwig-Ohm et al. (2022); Perez-Silva and Campos (2021); Rijnks et al. (2022); Rotz et al. (2019).
Macro	Barzagani and Deemyad (2024); Bissadu et al. (2025); Carbonero et al. (2020); Charlton et al. (2022); Christiaensen et al. (2020); Christiaensen et al. (2021); Fuentes-Peñailillo et al. (2024); Grift et al. (2008); Gwagwa et al. (2021); Kron et al. (2019); Marinoudi et al. (2019); Marinoudi et al. (2021); Marinoudi et al. (2024); Petcu et al. (2024); Sparrow and Howard (2021).

Micro-Level Analysis

Hansen and Stræte (2020) focus on the impact of new technologies—specifically Automatic Milking Systems (AMS)—on the job satisfaction of individual farmers, offering a detailed examination of personal experiences and the factors influencing workplace well-being. Lowenberg-DeBoer et al. (2019) review the economic literature on agricultural automation since 1990, with particular attention to studies assessing the profitability of mechatronic and robotic technologies at the farm level. Quendler et al. (2017) investigate a specific case within organic egg production, analyzing the physical and mental stress experienced by workers with biometric sensors. Schröder et al. (2022) explore the perspectives of a specific group within the agricultural value chain—horticultural employees—offering a detailed analysis of how digitalization and automation influence various aspects of their daily work routines.

Meso-Level Analysis

Alarcón et al. (2021) examine the integration of migrant workers in the agricultural sector of the Uppsala region (Sweden), analyzing the interaction between labor skills, agricultural automation, and digitalization in the context of local agrarian transformation. Assante et al. (2018) investigate the impact of digital transformation and IoT technology adoption on European SMEs, focusing on labor market training needs and policy initiatives supporting technological integration. Campos-Gonzalez et al. (2025) analyze the adoption rate of Agriculture 4.0 technologies in the United Kingdom, assessing changes in the intensity of routine tasks between 2011 and 2021. Cheein et al. (2015) address region-specific challenges—particularly in Argentina and Chile—highlighting structural issues such as natural events, climate change, and labor force migration, and emphasize the need for automation technologies in agriculture. Cho et al. (2010a) propose a context-aware service model for u-agriculture, based on workflow automation and the integration of sensor networks to support smart work processes. Cho et al. (2010b) presents the development of a workflow scenario using uWDL, designed to implement context-aware services in dynamic agricultural environments. Fassakhova et al. (2020) analyze the challenges of labor recruitment in agriculture, emphasizing the effects of global and regional urbanization trends and shifting social expectations among youth in rural Russia. Homrich et al. (2017) explore the role of Product-Service Systems (PSS) in fostering sustainability in small rural communities, through a case study on olive oil processing in the mountainous Mantiqueira region of Brazil. Ludwig-Ohm et al. (2022) investigate the integration of advanced digital technologies—including robotics, artificial intelligence, and sensor systems—in the German horticultural sector, within the context of the Horticulture 4.0 initiative supported by the Ministry of Agriculture. Perez-Silva and Campos (2021) focus on the impact of digital technologies on Chile's agricultural labor market, analyzing the relationship between automation, occupational structure, and task typologies. Posadas (2012) assesses the economic effects of mechanization and automation in specific farming businesses, such as nurseries and greenhouses, within a defined group of agricultural enterprises. Rijnks et al. (2022) examine the potential impact of automation on agricultural employment at the regional level, with particular attention to the availability of alternative occupations across different sectors. Rotz et al. (2019) analyze the impacts of agricultural digitalization on labor and rural communities, with a specific focus on the Canadian context.

Macro-Level Analysis

Barzagani and Deemyad (2024) provide a systematic review of the impacts of automation and robotics in agriculture, examining both technical challenges and socio-economic effects such as demographic shifts, economic sustainability, and labor market transformations. Bissadu et al. (2025) systematically address global challenges faced by traditional agriculture, advocating for a shift toward Agriculture 5.0, aligned with the broader vision of Society 5.0. Carbonero et al. (2020) analyze the impact of robotic automation on employment and international trade, with a particular focus on emerging economies. Charlton et al. (2022) explore the social implications of agricultural automation, focusing primarily on labor and employment from a global perspective. Christiaensen et al. (2021) examine structural changes in the global agri-food system, highlighting the decline of direct agricultural employment, the rise of digitalization, and long-term implications for labor, trade, and migration policies. In a complementary study, Christiaensen et al. (2020) assess global trends in the evolving role of agriculture in economic development, technological transformation, and migratory flows. Fuentes-Peñailillo et al. (2024) conduct an in-depth analysis of next-generation technologies in soilless horticulture, identifying their revolutionary potential in terms of yield, efficiency, and sustainability, while also discussing complex challenges related to high costs, technical skills, international regulations, and social implications. Grift et al. (2008) provide a global overview of agricultural automation research, assessing its potential to address future challenges such as population growth, labor shortages, and environmental impact. Gwagwa et al. (2021) examine the potential impact of artificial intelligence in African countries, with a focus on agriculture and related socio-economic and cultural implications. Kron et al. (2019)

address challenges associated with the transition of agricultural production to the digital economy, emphasizing the shortage of IT-skilled personnel and the limitations of current educational systems in providing the required competencies. Marinoudi et al. (2021) explore the transformation of the agricultural labor landscape in light of increasing robotization, mapping 17 occupational profiles based on the manual/cognitive and routine/non-routine nature of their tasks. Similarly, Marinoudi et al. (2019) analyze the shift toward digitalized and robotized agricultural systems, with specific attention to their implications for human labor and employment structures. Marinoudi et al. (2024) assess the impact of robotization on agricultural occupations, categorizing 15 job profiles according to their level of routineness and cognitive/manual components. Petcu et al. (2024) examine the systemic impact of artificial intelligence and advanced digital technologies on agriculture in the European Union, using a broad, cross-sectoral perspective that includes economic, social, and political dimensions. Finally, Sparrow and Howard (2021) explore the prospects of agricultural robotics, evaluating its economic, environmental, political, and cultural implications, as well as the ethical and regulatory issues associated with its deployment.

Thematic Results

In the thematic results, following an inductive approach, two distinct levels of analysis were identified – Occupational level and Worker level – to provide a structured and coherent account of the complex effects of agricultural automation on employment. This distinction reflects the emergence, from the analysis of the selected contributions, of differentiated impact trajectories: on the one hand, a macro-structural perspective, related to broader transformations in the agricultural labor market; on the other, a micro-individual perspective, focused on the working conditions of individual employees. This thematic articulation allows for greater analytical depth and supports the formulation of more targeted operational and policy implications, differentiated according to the actors involved (e.g., policy makers, firms, training systems, and the scientific community).

Occupational Level

Reduction in Employment Opportunities

The increasing adoption of automation, robotics, and digital technologies in agriculture is having a significant impact on employment dynamics, particularly within low-skilled labor segments. Numerous studies indicate that these innovations are reducing the demand for unskilled manual labor, disproportionately affecting migrant workers employed in seasonal and repetitive tasks such as harvesting vegetables and fruits, milking, or packaging (Alarcón, 2021; Sparrow & Howard, 2021; Grift et al., 2008). This transformation poses a tangible risk of job displacement in low-skilled sectors, although net effects vary depending on the socioeconomic context and the pace of technological adoption (Bazargani & Deemyad, 2024). In fact, automation tends to restructure the labor market rather than cause a linear decline in employment, shifting demand toward more qualified and specialized professions that are less tied to seasonality (Charlton et al., 2022; Fuentes-Peñailillo et al., 2024). An emerging effect is occupational polarization, where mid-level jobs are shrinking in favor of an expansion in both high-skilled roles—related to the management and maintenance of automated systems—and low-skilled roles, which are often characterized by greater precariousness and contractual instability. This dynamic may contribute to widening wage and social inequalities, particularly in rural areas lacking digital infrastructure and training opportunities (Marinoudi et al., 2019; Marinoudi et al., 2024; Perez-Silva & Campos, 2021; Rotz et al., 2019). However, in highly mechanized contexts, the introduction of automation technologies has not necessarily led to a reduction in total employment. Rather, it has prompted a selection process favoring specific skill sets, enabling firms to offer higher wages and retain qualified labor (Posadas, 2012). Moreover, automation can stimulate employment in complementary sectors such as logistics, food processing, technical maintenance, and digital services, especially when innovation is driven by external pressures like labor shortages or rising agricultural wages (Charlton et al., 2022). At the global level, significant heterogeneity persists. In regions where agriculture remains the primary source of employment—such as sub-Saharan Africa—the spread of automation could seriously undermine labor market stability for millions (Gwagwa et al., 2021). Nevertheless, the adoption rate of such technologies remains relatively low compared to other sectors. According to Campos-Gonzalez et al. (2024), agriculture has experienced a 7.69% reduction in routine task intensity—lower than in sectors like finance or information services—but has still lost approximately 19.6% of its workforce over the course of a decade, indicating a slower but nonetheless meaningful structural transition.

Labor Shortage in Agriculture

Several studies highlight a progressive decline in the availability of agricultural labor, attributed to factors such as the aging rural population, the low attractiveness of the sector for younger generations, increasing urbanization, and rising production costs (Bissadu et al., 2025; Fassakhova et al., 2020). In countries like Argentina and Chile, there has been a notable migration of the agricultural workforce toward industrial sectors, such as mining, which offer better economic conditions, resulting in a decline in primary agricultural output (Cheein et al., 2015). The literature also points to a decreasing influx of university graduates into agricultural occupations, accompanied by a growing disinterest in rural employment opportunities (Fassakhova et al., 2020). Overall, the analyses identify labor scarcity as a recurring factor associated with the spread of automated and robotic technologies in the agricultural sector (Grift et al., 2008).

Substitution of Human Labor

Numerous studies indicate that the introduction of agricultural robots, automated systems, and digital workflows is progressively replacing human labor in traditionally manual and routine tasks, such as sowing, harvesting, weeding, and environmental management of crops (Bazargani & Deemyad, 2024; Lowenberg-DeBoer et al., 2020; Cho et al., 2010a, 2010b). The analysis by Marinoudi et al. (2021, 2024) shows that agricultural occupations most exposed to automation are those with a high manual and routine content, with an average susceptibility rate of 59% for roles such as pickers, machinery operators, and sorting workers. In contrast, occupations involving cognitive and non-routine tasks—such as agricultural engineers and precision farming technicians—are less susceptible, with an average automation potential of 22%. Kron et al. (2019) estimate that up to 58% of agricultural workers could be replaced by automated systems, excluding creative and managerial roles. Similarly, Bazargani and Deemyad (2024) estimate that 45% of all agricultural tasks are currently automatable, while 60% of occupations may undergo partial substitution of at least 30% of their tasks. In some contexts, such as horticulture, there is a coexistence of automated processes and irreplaceable manual tasks, resulting in increased efficiency but also greater standardization of labor (Schröder et al., 2022; Ludwig-Ohm et al., 2023). In organic livestock farming, for instance, physically intensive activities remain largely non-automated (Quendler et al., 2017). The substitution process is not uniform across countries. According to Carbonero et al. (2020), a 24% increase in robot adoption between 2005 and 2014 led to a 5% reduction in employment in affected sectors, with a much greater impact in emerging economies (−11%) compared to industrialized ones (−0.43%). Perez-Silva and Campos (2021) report that despite high automation potential, Chilean agriculture has seen an increase in routine task intensity, maintaining the sector as a refuge for low-skilled workers. In rural areas with "thin labor markets"—characterized by limited occupational alternatives—the transition is more difficult for displaced workers (Rijnks et al., 2022). Moreover, technological substitution may be accompanied by deskilling and increased digital surveillance, leading to reduced operational autonomy for workers (Sparrow & Howard, 2021). Some studies highlight emerging models of human–robot coexistence, such as the use of collaborative robots (cobots), which shift skill requirements toward system supervision, configuration, and maintenance tasks (Cheein et al., 2015; Bissadu et al., 2025). This has been described as a technical and engineering-driven reorganization of agricultural labor, with a reduction in direct operational activities (Cho et al., 2010b). Finally, some studies note that agricultural automation has not yet led to widespread employment reduction in certain sectors, such as horticulture (Ludwig-Ohm et al., 2023). In high-income countries, direct agricultural labor has declined but has been offset by job growth in downstream segments of the agri-food supply chain. In contrast, in low-income countries, agricultural employment remains high, though it is often characterized by low productivity (Christiaensen et al., 2020; 2021).

New Educational Opportunities

The literature highlights a growing demand for advanced technical skills in the agricultural sector, driven by the widespread adoption of automated and digital technologies (Alarcón, 2021; Cho et al., 2010a). The implementation of intelligent systems is reshaping labor needs, decreasing the demand for repetitive manual tasks while increasing the need for qualified profiles in areas such as system supervision, technical maintenance, programming, and data processing (Fuentes-Peñailillo et al., 2024). The expansion of the agri-food value chain beyond the farm—particularly in processing, logistics, and food service sectors—has created new employment opportunities but has also raised the threshold of required competencies (Christiaensen et al., 2020). However, several studies point to a mismatch between the existing training offer and the actual needs of the agri-industrial sector, especially in digital and ICT domains (Assante et al., 2018; Kron et al., 2019). Some sector-specific training models have yielded above-average results. The case of Kazan State Agrarian University (KSAU) illustrates the effectiveness of integrated strategies combining technical education, career orientation, and partnerships with agricultural enterprises, resulting in significantly high employment placement rates (Fassakhova et al., 2020). Similarly, Petcu et al. (2024) find that employer investment in digital training for employees is statistically associated with a significant increase in agricultural value added and growth rate.

Economic Impacts

The large-scale adoption of advanced technologies in agriculture—such as robotics, the Internet of Things (IoT), and artificial intelligence—is associated with a potential global economic gain estimated at over USD 800 billion by 2050, due to improvements in crop yields, reductions in operational costs, and increased managerial efficiency (Bazargani & Deemyad, 2024). At the sectoral level, the analysis by Marinoudi et al. (2021) shows that approximately 70% of the U.S. agricultural workforce is engaged in manual and routine tasks, which are highly susceptible to automation. This segment, accounting for 56% of the annual operating budget of the U.S. agricultural sector, corresponds to around 350,000 workers, with an estimated economic impact of USD 8.8 billion per year. Fuentes-Peñailillo et al. (2024) highlight that the high initial costs and technical complexity of digital technologies represent significant barriers for small-scale farms, with the risk of exacerbating structural inequalities between large-scale industrial agriculture and smallholder farming. However, at the local level, there is evidence of technology transfer models based on result-oriented Product-Service Systems (PSS). For example, the study by Homrich et al. (2017) analyzed a system in which a large producer provides industrial olive oil extraction equipment to small farmers. This configuration contributed to the creation of a productive ecosystem capable of supporting the local economy, generating skilled employment, enhancing agricultural output, and mitigating economic risks for small-scale producers.

Labor Regulations

The widespread diffusion of agricultural automation raises a range of regulatory issues related to safety, labor rights, and the governance of autonomous systems. Several studies indicate that the integration of autonomous platforms into agricultural contexts requires the adaptation of existing legislation concerning occupational safety and legal liability, which often remains inadequate in addressing the complexities of digitized systems (Cheein et al., 2015; Ludwig-Ohm et al., 2023). The introduction of a “robotic ecosystem” brings forth new legislative and social demands concerning the coexistence of human operators and intelligent machines, and the need to establish shared standards for interaction, maintenance, and emergency procedures in the event of system failures (Marinoudi et al., 2019). According to Lowenberg-DeBoer et al. (2020), divergent national regulations regarding safety and insurance can significantly influence the overall cost of adopting automated technologies, highlighting the need for international regulatory harmonization processes. Finally, Charlton et al. (2022) emphasize that public policies promoting automation in the absence of real labor shortages or demand may result in unintended labor market distortions, including unemployment and wage stagnation—particularly in low-skilled and labor-intensive agricultural contexts.

Worker Level

Skill-Related Activities

Technological transformations in agriculture are substantially reshaping the structure of tasks and the competencies required at the individual level. Several studies report that workers lacking technical skills—particularly migrants or those employed in seasonal jobs—tend to be excluded from the core processes of agricultural production, remaining confined to low-skilled manual roles (Alarcón, 2021; Rotz et al., 2019). In such cases, limited access to adequate training pathways and precarious contractual conditions exacerbate the risk of marginalization from the agricultural labor market. Numerous contributions agree that the most vulnerable tasks to technological substitution are those characterized by repetitiveness and low cognitive content, whereas new employment opportunities are emerging for workers with technical, digital, or managerial skills (Charlton et al., 2022; Grift et al., 2008; Fuentes-Peñailillo et al., 2024). These new roles demand knowledge in areas such as sensor technologies, data analysis, remote management, and cybersecurity—posing significant challenges for traditional workers in the absence of targeted training programs. Some studies emphasize that not all tasks are subject to automation, particularly non-routine activities based on complex decision-making processes. For example, in agronomic practices such as pest monitoring, data collection can be digitalized, but the interpretation of results and operational decisions still require human input (Ludwig-Ohm et al., 2023; Perez-Silva & Campos, 2021). Even in highly automated contexts, such as shared olive oil extraction facilities, there is often a redefinition rather than an elimination of manual labor, with increasing demand for operators capable of managing complex machinery and adapting operational procedures (Homrich et al., 2017). Finally, macroeconomic evidence suggests that in emerging countries, workers engaged in routine and low-skilled tasks are among the most affected by automation. This is due in part to the erosion of the competitive advantage traditionally associated with low labor costs, which is increasingly challenged by automation in industrialized nations (Carbonero et al., 2020).

Hiring Barriers and Risk of Exclusion

Several studies highlight the emergence of systemic barriers to labor market entry and stabilization, particularly affecting individuals with limited technical skills. In the study by Alarcón (2021), agricultural employers expressed a conditional willingness to hire migrant labor, often constrained by production requirements that demand pre-trained personnel capable of operating advanced technologies. This situation restricts access to central roles within the agricultural value chain and reinforces labor marginalization among workers lacking up-to-date competencies. The risk of exclusion from innovative production processes is especially high for those employed in rural areas or in countries with underdeveloped or inflexible training systems. Assante et al. (2018), Bazargani and Deemyad (2024), and Bissadu et al. (2025) point out that in the absence of active training policies, technological accessibility, and participatory planning, digital transition may widen the gap between labor demand and supply, excluding low-skilled individuals and slowing the system's overall adaptability. Structurally, numerous sources underscore the inadequacy of current educational offerings relative to the skill requirements of the emerging technological landscape. Kron et al. (2019) observe that much of the agricultural workforce received training prior to the integration of ICT disciplines into educational curricula, while Petcu et al. (2024) identify digital illiteracy, particularly among older and lower-skilled workers—as a major obstacle to retraining efforts. Rijnks et al. (2022) also highlight the challenges faced by senior workers in terms of professional mobility and reskilling, given their lower propensity or capacity to engage in further education. At the individual level, multiple studies converge in identifying manual and routine tasks—most common among less qualified workers—as the most vulnerable to automation. In the absence of upskilling strategies, these workers face a high risk of exclusion from emerging production models (Grift et al., 2008; Sparrow & Howard, 2021; Lowenberg-DeBoer et al., 2020). Finally, Gwagwa et al. (2021) emphasize the risk of intersectional exclusion linked to gender, socioeconomic status, and access to resources. In Africa, women working in agriculture are particularly exposed due to limited land ownership, restricted access to credit, and underrepresentation in datasets used to train artificial intelligence systems. These dynamics may contribute both to a gradual deskilling of traditional professions and to the amplification of pre-existing social and economic inequalities.

Human–Machine Interaction

The review examines the modes of interaction between human operators and automated systems in agriculture. According to Cheein et al. (2015), the successful integration of robots into agricultural production environments is highly dependent on their ability to adapt to the social dynamics of labor. Robotic units must move predictably, respect operators' personal space, and exhibit behaviors perceived as "socially acceptable." Interaction is thus conceived as a bidirectional relationship, in which humans and machines mutually adapt in order to optimize productivity and well-being in the field. Additional studies confirm that the introduction of intelligent technologies entails a reorganization of the farmer's role. Cho et al. (2010a; 2010b) describe a scenario in which the daily activities of agricultural workers are increasingly mediated by autonomous digital systems. These systems, capable of monitoring environmental variables such as temperature, humidity, and soil pH, autonomously trigger specific functions, thereby reducing manual intervention and shifting the human role toward programming, information flow management, and the supervision of automated processes. Petcu et al. (2024) emphasize that effective interaction with artificial intelligence requires specific digital competencies, including the ability to interpret data from sensors, drones, satellite imagery, and predictive models. As a result, the farmer is required to manage a technologically complex environment that demands continuous adaptation and ongoing skill development. However, several studies also highlight the risks associated with this transformation. According to Sparrow and Howard (2021), the widespread use of robots in agriculture may reduce workers' decision-making autonomy, increase productivity-related pressures, and contribute to the gradual replacement of experiential knowledge with algorithmic decision-making systems.

Reskilling and Workforce Transformation

The introduction of advanced technologies in agriculture is profoundly reshaping the professional profile required of individual workers. Multiple studies underscore the urgent need to update technical competencies, particularly in fields related to robotics, artificial intelligence, embedded systems, sensor networks, remote management, cybersecurity, and precision agriculture (Assante et al., 2018; Bazargani & Deemyad, 2024; Fuentes-Peñailillo et al., 2024; Petcu et al., 2024). The transition toward digitalized production models—such as those characterizing Agriculture 5.0—necessitates a shift from repetitive, physical tasks to cognitive, analytical, and decision-oriented roles. Agricultural workers are increasingly expected to play an active role in managing intelligent systems, interpreting data, and engaging in strategic decision-making (Bissadu et al., 2025; Homrich et al., 2017; Ludwig-Ohm et al., 2023). In this context, certain technologies simplify operational activities (e.g., autonomous driving), while others demand a high degree of technical engagement (Marinoudi et al., 2019; Schröder et al., 2022). Beyond technical-specialist skills, new demands are also emerging for soft skills. Marinoudi et al. (2024) emphasize that occupations less exposed to automation tend to combine interdisciplinary knowledge with socio-emotional abilities, critical thinking, time management, communication, and adaptability. These skills are essential for operating in complex and technologically advanced agricultural environments. From a policy perspective, Fassakhova et al. (2020) and Petcu et al. (2024) highlight the effectiveness of innovative vocational training programs, the strengthening of university–enterprise partnerships, and the use of post-graduation employment-linked scholarships as tools to enhance inclusion and occupational stability in the sector. Moreover, there is broad consensus on the urgent need to implement continuous education programs aimed at improving digital skills among agricultural workers to support a fair and inclusive transition. Finally, according to Christiaensen et al. (2021) and Campos-González et al. (2024), reskilling represents both an opportunity and a risk. In high-income countries, the demand for advanced competencies is increasing, while in low-skilled contexts, often lacking adequate educational infrastructure, the risk of exclusion grows, particularly among those engaged in repetitive manual and cognitive tasks.

Well-being and Psychosocial Impacts of Automation

Several studies report heterogeneous effects of agricultural automation and digitalization on workers' well-being, highlighting both positive and negative dimensions. According to Hansen and Stræte (2020), dairy farmers using Automated Milking Systems (AMS) report higher levels of job satisfaction compared to those using Conventional Milking Systems (CMS), particularly regarding work schedule flexibility, safety, and the overall work environment. However, general satisfaction levels are also influenced by shared factors across both groups, such as income level, succession planning, willingness to remain in farming, and infrastructure modernization. From the perspective of individual workers, digitalization and mechanization often result in tangible benefits, such as reduced physical workload and improved occupational safety (Schröder et al., 2022; Posadas, 2012). In certain cases, increased job satisfaction has been attributed to a reduction in physical strain and enhanced operational autonomy. Nonetheless, Posadas (2012) also notes a rise in injury rates associated with machinery, particularly during early adoption phases, including sprains, cuts, and muscle fatigue. At the same time, several studies point to critical challenges posed by digital transformation. Schröder et al. (2022) and Quendler et al. (2017) document ambivalent effects of digitalization on worker well-being: while certain technologies help alleviate physical stress, they may also introduce new forms of psychological stress associated with equipment maintenance, technological reliability, and loss of control over production activities. Quendler et al. (2017) specifically highlight high levels of physical and psychological stress among women and less physically trained individuals, even in modernized organic farming contexts—calling for the development of tools to monitor and prevent occupational stress. Lastly, cultural and identity-based resistance also emerge in the review. Some workers express concerns over the potential displacement of manual tasks, which are viewed as core to their professional identity. Such perceived loss may adversely affect workers' sense of belonging and motivation (Schröder et al., 2022).

Concluding Remarks

The literature reveals that agricultural automation has been extensively examined in academic research, with increasing attention given to technological integration as a key driver of innovation in the sector. A consolidated trend emerges toward the convergence of various technologies—including robotics, sensors, artificial intelligence, and the Internet of Things—that, when combined, support the transition toward increasingly autonomous, intelligent, and interconnected agricultural systems. This technological evolution calls for a deeper analysis of its implications for the labor market, particularly in light of the growing complexity and interdependence of the technological domains involved (Tauger, 2010; Trivelli et al., 2019). Moreover, the geographical scope of the reviewed studies displays significant heterogeneity, ranging from nationally localized analyses to comparative research across multiple countries, and investigations conducted at macro-regional or global scales. This diversity reflects the growing relevance of agricultural automation in different socioeconomic contexts and underscores the importance of accounting for territorial specificities when evaluating the impact of technological change. The literature highlights that the diffusion of agricultural automation is driven by a dual dynamic. On one hand, the increasing scarcity of low-skilled labor across various geographical contexts has incentivized the adoption of technological solutions (Bissadu et al., 2025; Fassakhova et al., 2020; Grift et al., 2008; FAO, 2022). On the other hand, automation itself has contributed to a reduction in employment opportunities for low-skilled workers, particularly in segments involving manual and seasonal labor (Alarcón, 2021; Sparrow & Howard, 2021; Frey et al., 2013). This process does not necessarily imply a net loss of jobs but rather a profound restructuring of tasks, with labor demand increasingly shifting toward technical and specialized roles (Charlton et al., 2022; Filippi et al., 2023; Fuentes-Peñailillo et al., 2024), thereby prompting the need for new forms of vocational education and training (Arntz et al., 2016; Fassakhova et al., 2020; Petcu et al., 2024). Multiple studies confirm that the impacts of automation vary according to workers' education and income levels, generating a pattern of occupational polarization. This tends to reinforce both high-skilled positions—typically involved in the management and maintenance of digital systems—and low-skilled ones, often marked by greater job insecurity and contractual instability (Acemoglu & Restrepo, 2019; Arntz et al., 2016; Marinoudi et al., 2019; Marinoudi et al., 2024; Perez-Silva & Campos, 2021; Rotz et al., 2019). These findings highlight the need to accompany automation processes with inclusive strategies for skills development, professional retraining, and social protection to prevent the exacerbation of existing inequalities and to promote a fair and sustainable technological transition. The literature confirms that tasks most susceptible to technological substitution are those characterized by high repetitiveness and low cognitive content, posing significant risks of exclusion for vulnerable workers, such as migrants and older individuals (Alarcón, 2021; Petcu et al., 2024; Rijnks et al., 2022). At the same time, automation generates new employment opportunities for individuals with technical, digital, and managerial skills (Charlton et al., 2022; Grift et al., 2008; Fuentes-Peñailillo et al., 2024). However, several studies emphasize that many tasks are not entirely automatable but rather integrable with technological tools, thereby requiring forms of human–machine coexistence (Cheein et al., 2015; Cho et al., 2010a; Cho et al., 2010b; Homrich et al., 2017; Ludwig-Ohm et al., 2023; Perez-Silva & Campos, 2021). The adoption of automation technologies also leads to differentiated impacts on workers' well-being. On the one hand, increased job satisfaction is observed, particularly in relation to improved physical working conditions and greater autonomy (Hansen & Stræte, 2020; Schröder et al., 2022); on the other, several studies document the emergence of mental stress, especially among less physically prepared or socially disadvantaged groups, including women (Quendler et al., 2017). From a methodological perspective, the literature is predominantly composed of macro-level studies, offering generalist or global frameworks that describe the automation transition in aggregate terms. Nonetheless, many contributions adopt a meso-level focus, concentrating on specific agricultural sectors or geographically defined regions. These studies reflect the inherent complexity and heterogeneity of the agricultural sector, where technological change occurs gradually and unevenly depending on crop type, geographic location, and the nature of the tasks involved (FAO, 2022). Although less frequent, micro-level analyses remain critical: by examining individual actors or enterprises, they help identify adoption barriers and socio-economic exclusion risks, ultimately contributing to the development of more inclusive and equitable technologies (FAO, 2022).

Managerial Implications

The integration of automated technologies in agriculture poses significant managerial challenges. The transition toward higher-skilled tasks necessitates targeted investment in technical training and professional upskilling, particularly for at-risk groups such as migrant workers, seasonal laborers, and older employees. Simultaneously, the growing shortage of agricultural labor demands strategies to attract new generations and enhance the value of existing human capital by promoting safer, more flexible, and stable working conditions. The increasing human–machine interaction requires a redefinition of roles, shifting the emphasis from manual labor to digital and managerial competencies. Agricultural managers must facilitate this transformation by adopting updated and interdisciplinary training models. Furthermore, monitoring of worker well-being is essential to prevent risks associated with operational stress and the loss of individual autonomy. In low-capital contexts, the implementation of cooperative models and shared solutions may enhance access to advanced technologies, promote employment equity, and strengthen territorial cohesion. These considerations underscore the need for a proactive and inclusive management approach to ensure a sustainable and socially balanced technological transition in the agricultural sector.

Policy Implications

The expansion of agricultural automation necessitates a coherent update of regulatory frameworks in three critical domains: occupational safety, legal liability, and the governance of autonomous systems. Policymakers should develop targeted regulations governing human–machine interaction, including clear operational standards and risk management protocols associated with the use of robotic technologies. Regulatory fragmentation across countries constitutes a significant barrier to the efficient and sustainable adoption of automation. Therefore, international harmonization processes are essential to reduce transition costs and facilitate the diffusion of innovation across diverse agricultural systems. Moreover, public policies must be aligned with actual labor market needs. Automation incentives that are poorly calibrated to local employment dynamics may produce adverse outcomes, including rising unemployment, precarious work conditions, and the exacerbation of social inequalities—especially in low-skilled agricultural segments. A more integrated and participatory approach to technological planning is thus crucial to ensure both equity and effectiveness in the digital transition of the agricultural sector.

Theoretical and Contextual Contribution

This study contributes to the literature on technological change and labor in agriculture from both a theoretical and contextual perspective. Theoretically, it engages with ongoing debates that move beyond substitutionist frameworks—such as those proposed by Frey and Osborne (2013), which emphasize the susceptibility of jobs to automation—by incorporating more dynamic models that consider task transformation and reintegration. In particular, the study applies the approach of Acemoglu and Restrepo (2019), highlighting how new technologies can displace certain forms of labor while simultaneously creating new roles that capitalize on human comparative advantages in technical, cognitive, and adaptive skills. The introduction of a dual-level analytical framework—distinguishing between occupational-level and worker-level impacts—offers an original contribution to the field. This structure allows for a more granular understanding of how automation affects not only aggregate employment trends but also the lived experiences of workers, including skill requirements, training needs, and psychosocial outcomes. It advances theoretical models by bridging macro-structural transformations with micro-level dynamics of labor adaptation and exclusion. Contextually, the paper responds to the urgent need for a more differentiated understanding of automation in agriculture—an area often overshadowed by industrial and service sector analyses. By synthesizing evidence from a diverse and globally distributed set of studies, the review captures the heterogeneous and place-specific nature of automation's impact across agricultural systems. It reveals that factors such as crop type, farm size, institutional capacity, and digital infrastructure play a crucial role in shaping outcomes for workers and communities. Beyond academic relevance, the study provides practical insights for those designing policy, education, and innovation strategies. It underlines the importance of aligning technological advancement with inclusive labor policies and training systems capable of supporting vulnerable groups during periods of transition. In doing so, it contributes to a broader effort to frame agricultural innovation not only as a technical process, but as a social and economic transformation requiring careful governance.

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