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REVIEW ARTICLE

# Robotics redefining wheat farming: Bridging efficiency and sustainability

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## Abstract

Automation in wheat cultivation has revolutionized precision, sustainability and overall productivity by integrating advanced robotics and cutting-edge technology. High-clearance robots automate all growth stages by employing adaptive Kalman filters and fuzzy PID controllers for precisely controlled navigation and acquisition of phenotypic data. Swarm robots are cost-effective and exhibit adaptability to varied field conditions challenging traditional economies of scale, enabling smaller farms to achieve competitive production costs. Advances in image processing have overcome the challenges of canopy closure, enabling sub-50 mm accuracy in wheat row tracking, critical for early-growth interventions. Integration of LiDAR, spectral sensors and aerial robotics complements ground-based systems, offering robust data for decision support. Deployment of mobile robots has enhanced precision seeding with accuracy reaching over 93 % while high-throughput phenotyping platforms utilize robotics and machine learning to transform disease resistance assessments, such as Fusarium Head Blight (FHB). Algorithms like DeepLabV3+ have achieved over 96 % accuracy in identifying wheat ears, significantly reducing labour in breeding resistant varieties. The seed screener platform automates the analysis of single wheat kernels, combining RGB imaging and near-infrared (NIR) spectroscopy to evaluate 3D morphological and biochemical traits. The seed screener uses the marching cubes algorithm to extract precise morphological data from 3D visual models. This high-precision, high-throughput platform demonstrates significant potential for commercialisation, providing breeders with an advanced tool to facilitate wheat improvement programmes. These innovations address critical challenges, including phenotypic characterisation, planting uniformity and real-time adaptability, offering transformative solutions for precision agriculture. Automation in wheat cultivation provides a pathway to achieving food security while ensuring sustainability, ushering in a new era in agricultural practices.

**Keywords:** automation; imaging; robot; sensor; wheat

## Introduction

Wheat (*Triticum aestivum*) is the most widely cultivated cereal crop that serves as a staple food for a substantial portion of the global population following rice and maize. It serves as a critical component in food security serving around 40 % of the consumption ratio (1). The increase in demand for food supply coupled with the implications of climatic fluctuations and extreme weather events, has disrupted the balance between food supply and demand. Considering climate change, there is an urgent need for efficient wheat cultivation methods to achieve food security goals.

The integration of robotics in agriculture has become a key solution to the challenges of food security and sustainable intensification. Wheat contributes around 20 % of the global energy and carbohydrate intake (2, 3). With the increasing global population continuing to rise, the demand for wheat production is expected to increase significantly. The increased frequency and intensity of droughts, erratic rainfall and natural disasters have significantly reduced the production efficiency of the agricultural sector, necessitating the exploration of innovative solutions and practices (4, 5). However, its production efficiency is hampered by several factors including the prevalence of fungal diseases such as Fusarium Head Blight (FHB), which can lead to yield losses ranging from 10-40 % in epidemic years (6). The frequency of FHB occurrence, primarily caused by *Fusarium graminearum*, highlights the need for innovative strategies to enhance wheat yield and quality. Traditional methods of disease management including chemical methods have limitations both in terms of efficacy and environmental impact (7). The integration of automation has garnered significant interest and emerged as a necessity for improving existing agricultural practices (8). Recent advancements in computer vision, machine learning and robotics have opened new avenues for precision agriculture, enabling more efficient monitoring and management of crops.

Critical tasks such as planting, weeding and disease detection can be automated reducing costs and increasing operational efficiency (9). For instance, autonomous weeding robots utilize advanced navigation systems to minimize crop damage while effectively controlling weed populations. Similarly, UAVs with image processing capabilities enable real-time monitoring of crop health and disease outbreaks (10, 11). The drive for greater efficiency, lower labour costs and the capacity to perform precise agricultural operations has led to the evolution of agricultural robotics. Since conventional farming techniques struggle to meet the demands of modern agriculture, the adoption of robotics technologies has become crucial (12). Countries such as Japan and the United States have been at the forefront of agricultural robotics research, developing sophisticated systems that enhance productivity and sustainability (13–16). In contrast, while China has made strides in this field, it still faces technological gaps compared to its Western counterparts (17). The advent of robotics significantly enhances crop quality by boosting producers' profitability and expanding consumer access to high-quality food. Consequently, the adoption aids in a well-regulated distribution of resources to mitigate environmental impact. Contemporary robots possess the intelligence and advanced perception skills to comprehend, interpret and represent their surroundings and their components, including crops, leaves and various productive entities such as plants, trees, pests and pathogens (18-20). For wheat cultivation, operations include automated precision seeding, automated harvesting, real-time disease detection and crop monitoring. For instance, precision seeding techniques have been shown to improve wheat yields significantly, with studies indicating increases of 7.5-22.3 % compared to traditional methods (21, 22). The integration of technologies such as machine vision, deep learning and crop discrimination enables the development of systems capable of detecting and classifying diseases, weeds and pests with high accuracy, thereby facilitating timely interventions (23, 24). Despite the promising advancements, the integration of robotics in agriculture comes with its challenges. High initial investment costs, the complexity of agricultural environments and the need for robust navigation and decision-making capabilities remain significant hurdles (25). Additionally, the economic implications of adopting robotic technologies must be carefully considered as profitability is a critical factor influencing farmers' willingness to invest in new technologies (26).

This review aims to explore the implications of robotics in wheat cultivation, highlighting the potential benefits and limitations of the practice. The integration of robotics in agriculture marks a major shift towards more efficient, precise and sustainable farming. As the agricultural sector continues to evolve, understanding the implications of technological advancements will be crucial for researchers, policymakers and practitioners alike. A comprehensive analysis focussing on wheat cultivation and its potential for automation will enhance our understanding of precision agriculture and support efforts to address food security challenges.

## Evolution of agricultural robotics

Robotics in agriculture has initiated a revolution by enabling a range of tasks through multi- functional systems. These robots provide a platform to integrate various machinery onto a single chassis, paving the way for advanced capabilities in perception, control and precise execution. They can operate effectively in complex and challenging environments that are typically inaccessible to human intervention (27). Robotics have been widely used in the industrial sector for tasks such as material handling, processing, inspection and quality control. The core concept focuses on automation and minimizing human error. The evolution of robotic agriculture has been marked by several successful implementations, demonstrating its potential to transform the sector as in Fig. 1. The primary objectives behind the adoption of agricultural robotics include enhancing food quality and productivity, minimization of labour costs and reduction of operational time. Shortage of skilled labour has been a persistent driver for incorporation of mechanization of agriculture which becomes a key factor for hindrance of agricultural development in developing nations. Over time, robots have been effectively deployed in various agricultural tasks including seeding, weed control harvesting, chemical applications and field supervision underscoring their increasing role in modern agricultural practices (28, 29). The advent has been marked by significant advancements in

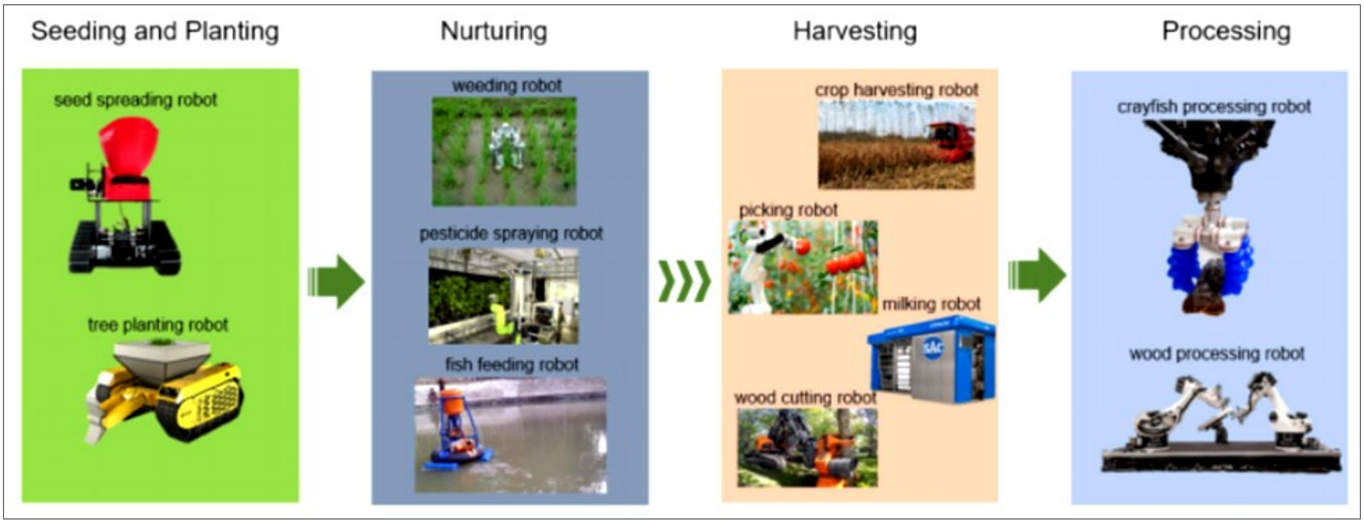


**Fig. 1.** Utilization of agricultural robots over the prospect of automation in agricultural process (40).

technology and application, transforming traditional farming practices into more efficient, automated processes. Initially, agricultural robots were primarily designed for basic tasks, but they have since evolved to incorporate advanced perception, autonomous decision-making and precise execution capabilities. This evolution has enabled these machines to operate effectively in complex and often harsh environments, thereby enhancing productivity and safety in agricultural operations (29).

A key aspect of development is marked by navigation and control systems as navigation algorithms leverage perception technology, which is crucial for the autonomous movement of agricultural robots (30). Similarly, the utilisation configuration approach to improve the decision-making capabilities of UAVs has led to better efficacy both in terms of navigation and detection (31). These innovations have paved the way for more sophisticated field robots capable of performing a variety of tasks, from tilling and seeding to crop protection and harvesting. The design of specialized robots has also expanded significantly. Field robots are now equipped with advanced sensors and algorithms, enabling them to perform tasks like tilling, seeding and crop protection with minimal human involvement (32, 33). Tillage robots have emerged as a solution to the labour-intensive nature of land cultivation, with systems like those developed in Japan that showcase the potential for automation in large-scale farming (34). These robots utilize technologies such as Real-Time Kinematic Global Navigation Satellite System (RTK-GNSS) and IMU for precise navigation, reflecting a shift towards more intelligent agricultural machinery (35). Advanced seeding robots are designed to ensure accurate seed placement and efficient fertilization. Innovations in this area have led to robots that can autonomously dig, plant and cover seeds, significantly reducing the time and labour required for these tasks (36). The integration of IoT systems has further enhanced the capabilities of these robots, allowing complete automation in seeding processes. Crop protection has also seen a technological leap, moving away from traditional manual spraying methods to intelligent robotic systems that can apply pesticides with precision. This shift not only improves the efficiency of pesticide application, but also addresses environmental concerns associated with overuse (37, 38). Robots such as the Yamaha R-MAX have set benchmarks in aerial pesticide spraying, while new modular systems are being developed to optimise pesticide usage based on real-time data (39). The integration of sophisticated algorithms and machine vision systems with harvesting robots, detection and harvest of the crops can be carried out with remarkable accuracy. In general, the evolution of robotics in agriculture reflects a broader trend toward automation and efficiency in food production. As agricultural robots continue to advance, they are expected to become essential in tackling modern agricultural challenges including environmental sustainability, labour shortages and the need for higher productivity (5). The integration of advanced technologies such as machine learning, computer vision and IoT will further enhance the capabilities of these robots, paving the way for a new era in agricultural practices.

## Integration of robotics with wheat cultivation

Wheat is one of the most important cereals to be consumed by humankind. A sustained increase in its production and productivity is required to meet food security goals. With an increasing demand for climate variability and labour shortages, the integration of robotics in wheat cultivation is the need of the hour. The integration promulgates automated seeding, precise weed control, real-time phenotyping, autonomous harvesting and post-harvest processing that ultimately contribute to efficient resource utilization and optimal yields. The integration approaches the directive automation in cultivation practices to reduce resource wastage.

### Autonomous seeding and planting

Precise systems for wheat seeding aimed at sowing efficiency, area coverage and overall productivity. A notable development is the high no-tillage wheat seeder, designed for both high and low borders, which significantly improves water use efficiency and optimizes yields (41). Integration of an intelligent simulation system with a self-seeding apparatus effectively manages the seeding rate, thousand-grain weight and seeding space via width modulation and dynamic pulse control. Therefore, it can be utilised to address limitations in traditional ground-wheel-driven seeding methods (42). Additionally, an automatic seed-fertilizer supply device featuring a three-degree-of-freedom mechanical arm (2180 mm) has been designed, achieving a conveying efficiency of 0.854 kg $s^{-1}$ with a conveying loss rate of 3.82 % (43). Similarly, the inadequacies of seed box replenishment have been mitigated through the implementation of an automatic dispenser that uses a mechanical arm and redirected trajectory planning (44). Various drilling machines, combination seeders and centrifugal seeders are now employed for wheat seeding, with planters like the SN14 seed planter demonstrating significant improvements when paired with automated delivery systems (45). Mechanised sowing of wheat in a single-line pathway exhibits increased efficacy over the traditional systems. Furthermore, the advent of a speed-adaptive wheat control system addresses the challenges of missed seeding and uneven row spacing, which are often caused by wheel slippage in conventional seeders. The system is equipped with a pneumatic wheat seeding device and an automatic speed-following control mechanism that dynamically adjusts motor speed based on real-time forward speed, achieving row spacing consistency below 3.9 % and seeding stability within 1.3 % using fuzzy PID control (46). Moreover, the amalgamation of air-flow velocity with seed delivery systems in pneumatic setups have led to a more uniform seeding process by leveraging the Reynolds number and the dynamic inertia of seeds, thereby facilitating uniform crop stands without human intervention (47). The no-till precise seeding of wheat has emerged as a pioneering approach in the realm of seeding robotics, establishing a benchmark for precision that surpasses other robotic systems (48). Consequently, the convergence of automation and mechanization in wheat cultivation has fostered a paradigm shift towards achieving optimal yields with minimal input.

**Tillage automation in wheat cultivation**

Automation of the physical manipulation of the topsoil for cultivation inevitably increases the efficacy of the process and overall land utilisation efficiency. Due to the short sowing window of wheat and perilous crop residue management of previous crops, the automation measures come in handy for increased optimization and sustaining yields. It utilizes an advanced navigation system for precise movements across the field (49). Machine vision is utilised to identify the tilled and non-tilled land and to guide the machinery accordingly. Problems such as uneven depth, compaction and crop stubbles are solved utilizing navigation-path detection such that high crop stubble with up to 96.7 % segmentation accuracy and a processing time of mere 0.6 sec can be detected and pathways may be generated to minimize the arduous task (50-52). Unmanned agricultural tractors are one of the key components of the tillage robots such that they provide a new array of automation as they reduce the need for human interventions while enhancing the efficacy and precision of mechanized operations (53). Crop row-based tillage and field preparation achieved a compensation accuracy of less than 2.5° and an average deviation from the target path of 4.59 cm, due to the integration of multi-source data and autonomous navigation with electrical control modules in tillage robots (54-57). To summarize, the use of tillage robots in wheat production represents a significant development in agricultural methods, providing more efficiency, precision and sustainability. These new devices not only optimize human resources by automating soil preparation and decreasing the need for traditional tillage methods, but they also increase soil health and reduce environmental impact. As the agricultural sector embraces technology, the use of tillage robots is anticipated to play an important role in fulfilling the rising global demand for wheat while also maintaining the resilience of farming systems in the face of climate change. Adopting this technological innovation would enable farmers to cultivate more successfully, opening the path for a more sustainable and productive future in wheat farming.

**Crop protection robot**

Data-driven agriculture and advanced farm management systems are transforming the agrarian sector. Robots with sensors and cameras can detect pest infestations early, enabling timely and targeted treatment (58). Automated systems can apply pesticides on a need basis, minimising chemical load and environmental impact (59). Robotic systems can accurately detect and differentiate between crops and weeds (up to 99 % accuracy) enabling precise herbicide application (60). This precision helps in managing weed populations effectively while conserving resources and reducing herbicide runoff. Robots can monitor symptoms of diseases using hyperspectral imaging techniques and machine learning algorithms (61). The extensive data gathered on soil conditions; crop health and environmental factors provide valuable insights for enhanced decision-making (62). The data-driven approach enhances understanding of crop protection and optimizes crop management practices as well (63). Automation of spraying and monitoring reduces labour-intensive tasks, creating the possibility for a holistic approach towards agriculture in a digital framework.

**Harvesting robot**

A harvesting robot significantly enhances the efficiency of the harvesting process. It is designed to operate autonomously not only extracting the plant from the field but also selectively separating the economic yield from the biological residue. It includes such platforms mounted with grasping, cutting and vacuum suction plucking systems. The harvesting module is retrofitted with sensors and harvesting mechatronics when coupled improves the operation efficacy of the overall process (64). Certain unmanned ground vehicles are equipped with high-tech cameras such as red-green-blue (RGB) cameras, time -of-flight cameras, light detection ranging (LiDAR), stereo vision cameras and near-infrared cameras (65). Kinematic models integrated with robotic grippers and sensor-based control approaches are used for precise manipulation and task execution (66). A harvester combined with a GPS receiver and grain level sensor increased the yields from 2.62 to 6.22 t $ha^{-1}$ (67). Integration of mobile platforms with single-rail dual-arm manipulator and five-DOF manipulator was found to be effective in wheat harvest (68–70). Sensors are used for trajectory mapping, tracking and localizing surroundings with the help of active beacons, using GPS, global navigation satellite systems (GNSS) and image sensing systems to localize themselves (71).

**Monitoring and inspection robot**

Monitoring plants is essential for timely interventions to mitigate losses caused by biotic and abiotic stresses (72). Early detection of stress allows for effective planning and management of these challenges. Accurate plant inspection employs thermal and spectral imagery to generate robust, low-noise data (73). The utilization of this data for disease detection relies on correlating thermal changes, leaf cuticle integrity and other physiological disturbances (74). The integration of robotic mobility, spectral sensing, computer vision and machine learning enables scalable and autonomous monitoring of wheat. In narrow-spaced cereal crops, techniques such as linear regression and Kalman filtering are employed. Robots are designed with high clearance to facilitate real-time, non-destructive acquisition of growth parameters using active-light resources. This approach achieves an accuracy of up to 97 % with YOLOv8 and YOLOv10 for detecting spikes and stubble, with precision rates of 79.5% and 77% respectively (75, 76). Robots like Agrobot utilizing Raspberry Pi technology have demonstrated high efficiency in the early detection of diseases such as yellow rust, powdery mildew and septoria with remarkable precision (77). Additionally, machine learning models integrated within robotic frameworks have achieved an impressive accuracy of 99.8 % in early disease detection.

Weed identification is enhanced through the analysis of distribution patterns. Unmanned aerial vehicles (UAVs) are employed for site-specific weed management, utilizing crop discrimination and detection techniques to create prescription weed maps. This enables effective weed control through targeted chemical applications, weed uprooting, or laser ablation (78-81). Robots are vital in crop monitoring by leveraging advanced sensors and imaging technologies to collect real-time data on plant health, growth conditions and environmental factors, as illustrated in Fig. 2. This automation enhances monitoring accuracy and efficiency, enabling early detection of diseases, pests and nutrient deficiencies (82). By providing farmers with actionable insights, robotic systems enhance informed decision-

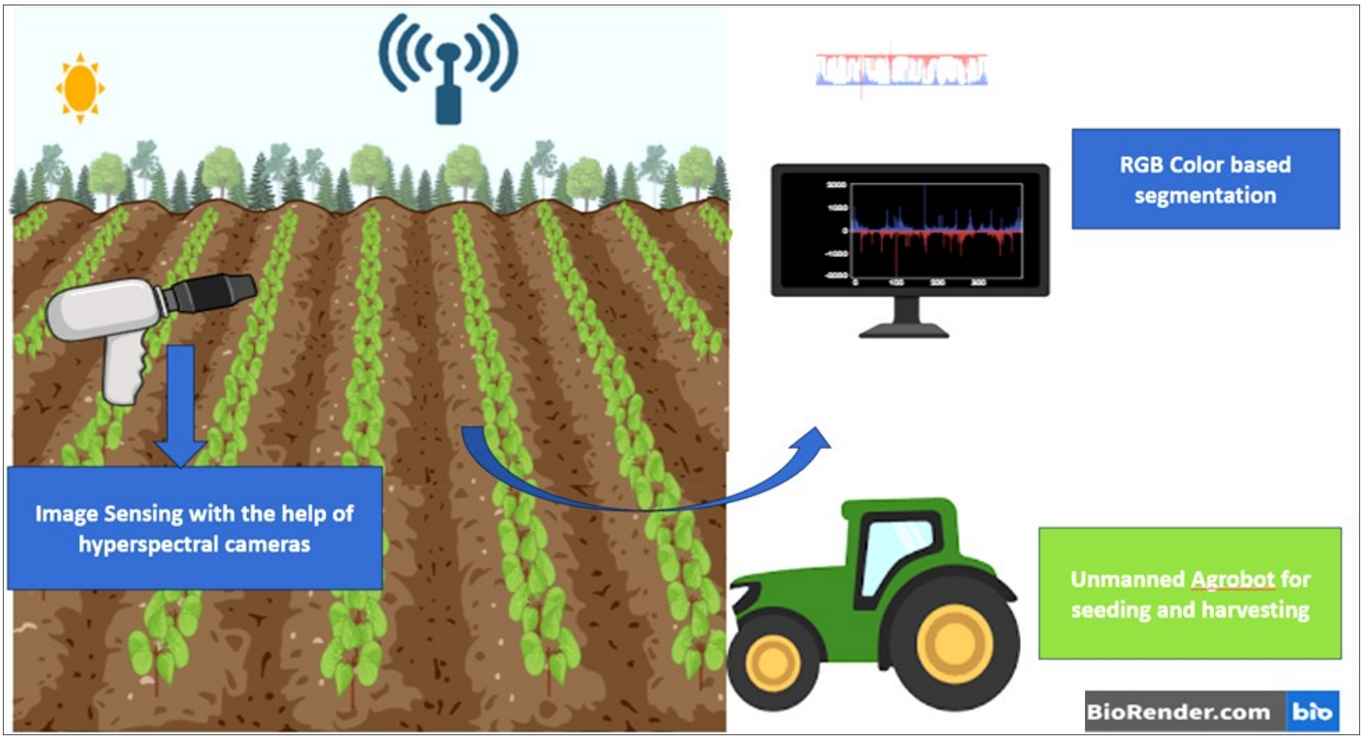


**Fig. 2.** Data acquisition process in automated crop monitoring.

making, optimize resource allocation and ultimately contribute to remarkable improvement in yields thereby, promoting sustainable agricultural practices (83).

## Wheat phenotyping

Phenotyping robots mainly focus on navigation in the unknown environment to collect data and plant samples (84). It could be a field-based ground phenotyping system or a robotic mobile platform which may be wheeled, tracked or legged depending on the topography to ensure easy manoeuvrability (85, 86). Large high-clearance robots acquire close-range data throughout the growth cycle of the crop. The system features a 1.6-m high chassis with an adaptive Kalman filtering-based GNSS/INS positioning algorithm to counteract poor GNSS signals in obstructed areas. A fuzzy PID control strategy is used to adjust PID parameters dynamically, reducing deviations from environmental disturbances (87). The recorded average angular velocity error for the left and right hub motors was 0.08 rad/s, with average position and heading deviations of 0.225 m and 0.308 ° respectively. The trajectory tracking controller, utilizing the fuzzy PID approach, achieved mean lateral and heading deviations of 0.076 m and 1.746 ° respectively thus enhancing and preventing crop damage during movement while allowing for phenotype observations at various growth stages (88). The monitoring involves multi-scale, multi-sequential and multi-source data acquisition such that phenotyping sensors, platform controlling systems and data processing algorithms are integrated to form a unified real -time data processing model (87). Sensors include near-infrared and infrared sensors (89), thermal cameras (90) and depth-sensing hyperspectral cameras (91) to detect phenotypic traits such as grain quality, thermal response, lodging resistance, canopy height and more-all while minimizing the effects of leaf occlusion. The phenotyping data processing utilizes machine vision and 3D reconstruction of crop morphology to be analyzed by processing software to extract shape, size, colour and spectral characteristics from complex images to run descriptive statistical modelling (92). It provides a multi-sensor integration to create a unified standardised system for the analysis of the crop yield, resistance, quality, nutrition and storage in real-time (93). In conclusion, the development of high-throughput wheat phenotyping robots represents a significant advancement in agricultural technology, enabling precise, efficient and non-destructive data acquisition throughout the wheat growth cycle, thereby enhancing breeding efforts and contributing to improved crop management and food security.

## Challenges and limitations

Despite the innumerable advantages of robotic automation in agriculture, the actual adoption and utilization remain low. Numerous operational and economical deficits are present in the current agricultural scenario that led to a lower rate of commercial deployment of robots. One of the major limitations is the lack of initial investment and small land holding of the farmer, as a minimum amount of USD 319864 is required in investment to gain any actual profit (94). While the long-term benefits of reduced operational costs and increased yields can offset these initial expenses, financial support mechanisms such as subsidies or cooperative purchasing models may be necessary to encourage widespread adoption. Additionally, the current research landscape has predominantly focused on horticultural crops, leaving a gap in economic studies and technological development for non-horticultural crops like wheat. Future research should prioritize the economic viability of robotic systems in wheat cultivation, ensuring that farmers can confidently invest in these technologies (95). The design of robotic manipulators can be a significant challenge, particularly for large farms. Single-arm designs may not be effective and achieving rapid harvesting rates with multi-degree-of-freedom (DOF) robots remains difficult due to the need for precise sensing and movement. Current robotic platforms may not be fully autonomous and challenges exist in accurately identifying field alleys, which are crucial for effective navigation and operation in crop rows (96). The ease of use and maintenance of robotic systems compared to traditional methods can be a concern for farmers, affecting their willingness to adopt new technologies. Although, the hesitation to adopt these systems is understandable, the integration of robotics in wheat management holds significant promise. This can be attributed to the fact that net returns can increase by upto 22 % compared to conventional practice. The agricultural robotics industry alone holds a market potential of USD 12 billion, which can be leveraged to achieve greater efficiency while contributing to food security goals (83, 97).

## Conclusion

The integration of robotics in wheat cultivation marks a transformative shift in agricultural practices, offering innovative solutions to the myriad challenges faced by modern farmers. As global wheat demand rises due to population growth and shifting dietary preferences, the need for efficient, sustainable and precise farming methods has become more critical than ever. This review has highlighted the multifaceted roles that robotics can play in wheat cultivation, encompassing various operations including planting, monitoring, pest and weed management and harvesting. By leveraging advanced technologies, agricultural robots can significantly enhance productivity, reduce labour costs and minimize environmental impacts, thereby contributing to a more sustainable agricultural future. One of the most compelling advantages of robotics in wheat cultivation is their multifunctionality. Modern agricultural robots are designed to perform tasks that once required multiple machines or manual labour. For example, robots with advanced sensors and imaging technologies can monitor crop health, detect pests and diseases and assess soil conditions in real-time. This enables the farmers to make informed decisions based on accurate data, optimizing resource allocation, averting potential risks. Furthermore, robots can automate labour-intensive tasks such as planting and weeding, which not only reduces the physical burden on farmers but also enhances operational efficiency. The ability to deploy a swarm of smaller robots for specific tasks, such as inter-row weeding or targeted pesticide application, exemplifies the potential for precision agriculture, where interventions are tailored to the specific needs of the crop. Looking ahead, the future of robotics in wheat cultivation is promising, with the potential for significant advancements in technology and application. The adoption of open-source robotics frameworks can facilitate collaboration and knowledge sharing among researchers and developers, accelerating the pace of innovation. As the agricultural robotics industry continues to grow, it is crucial to focus on creating cost-effective solutions that are accessible to farmers of all scales. Integrating robotics with emerging technologies like the Internet of Things (IoT) and precision agriculture tools can boost the capabilities of robotic systems, resulting in smarter and more efficient farming practices. In conclusion, the role of robotics in wheat cultivation is multifaceted and transformative, offering solutions that can enhance productivity, sustainability and profitability. As the agricultural sector navigates the challenges of a changing climate and rising food demand, the continued development and adoption of robotic technologies will be essential. By addressing current limitations and fostering innovation, the future of wheat cultivation can be defined by greater efficiency, reduced environmental impact and enhanced food security for generations to come.

## Authors' contributions

AM contributed to writing and editing the manuscript. SR contributed to editing and writing the manuscript, as well as data conceptualization. TR was involved in data curation, formatting and supervision. SM, MB and PJ contributed to data collection, compilation and editing. ASS contributed to data curation, conceptualization and editing. All authors have read and approved the final manuscript.

## Compliance with ethical standards

**Conflict of interest:** The authors declare no conflict of interest.

**Ethical issues:** None.

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