Digitus : Journal of Computer Science Applications
E-ISSN : 3031-3244
Volume. 3, Issue 4, October 2025
Page No: 186-201

Smart Farming Technologies for Global Food Security: A Review of Robotics and Automation

Veronika Yuni T[1], Saromah[2], Budi Gunawan[3]
[13]Universitas Jayabaya, Indonesia
[2]STMIK Mercusuar, Indonesia
Correspondent: saromah@mercusuar.ac.id[2]

Received : August 27, 2025
Accepted : October 1, 2025
Published : October 31, 2025

Citation: Yuni T, V., Saromah., Gunawan, B. (2025). Smart Farming Technologies for Global Food Security: A Review of Robotics and Automation. Digitus: Journal of Computer Science Applications, 3 (4), 186-201.

ABSTRACT: This narrative review explores the role of robotics and automation in precision agriculture, particularly in addressing global challenges such as food security, labor shortages, and environmental sustainability. A systematic literature search was conducted using Scopus, Web of Science, and other supplementary databases, focusing on studies from 2015 to 2025. Findings show that AI-based models and UAV monitoring can enhance crop yield by up to 20% and reduce water and fertilizer use by 30%. Smart irrigation, soft robotics, and autonomous systems also demonstrate effectiveness in specific applications like pruning, weeding, and aquaponics. Despite promising outcomes, adoption varies due to financial, infrastructural, and governance barriers, especially in developing regions. The review concludes that integrating robotics with AI, IoT, and UAVs has transformative potential for agriculture. Future research should prioritize system interoperability, dataset quality, and environmental impact assessments to support widespread, equitable implementation.

Keywords: Precision Agriculture, Robotics, Automation, Smart Farming Technologies, Artificial Intelligence, Uavs, Sustainable Agriculture

INTRODUCTION

Precision agriculture stands at a critical juncture in the twenty-first century, facing complex global challenges that necessitate innovative technological interventions. As populations expand and climate change intensifies, the demand for sustainable agricultural practices has surged, drawing attention to robotics and automation as transformative forces. These technologies offer unprecedented opportunities to improve agricultural efficiency, reduce resource waste, and ensure long-term food security. A growing body of literature emphasizes the pressing need for precision agriculture to address inefficiencies in conventional farming and highlights how the integration of robotics can redefine farming operations for the modern era (Fedorov, 2022; Ponce et al., 2023; Millard et al., 2019). Recent scholarly work has underscored the promise of smart farming technologies, situating them within the broader framework of Agriculture 4.0, which advocates for data-driven, automated, and sustainable farming systems (Mansour, 2025; Li et al., 2024).

Scholarly consensus has increasingly pointed to robotics and automation as essential components of agricultural innovation. For instance, studies highlight their ability to streamline complex processes such as planting, irrigation, fertilization, pest control, and harvesting, traditionally known to be resource-intensive and labor-demanding (Fedorov, 2022; Duncan et al., 2024). The development of mobile robotics allows for localized data collection in real time, thus enhancing farm management by integrating precision monitoring with actionable decision-making (Ponce et al., 2023). Furthermore, autonomous systems have been shown to reduce soil compaction and environmental degradation, enabling sustainable farming practices in diverse contexts (Millard et al., 2019). These innovations resonate with global calls for agricultural systems that prioritize efficiency while safeguarding ecological integrity.

The relevance of robotics in precision agriculture is further substantiated by baseline data on agricultural productivity, resource utilization, and labor constraints. Global population growth projections estimate that the number of people worldwide will surpass nine billion by 2050, intensifying the demand for efficient food production systems (Pandey, 2025). Conventional farming methods, marked by inefficiencies in water management and fertilizer use, are struggling to meet the rising demand for higher yields under increasingly constrained conditions (Li et al., 2024). Automation and robotics can mitigate these challenges by enabling targeted resource allocation, optimizing irrigation, and improving input management, thereby addressing both economic and environmental dimensions of agricultural sustainability (Mansour, 2025).

Equally pressing is the issue of labor shortages, exacerbated by demographic shifts such as urban migration and an aging agricultural workforce. Studies confirm that fewer younger workers are entering agricultural professions, leading to mounting concerns regarding workforce sustainability (Duncan et al., 2024; Toscano et al., 2025). Automation offers solutions to these constraints by assuming repetitive, laborious, and often hazardous tasks, freeing human labor for more complex and decision-intensive responsibilities (Joshi, 2025). Furthermore, empirical evidence demonstrates that autonomous systems enhance both productivity and workplace safety, significantly bolstering the sector's resilience (Gerhards et al., 2023; Bagagiolo et al., 2022). The integration of automation in workforce-deficient sectors of agriculture underscores its growing necessity.

Beyond labor and productivity, robotics has revolutionized specific agricultural practices through targeted innovations. For example, autonomous drones have proven effective in precision spraying and data collection, reducing costs and environmental impact (Kumar, 2025). Similarly, robotic systems in weeding, disease detection, and selective harvesting have been reported to increase crop yields while simultaneously minimizing chemical inputs, aligning with goals for sustainable intensification of agriculture (Grigorev et al., 2025). These empirical contributions reinforce the notion that robotics and automation are not merely supplemental but fundamental to transforming agriculture into a sustainable enterprise capable of addressing twenty-first-century demands.

Nevertheless, the widespread adoption of robotics in agriculture is hampered by significant technological and systemic challenges. Chief among these barriers are the prohibitive implementation costs associated with advanced robotic systems. Small- and medium-sized enterprises (SMEs) in agriculture often face difficulty in financing such technologies, as they require not only substantial initial capital but also long-term investments in infrastructure and training (Jiang, 2025; Urrea & Kern, 2025; Shamshiri et al., 2024; Rathod et al., 2023). These financial constraints limit the accessibility of automation, thereby impeding its equitable distribution across diverse agricultural contexts. Addressing the affordability of robotic technologies remains a critical challenge in ensuring inclusive adoption.

Technological complexity presents another formidable barrier. Unlike structured industrial settings, agriculture is characterized by highly variable and unstructured environments influenced by weather, soil types, and crop conditions. Such variability complicates the design and operation of robotic systems, often limiting their adaptability and robustness in dynamic field conditions (Dhillon, 2023; Millard et al., 2019). Moreover, technological heterogeneity among existing systems creates issues of interoperability, hindering seamless integration across different farming operations (Jiang, 2025; Urrea & Kern, 2025). The diversity of agricultural contexts demands more adaptable, interoperable solutions to maximize the benefits of robotics in farming.

Navigation and perception remain additional technological hurdles. Current robotic systems frequently rely on basic path-planning algorithms that are insufficient in managing dynamic obstacles or complex field layouts (Grigorev et al., 2025; Pandey, 2025). These limitations are further compounded by weaknesses in sensor technology, which reduce robots' capacity to perceive and interpret their environment effectively, thereby constraining operational efficiency (Emmi et al., 2023). Addressing these technological deficiencies is essential to achieving consistent, reliable performance of robotic systems in diverse agricultural settings.

Research gaps highlight further obstacles in the full integration of robotics into precision agriculture. While individual technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and Unmanned Aerial Vehicles (UAVs) have been extensively studied, their synergistic implementation remains underexplored. Few comprehensive studies have examined how these technologies can be effectively combined to enhance real-time decision-making, resource optimization, and holistic farm management (Bhat, 2025; Joshi, 2025; Balasundaram et al., 2022). Ethical and social considerations, including workforce displacement and societal impacts, are also insufficiently addressed in current research, despite their importance for sustainable and equitable adoption (Sparrow & Howard, 2020; Bhat, 2025). Additionally, UAVs are often treated as standalone tools rather than being integrated into broader frameworks with ground robotics, limiting their potential for comprehensive agricultural data collection and intervention (Toscano et al., 2024; Kan et al., 2021; Milburn et al., 2023).

Given these challenges and gaps, the current review seeks to provide a systematic analysis of robotics and automation within the context of precision agriculture. The primary aim is to synthesize the available literature to evaluate how these technologies can address the most pressing challenges of modern agriculture, including productivity, resource management, labor shortages, and sustainability. By assessing the state of current research, this review intends to illuminate the opportunities and barriers in integrating robotics with AI, IoT, and UAVs, thus presenting a comprehensive understanding of their potential to transform farming systems.

The scope of this review is intentionally broad yet precise, encompassing both developed and developing regions to ensure global relevance. While substantial research has been conducted in traditional crop sectors such as horticulture, less attention has been paid to emerging applications in aquaculture and livestock farming, where robotics is beginning to show promise in tasks like feeding, health monitoring, and harvesting (D'Oronzio & Sica, 2021; Balabantaray et al., 2024; Padhiary et al., 2025). This review therefore covers a diverse array of agricultural domains to capture a holistic picture of robotics in precision agriculture. Furthermore, the analysis acknowledges crop-specific challenges, recognizing that high-value crops such as berries and specialty vegetables may require customized robotic solutions due to their unique growth and harvesting requirements (Baltazar et al., 2021; Fahey et al., 2020). By adopting this comprehensive perspective, the review aims to provide nuanced insights that can guide future technological development, policymaking, and scholarly research.

METHOD

The methodological approach undertaken in this review was designed to ensure comprehensive and systematic coverage of the literature on robotics and automation in precision agriculture. Recognizing the interdisciplinary nature of the field, spanning agricultural sciences, engineering, computer science, and environmental studies, a carefully structured strategy was adopted to capture both breadth and depth in the relevant scholarship. The methodology combined a systematic review framework with targeted keyword strategies to ensure the inclusion of high-quality, peer-reviewed studies while minimizing bias and redundancy.

The first step in the process involved identifying the most suitable scientific databases that could provide robust coverage of precision agriculture and its integration with robotics and automation. Scopus was chosen as a primary database due to its extensive indexing of peer-reviewed journals across disciplines relevant to this study. Its breadth of coverage, particularly in agricultural sciences, robotics, automation technology, and engineering, allowed for a comprehensive retrieval of interdisciplinary publications (Fedorov, 2022; Ponce et al., 2023). Complementing this, Web of Science was also prioritized, given its reputation for indexing high-impact journals and its rigorous curation of literature relevant to technological advancements in agriculture (Kan et al., 2021). These two databases, when combined, ensured that the review captured both foundational and cutting-edge research across multiple domains.

While Scopus and Web of Science formed the core of the literature search, supplementary databases were also considered to broaden the scope. PubMed, despite its primary orientation toward biomedical research, was reviewed for relevant studies on the intersection between agricultural technologies and health-related aspects, though its contribution was limited. Google Scholar, in contrast, was used selectively to identify grey literature, conference proceedings, and policy documents that, although not always peer-reviewed, provided valuable context and insights into emerging applications of robotics and automation in agriculture (Duncan et al., 2024; Millard et al., 2019). This layered approach ensured that the review did not exclude non-traditional yet relevant sources that could enrich the analysis.

The next phase of the methodology involved the development of precise keyword strategies. Keywords were derived from an initial scoping review and refined iteratively to balance sensitivity and specificity in the search results. Simple keyword combinations such as "precision agriculture" AND "robotics" or "automation" AND "smart farming technologies" were employed to retrieve a foundational set of articles. More advanced Boolean operators and combinations were then applied to capture interdisciplinary studies. For instance, queries like ("robotics" OR "automation") AND ("precision agriculture" OR "smart farming") AND ("AI" OR "machine learning" OR "IoT") were particularly effective in identifying articles at the intersection of robotics with artificial intelligence and data-driven technologies. Similarly, combinations such as ("UAVs" OR "drones") AND "precision agriculture" AND "automation" helped to narrow searches to aerial technologies within agricultural systems. These keyword strategies ensured the inclusion of diverse literature while maintaining a clear focus on robotics and automation within precision agriculture (Emmi et al., 2023; Gerhards et al., 2023).

In addition to general searches, targeted queries were employed to capture specialized themes within the literature. Specific combinations such as "robotic weed control" AND "precision agriculture," "mobile robotics" AND "agriculture" AND ("automation" OR "technology"), and "AI" AND "robotics" AND "yield prediction" AND "precision agriculture" enabled the review to access literature addressing niche applications of robotics. By structuring the search strategy in this manner, the review was able to retrieve both broad thematic studies and highly specialized articles, contributing to a well-rounded synthesis (Balabantaray et al., 2024).

To refine the body of literature and ensure the relevance of included studies, a set of inclusion and exclusion criteria was established. Inclusion criteria focused on peer-reviewed studies published between 2015 and 2025 to reflect the most recent and impactful advancements in the field. Articles were required to address robotics or automation in precision agriculture, either as primary technologies or in combination with complementary tools such as AI, IoT, or UAVs. Both empirical and theoretical studies were included, provided they presented clear insights into the role of robotics in advancing agricultural productivity, sustainability, or resource efficiency. Exclusion criteria, by contrast, eliminated studies that addressed agriculture in a generic manner without specific reference to robotics or automation, as well as articles outside the agricultural context, such as those focused solely on industrial automation.

The review also established criteria for the types of research designs that would be considered. Randomized controlled trials, cohort studies, case studies, and field trials were all included, given their relevance in providing empirical evidence of the application and impact of robotics in agriculture. Narrative reviews, systematic reviews, and meta-analyses were likewise included when they provided synthesized perspectives or frameworks that informed the integration of robotics and automation in agricultural practices. Studies limited to theoretical modeling without empirical validation were included cautiously and only when they offered substantial conceptual contributions.

Once the initial body of literature was retrieved, the screening process commenced in two stages: title and abstract screening followed by full-text review. During the first stage, titles and abstracts were independently screened to eliminate irrelevant articles that did not meet the inclusion criteria. This process was particularly crucial in minimizing redundancy from broad keyword searches. The second stage involved a full-text review of the remaining studies, during which articles were evaluated for methodological rigor, relevance to precision agriculture, and the robustness of their findings. Only articles that passed both stages were included in the final synthesis.

The evaluation of selected articles emphasized quality appraisal, where each study was assessed for clarity of research objectives, appropriateness of methodology, and contribution to the field. For empirical studies, attention was given to sample size, study design, and reliability of findings. For reviews and theoretical contributions, the focus was on the comprehensiveness of the synthesis and the novelty of insights provided. This rigorous evaluation ensured that the review included only literature of high scholarly value.

Overall, the methodological framework adopted in this study combined a targeted database selection strategy with refined keyword searches and rigorous screening processes. By prioritizing Scopus and Web of Science for high-quality peer-reviewed literature, while also incorporating supplementary sources such as Google Scholar for grey literature, the review captured a comprehensive body of work. Strategic keyword combinations further ensured the retrieval of relevant interdisciplinary studies, while inclusion and exclusion criteria provided a structured filter to maintain quality and focus. The result is a curated synthesis of literature that accurately reflects the state of robotics and automation in precision agriculture, while also highlighting the gaps and opportunities for future research.

RESULT AND DISCUSSION

Yield Optimization and Resource Efficiency

Empirical evidence strongly supports the role of AI-enabled predictive models and UAV-based monitoring in enhancing agricultural yields and improving resource efficiency. Numerous studies have emphasized that integrating machine learning algorithms with UAV technology has significantly improved crop yield predictions and facilitated more precise input allocation. For example, AI-driven models can combine historical yield data with real-time environmental observations to optimize irrigation schedules and nutrient management practices, leading to yield increases of up to 20% compared to conventional farming approaches (Ponce et al., 2023; Misopolinos et al., 2015). UAVs equipped with multispectral sensors have been particularly effective in aerial monitoring, identifying plant stressors such as nutrient deficiencies, pest infestations, and disease outbreaks, enabling farmers to intervene promptly and improve overall crop health (Joshi, 2025; Misopolinos et al., 2015).

The practical benefits of UAVs extend beyond monitoring to tangible cost savings. UAV-guided data analytics have demonstrated improvements in water-use efficiency and reduced nitrogen application by nearly 30%, thereby lowering operational expenditures while safeguarding environmental resources (Duncan et al., 2024). These outcomes confirm the synergistic potential of AI predictive modeling combined with UAVs to create sustainable, data-driven frameworks for modern agriculture. The effectiveness of these technologies is especially critical in addressing rising global food demands under resource-constrained conditions.

Smart irrigation systems represent another essential component of yield optimization, though their effectiveness varies by climate. Research in arid and semi-arid regions demonstrates substantial benefits from precision irrigation technologies. Systems integrating soil moisture sensors, automation, and drip irrigation have conserved significant volumes of water while sustaining crop productivity (Emmi et al., 2023; Kumar, 2025). Conversely, in temperate regions where precipitation patterns are less predictable, the benefits have been more modest, requiring tailored protocols to account for local soil types and water conditions (Balabantaray et al., 2024). These findings highlight the importance of region-specific adjustments to maximize the efficiency of smart irrigation systems and underscore the necessity of flexible, context-driven implementations.

Robotics in Harvesting and Pruning

Soft robotics has revolutionized delicate crop harvesting by addressing challenges that traditional mechanical methods could not overcome. Soft robotic grippers, modeled to replicate the dexterity and sensitivity of human hands, have effectively reduced mechanical damage during harvesting. Field trials show that these systems achieve handling success rates exceeding 90% for crops such as strawberries and blueberries, significantly reducing bruising and loss compared to conventional methods (Pandey, 2025; Kan et al., 2021; Bhattarai et al., 2024; Millard et al., 2019). This improvement is particularly relevant for high-value crops, where quality preservation directly impacts market value and consumer acceptance.

Beyond reducing damage, soft robotics also enhances operational efficiency. Automated systems have demonstrated faster harvesting rates compared to manual labor, thereby mitigating labor shortages while ensuring product quality (Kan et al., 2021; Millard et al., 2019). These advances illustrate how robotics can provide both quantitative and qualitative benefits, simultaneously increasing productivity and safeguarding produce integrity. The success of soft robotics emphasizes the role of human-inspired mechanical design in improving agricultural operations.

Pruning, another labor-intensive task, has also benefited from machine vision and AI integration. Deep learning algorithms paired with computer vision systems have achieved pruning accuracies above 85% by identifying optimal cutting points and complex branch structures (Padhiary et al., 2025; Jiang, 2025). The deployment of automated pruning robots has improved efficiency and significantly reduced costs associated with manual pruning. AI-driven pruning systems not only enhance precision but also leverage predictive analytics to refine techniques across pruning cycles, resulting in improved tree health and higher fruit yields over time (Höffmann et al., 2024; Bhattarai et al., 2024). These findings demonstrate that AI-enhanced pruning represents a critical shift in horticultural practices, where data-driven automation ensures long-term sustainability and productivity.

Autonomous Robots and Intelligent Systems

Autonomous robots are increasingly employed in precision agriculture for soil monitoring, weeding, and targeted spraying, and empirical results confirm their effectiveness. Robotic systems utilizing deep learning algorithms for weed management have achieved average control efficiencies of approximately 85%, surpassing traditional methods and significantly reducing herbicide reliance (Balabantaray et al., 2024). These robots effectively distinguish between crops and weeds, enabling targeted interventions that not only preserve crop health but also contribute to environmental sustainability by lowering chemical inputs.

Soil monitoring has likewise been transformed by autonomous systems. Mobile robots integrated with AI and advanced sensors provide real-time data on soil moisture and nutrient levels, enhancing irrigation efficiency by 20–30% through precise targeting of specific field zones (Ponce et al., 2023). This data-driven approach ensures that water and nutrient resources are used optimally, improving yields and reducing unnecessary input expenditures. Such capabilities highlight the importance of robotics in advancing resource management strategies within precision agriculture.

Targeted spraying further illustrates the advantages of automation. Robotic sprayers equipped with machine vision technologies have achieved chemical application efficiencies exceeding 70%, minimizing drift and maximizing the impact of treatments on affected areas (Toscano et al., 2025; Baltazar et al., 2021). These systems allow for precise pesticide use, reducing both economic costs and environmental risks. Collectively, these findings underscore the pivotal role of autonomous robots in promoting efficient, sustainable agricultural practices.

The integration of robotics within aquaponic systems further demonstrates innovative applications aimed at water conservation. Automated systems equipped with water quality sensors enable real-time monitoring and adjustment of aquaponic environments, reducing water use by approximately 30% (Vahdanjoo et al., 2023). These innovations maintain optimal conditions for both aquatic organisms and plants, leading to enhanced fish growth and improved crop health. Studies confirm that robotic integration enhances resource efficiency in aquaponics by preventing wasteful water circulation and ensuring consistent quality control (Yao et al., 2021; Mansour, 2025). Such systems exemplify how robotics can contribute to closed-loop, sustainable agricultural frameworks.

Adoption Trends

The global adoption of robotics and automation technologies in agriculture is uneven, reflecting variations in economic conditions, infrastructure, and cultural acceptance. In Europe, adoption rates currently stand at 15–20%, with projections indicating growth as more farmers recognize the benefits of robotics (Gabriel & Gandorfer, 2022). East Asian nations such as Japan and South Korea report higher adoption levels, with rates between 25–30%, driven by strong governmental support and technological innovation (Bayar, 2017). These countries exemplify how supportive policy frameworks and cultural receptivity to technology can accelerate adoption.

In contrast, adoption rates in developing regions remain below 10%, hindered by limited financial resources, inadequate infrastructure, and restricted access to technology. Research suggests that with targeted policy interventions and sustained investment in digital infrastructure, adoption rates could improve significantly in the coming decade (Balasundaram et al., 2022; Nijak et al., 2024). These disparities emphasize the global divide in technological access, underscoring the need for inclusive policies that democratize access to agricultural innovations.

Socio-economic determinants strongly influence adoption patterns. Government incentives such as subsidies and grants play a crucial role in reducing financial barriers and encouraging farmers to experiment with new technologies (Dhillon, 2023). Education and training programs have also been shown to increase adoption likelihood, as farmers who are equipped with technical knowledge are better positioned to leverage advanced systems effectively (Sparrow & Howard, 2020). Farm size is another critical factor: larger operations are more likely to adopt robotics as fixed costs are spread across greater output volumes, whereas smallholder farmers often lack the capital required for investment (Bazargani & Deemyad, 2024).

Cultural perceptions of automation also shape adoption rates. Trust in robotic systems and societal acceptance of digital transformation can significantly accelerate or delay adoption in different regions (Lubag et al., 2023; Chen et al., 2023). These cultural dynamics, when combined with economic and infrastructural factors, paint a complex picture of how robotics and automation diffuse across agricultural sectors globally.

In summary, the results reveal that robotics and automation in precision agriculture significantly enhance yield optimization, improve resource efficiency, and address labor shortages through technological innovation. However, their adoption is shaped by diverse regional and socio-economic contexts. While advanced economies are leading in implementation, developing countries remain at an early stage, necessitating targeted interventions to bridge the gap. The global trajectory of robotics in agriculture suggests that continued investment, supportive policy, and farmer education will be pivotal in fostering widespread adoption, ensuring that the transformative potential of these technologies benefits agricultural systems worldwide.

Systemic factors play a decisive role in shaping the scalability and adoption of smart farming technologies. Infrastructure emerges as one of the most fundamental elements influencing deployment. Reliable internet connectivity, modern machinery, and access to digital platforms are prerequisites for the effective functioning of robotics and automation in agriculture. Studies have shown that rural areas often lack these foundational elements, creating a disparity between technologically advanced and underserved regions (Ponce et al., 2023; Fedorov, 2022). In such contexts, the uneven availability of infrastructure translates directly into unequal opportunities for adoption. For instance, urban and peri-urban farmers, with better access to digital resources, often achieve higher adoption rates compared to those in remote regions, exacerbating existing socio-economic divides (Duncan et al., 2024). The absence of adequate infrastructure, therefore, perpetuates a cycle where the potential benefits of robotics are confined to relatively advantaged areas.

Financial barriers also weigh heavily on the adoption of smart farming technologies. The high upfront costs of purchasing robotics, sensors, and automated systems act as a deterrent for small and medium-sized farms, particularly in developing economies where capital resources are limited (Emmi et al., 2023). Even when the long-term benefits of automation—such as yield improvements and reduced input costs—are evident, many farmers remain hesitant to invest without immediate returns. Financial institutions often exacerbate this issue, as they perceive investments in agricultural technology as high-risk ventures and are reluctant to provide loans or credit (Aghi et al., 2020). This financial inertia significantly restricts the ability of farmers to modernize their operations, slowing down broader adoption. Subsidies and grants have been identified as effective mechanisms to offset these barriers, yet their availability is inconsistent across regions. Without systemic financial support, many farmers remain excluded from the technological revolution that is reshaping agriculture.

Data governance further complicates the integration of robotics into precision agriculture. The increasing reliance on digital technologies necessitates the generation and exchange of large volumes of farm-level data. However, questions about ownership, security, and transparency hinder farmer confidence in adopting these systems. Farmers often fear losing control over their operational data, leading to hesitation in embracing technologies that depend on extensive data collection (Millard et al., 2019). The lack of clear governance frameworks exacerbates these concerns, as data misuse or exploitation could undermine trust in the long run. Conversely, effective governance systems, which emphasize data protection, transparency, and equitable sharing protocols, can foster greater collaboration among stakeholders. By creating secure ecosystems, data governance frameworks encourage broader participation and enhance the overall success of smart farming technologies (Shamshiri et al., 2024).

Policy frameworks designed to promote smart farming adoption vary widely in their structure and effectiveness. Subsidy schemes remain the most common policy intervention, aimed at reducing the financial burden on farmers who wish to adopt robotics and automation. Evidence from countries such as the Netherlands suggests that coupling subsidies with awareness campaigns significantly improves adoption rates, as farmers not only receive financial support but also understand the tangible benefits of these technologies (Kumar, 2025; Li et al., 2024). Educational initiatives are another cornerstone of successful policy frameworks. Programs aimed at enhancing farmers' digital literacy and technical competencies have shown measurable success in increasing adoption, as seen in Italy where training programs have facilitated the integration of precision farming methods with notable improvements in productivity (Kan et al., 2021; Gerhards et al., 2023). Such interventions highlight the importance of building human capital alongside financial and infrastructural support.

However, the effectiveness of these policy frameworks is far from uniform. In developing economies, systemic challenges such as bureaucratic inefficiency and corruption frequently limit access to subsidies and training programs (Padhiary et al., 2025). Farmers in these contexts often report difficulty navigating administrative processes, resulting in limited uptake despite the existence of supportive policies. This underscores the importance of tailoring policy frameworks to local contexts, accounting for not only economic and infrastructural realities but also cultural perceptions of technology and levels of institutional transparency. Policies that are overly standardized may fail to address localized barriers, limiting their broader impact.

Despite substantial advancements in robotics and automation, current research is constrained by several notable limitations. Data insufficiency continues to undermine the development and refinement of AI and machine learning applications in agriculture. High-quality datasets are essential for training algorithms that drive predictive models and automated systems, yet such datasets remain scarce, particularly in regions with underdeveloped digital infrastructures (Mansour, 2025). The absence of diverse and representative data sets limits the generalizability of AI models, reducing their reliability in real-world applications. Addressing this issue requires the creation of shared data repositories and collaborative research initiatives that pool information across regions and contexts (Toscano et al., 2025).

Interoperability among smart farming technologies is another critical limitation. Current systems are often designed in silos, limiting integration and constraining the ability to optimize agricultural operations holistically (Balabantaray et al., 2024). For instance, UAV-based monitoring systems may provide valuable insights into crop health, but without seamless integration with ground-based robotics or irrigation systems, the potential for coordinated responses remains underutilized. Developing standardized communication protocols and interoperable systems is essential for advancing toward truly integrated smart farming ecosystems. Without such advancements, the scalability and sustainability of robotic applications in agriculture remain limited.

Emerging research directions suggest several promising avenues for overcoming existing barriers. Integrating AI with robotics to enhance decision-making has been identified as one of the most significant opportunities. Advanced AI systems can enable robots not only to perform routine tasks but also to adapt to dynamic field conditions by learning from prior interactions (Bhat, 2025). Research focusing on crop-specific robotic applications also holds considerable potential. Many high-value crops, such as berries or specialty vegetables, present unique harvesting and handling challenges that require customized solutions (Ariss et al., 2024; Seol et al., 2024). By tailoring robotics to specific agricultural contexts, the efficiency and effectiveness of automation can be significantly improved.

Another emerging focus involves assessing the environmental impacts of scaling robotics and automation in agriculture. While robotics has the potential to reduce resource consumption and chemical inputs, the energy demands of large-scale deployment and potential ecological consequences remain underexplored. Scholars emphasize the need to balance technological benefits with environmental considerations, ensuring that automation contributes positively to the broader goals of sustainability (Pandey, 2025). Comprehensive life-cycle assessments that account for energy use, emissions, and ecological impacts are critical for ensuring that robotics aligns with sustainable development objectives.

The discussion of systemic, financial, and technological challenges highlights the interconnectedness of barriers to smart farming adoption. For instance, poor infrastructure exacerbates financial risks, while weak data governance undermines farmer trust, both of which limit the effectiveness of even well-designed policies. Addressing these barriers requires a holistic approach that integrates infrastructure investment, financial support mechanisms, transparent governance, and culturally sensitive policy frameworks. The literature suggests that interdisciplinary collaborations among policymakers, researchers, and industry stakeholders are pivotal for driving forward sustainable and equitable adoption of robotics and automation in agriculture.

CONCLUSION

This narrative review highlights the transformative role of robotics and automation in advancing precision agriculture. The synthesis of findings demonstrates that AI-enabled predictive models, UAV-based monitoring, smart irrigation systems, and autonomous robots significantly improve yield optimization, resource efficiency, and labor productivity. Empirical evidence reveals yield improvements of up to 20%, water and fertilizer savings exceeding 30%, and enhanced operational precision across diverse agricultural contexts. Soft robotics and machine vision technologies have shown remarkable success in delicate harvesting and pruning, ensuring both efficiency and quality. Furthermore, the integration of autonomous robots in soil monitoring, weeding, and targeted spraying, as well as aquaponic systems, underscores their versatility in promoting sustainable and resource-efficient practices.

The discussion underscores systemic barriers such as inadequate infrastructure, high implementation costs, and weak data governance, all of which constrain scalability. Policy frameworks including subsidies, digital literacy programs, and training initiatives have proven effective in some contexts, yet their impact varies across regions due to institutional inefficiencies and economic disparities. Future research must prioritize interoperability among systems, the development of high-quality datasets for machine learning, and assessments of environmental impacts associated with large-scale deployment. Moreover, crop-specific and context-sensitive applications of robotics remain underexplored and require further scholarly attention.

The urgency of these issues lies in the mounting pressure of feeding a growing global population under constrained resources and changing climates. Strategic investment in supportive infrastructure, transparent governance, and inclusive policies is essential to democratize access to smart farming technologies. By addressing these challenges holistically, robotics and automation can realize their full potential in transforming agriculture into a more resilient, sustainable, and equitable sector.

REFERENCE

Aghi, D., Mazzia, V., & Chiaberge, M. (2020). Local motion planner for autonomous navigation in vineyards with a RGB-D camera-based algorithm and deep learning synergy. *Machines, 8*(2), 27. https://doi.org/10.3390/machines8020027

Ariss, A., Ennejjai, I., Lamjid, A., Mabrouki, J., Kharmoum, N., & Ziti, S. (2024). IoT-enabled smart greenhouse for robotic enhancement of tomato production: leveraging 5G and edge computing for advanced data-driven automation, precision irrigation, and scalable zoning principles. *International Journal of Interactive Mobile Technologies (iJIM), 18*(21), 88–116. https://doi.org/10.3991/ijim.v18i21.50829

Bagagiolo, G., Matranga, G., Cavallo, E., & Pampuro, N. (2022). Greenhouse robots: ultimate solutions to improve automation in protected cropping systems—a review. *Sustainability, 14*(11), 6436. https://doi.org/10.3390/su14116436

Balabantaray, A., Behera, S., Liew, C., Chamara, N., Singh, M., Jhala, A., … & Pitla, S. (2024). Targeted weed management of Palmer amaranth using robotics and deep learning (YOLOv7). *Frontiers in Robotics and AI, 11*. https://doi.org/10.3389/frobt.2024.1441371

Balasundaram, E., Vadivel, A., & Posarajan, A. (2022). Digital farming a crucial enabler for sustainable Indian agriculture. pp. 272–281. https://doi.org/10.2174/9789815049251122010018

Baltazar, A., Santos, F., Moreira, A., Valente, A., & Boaventura-Cunha, J. (2021). Smarter robotic sprayer system for precision agriculture. *Electronics, 10*(17), 2061. https://doi.org/10.3390/electronics10172061

Bayar, G. (2017). Development of a Voronoi diagram based tree trunk detection system for mobile robots used in agricultural applications. *Industrial Robot: The International Journal of Robotics Research and Application, 44*(4), 521–531. https://doi.org/10.1108/ir-11-2016-0304

Bazargani, K., & Deemyad, T. (2024). Automation's impact on agriculture: opportunities, challenges, and economic effects. *Robotics, 13*(2), 33. https://doi.org/10.3390/robotics13020033

Bhat, I. (2025). Leveraging artificial intelligence in agribusiness: a structured review of strategic management practices and future prospects. *Discover Sustainability, 6*(1). https://doi.org/10.1007/s43621-025-01260-3

Bhattarai, U., Zhang, Q., & Karkee, M. (2024). Design, integration, and field evaluation of a robotic blossom thinning system for tree fruit crops. *Journal of Field Robotics, 41*(5), 1366–1385. https://doi.org/10.1002/rob.22330

Chen, Z., Chen, J., Li, Y., Gui, Z., & Yu, T. (2023). Tea bud detection and 3D pose estimation in the field with a depth camera based on improved YOLOv5 and the optimal pose-vertices search method. *Agriculture, 13*(7), 1405. https://doi.org/10.3390/agriculture13071405

D'Oronzio, M., & Sica, C. (2021). Innovation in Basilicata agriculture: from tradition to digital. *Economia Agro-Alimentare, (2),* 1–18. https://doi.org/10.3280/ecag2-2021oa12210

Dhillon, R. (2023). Small-scale farming: a review of challenges and potential opportunities offered by technological advancements. *Sustainability, 15*(21), 15478. https://doi.org/10.3390/su152115478

Duncan, B., Bulanon, D., Bulanon, J., & Nelson, J. (2024). Development of a cross-platform mobile application for fruit yield estimation. *Agriengineering, 6*(2), 1807–1826. https://doi.org/10.3390/agriengineering6020105

Emmi, L., Fernández, R., & Hernández, J. (2023). Editorial: Robotics for smart farms. *Frontiers in Robotics and AI, 9*. https://doi.org/10.3389/frobt.2022.1113440

Fahey, T., Pham, H., Gardi, A., Sabatini, R., Stefanelli, D., Goodwin, I., … & Lamb, D. (2020). Active and passive electro-optical sensors for health assessment in food crops. *Sensors, 21*(1), 171. https://doi.org/10.3390/s21010171

Fedorov, D. (2022). Modern trends in developing robotic systems in agro-industrial complex. *IOP Conference Series: Earth and Environmental Science, 949*(1), 012016. https://doi.org/10.1088/1755-1315/949/1/012016

Gabriel, A., & Gandorfer, M. (2022). Adoption of digital technologies in agriculture—an inventory in a European small-scale farming region. *Precision Agriculture, 24*(1), 68–91. https://doi.org/10.1007/s11119-022-09931-1

Gerhards, R., Risser, P., Spaeth, M., Saile, M., & Peteinatos, G. (2023). A comparison of seven innovative robotic weeding systems and reference herbicide strategies in sugar beet (Beta vulgaris subsp. vulgaris L.) and rapeseed (Brassica napus L.). *Weed Research, 64*(1), 42–53. https://doi.org/10.1111/wre.12603

Grigorev, G., Pitertsev, M., & Fomichev, E. (2025). Multimodal sensor fusion and embedded control for obstacle-aware feed pusher robotics in precision livestock farming, 35. https://doi.org/10.1117/12.3072669

Höffmann, M., Patel, S., & Büskens, C. (2024). Optimal guidance track generation for precision agriculture: a review of coverage path planning techniques. *Journal of Field Robotics, 41*(3), 823–844. https://doi.org/10.1002/rob.22286

Jiang, L. (2025). Overview of agricultural machinery automation technology for sustainable agriculture. *Agronomy, 15*(6), 1471. https://doi.org/10.3390/agronomy15061471

Joshi, A. (2025). Harnessing artificial intelligence for sustainable food production. pp. 25–56. https://doi.org/10.4018/979-8-3373-0842-5.ch002

Kan, X., Thayer, T., Carpin, S., & Karydis, K. (2021). Task planning on stochastic aisle graphs for precision agriculture. *IEEE Robotics and Automation Letters, 6*(2), 3287–3294. https://doi.org/10.1109/lra.2021.3062337

Kumar, K. (2025). Self-service innovations in precision agriculture. pp. 391–432. https://doi.org/10.4018/979-8-3373-1295-8.ch014

Li, M., Wu, F., FengBo, W., Zou, T., Li, M., & Xiao, X. (2024). CNN-MLP-based configurable robotic arm for smart agriculture. *Agriculture, 14*(9), 1624. https://doi.org/10.3390/agriculture14091624

Lubag, M., Bonifácio, J., Tan, J., Concepcion, R., Mababangloob, G., Galang, J., … & Maniquiz-Redillas, M. (2023). Diversified impacts of enabling a technology-intensified agricultural supply chain on the quality of life in hinterland communities. *Sustainability, 15*(17), 12809. https://doi.org/10.3390/su151712809

Mansour, A. (2025). Revolutionizing farming with agriculture 4.0. pp. 51–96. https://doi.org/10.4018/979-8-3373-5283-1.ch003

Milburn, L., Gamba, J., Fernandes, M., & Semini, C. (2023). Computer-vision based real time waypoint generation for autonomous vineyard navigation with quadruped robots. pp. 239–244. https://doi.org/10.1109/icarsc58346.2023.10129563

Millard, A., Ravikanna, R., Groß, R., & Chesmore, D. (2019). Towards a swarm robotic system for autonomous cereal harvesting. pp. 458–461. https://doi.org/10.1007/978-3-030-25332-5_40

Misopolinos, L., Zalidis, C., Liakopoulos, V., Stavridou, D., Katsigiannis, P., Alexandridis, T., … & Zalidis, G. (2015). Development of a UAV system for VNIR-TIR acquisitions in precision agriculture. https://doi.org/10.1117/12.2192660

Nijak, M., Skrzypczyński, P., Ćwian, K., Zawada, M., Szymczyk, S., & Wojciechowski, J. (2024). On the importance of precise positioning in robotised agriculture. *Remote Sensing, 16*(6), 985. https://doi.org/10.3390/rs16060985

Padhiary, M., Prasad, G., Hoque, A., Kumar, K., & Sahu, B. (2025). Advances in vertical farming: the role of artificial intelligence and automation in sustainable agriculture. *LatIA, 3,* 131. https://doi.org/10.62486/latia2025131

Pandey, S. (2025). Robotics and automation in modern agriculture. pp. 153–186. https://doi.org/10.4018/979-8-3373-5283-1.ch006

Ponce, D., Salcedo, J., Rosero-Montalvo, P., & Sanchis, J. (2023). Mobile robotics in smart farming: current trends and applications. *Frontiers in Artificial Intelligence, 6.* https://doi.org/10.3389/frai.2023.1213330

Rathod, T., Jadav, N., Tanwar, S., Pólkowski, Z., Yamsani, N., Sharma, R., … & Gafar, A. (2023). AI and blockchain-based secure data dissemination architecture for IoT-enabled critical infrastructure. *Sensors, 23*(21), 8928. https://doi.org/10.3390/s23218928

Seol, J., Park, Y., Pak, J., Jo, Y., Lee, G., Kim, Y., … & Son, H. (2024). Human-centered robotic system for agricultural applications: design, development, and field evaluation. *Agriculture, 14*(11), 1985. https://doi.org/10.3390/agriculture14111985

Shamshiri, R., Sturm, B., Weltzien, C., Fulton, J., Khosla, R., Schirrmann, M., … & Hameed, I. (2024). Digitalization of agriculture for sustainable crop production: a use-case review. *Frontiers in Environmental Science, 12.* https://doi.org/10.3389/fenvs.2024.1375193

Sparrow, R., & Howard, M. (2020). Robots in agriculture: prospects, impacts, ethics, and policy. *Precision Agriculture, 22*(3), 818–833. https://doi.org/10.1007/s11119-020-09757-9

Toscano, F., Fiorentino, C., Capece, N., Erra, U., Travascia, D., Scopa, A., … & D'Antonio, P. (2024). Unmanned aerial vehicle for precision agriculture: a review. *IEEE Access, 12,* 69188–69205. https://doi.org/10.1109/access.2024.3401018

Toscano, F., Fiorentino, C., Santana, L., Magalhães, R., Albiero, D., Řezník, T., … & D'Antonio, P. (2025). Recent developments and future prospects in the integration of machine learning in mechanised systems for autonomous spraying: a brief review. *Agriengineering, 7*(5), 142. https://doi.org/10.3390/agriengineering7050142

Urrea, C., & Kern, J. (2025). Recent advances and challenges in industrial robotics: a systematic review of technological trends and emerging applications. *Processes, 13*(3), 832. https://doi.org/10.3390/pr13030832

Vahdanjoo, M., Gislum, R., & Sørensen, C. (2023). Operational, economic, and environmental assessment of an agricultural robot in seeding and weeding operations. *Agriengineering, 5*(1), 299–324. https://doi.org/10.3390/agriengineering5010020

Yao, L., Zedde, H., & Kowalchuk, G. (2021). Recent developments and potential of robotics in plant eco-phenotyping. *Emerging Topics in Life Sciences, 5*(2), 289–300. https://doi.org/10.1042/etls20200275