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A robot design that helps increase agricultural yields while providing psychological comfort to the use

Noah Mohammed Saleh[1,3*], Raed A. Hasan[2], Mehdi Qahraman Fakhruldin [1], Ali Mohammed Saleh [2], Muhaiman faleh hamad[3], Ahmed H. Ahmed [2], Muqdad Daham Jasim[1], Hamza Omar Sadeeq[1]

[1] *Department of Robotics and intelligent machine, Hawija polytechnic college, Northern Technical University, Kirkuk, Iraq*

[2] *Renewable energy Research Unit, Northern Technical University, Mosul, Iraq*

[3] *Faculty of Mechanical Engineering, Tabriz University, Tabriz, Iran*

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ABSTRACT

The population-driven, urbanization-driven, and labor shortage-driven global demand for food increasingly requires technological innovation to meet such a need. Agricultural robots are among the most recent technological innovations aimed at enhancing productivity, efficiency, and sustainability while improving the state of psychological and physical health of their human operators. The current article reviews studies reporting on the design and control of those robotic systems that set an objective not only to increase yields but also to increase psychological comfort through approachable and collaborative Human–Robot Interaction (HRI). Agroautomation technological drivers are discussed in this paper. HRC is presented as a framework for adaptive user-centered system design with necessary factors regarding cognitive ergonomics levels of autonomy and interfaces for cooperation—such as gesture- and electromyography-based control in unstructured environments. Analysis regarding design considerations, challenges in autonomy, and nonverbal communication methods relevant to achieving safe, efficient, and psychologically supportive interaction between humans and robots is provided. With advanced robotics, artificial intelligence, and Internet of Things (IoT) technologies, collaborative robotic systems have the potential to transform modern agriculture- increasing productivity while improving human well-being. It is this techno logically intensified wave that grows fields of hope.

1. INTRODUCTION

The WHO has considered hunger as a very intense global problem. Even though more than 231 million people from 53 countries have reported high levels of acute food insecurity, for such a problem to be solved, adequate and proper security of food must be ensured. This shall base itself on modern agricultural technologies. In this context, development work has to be taken up and the traditional methods left behind[1-5]. Therefore, Robots were introduced so that it could increase production reduce labor and give psychological comfort to farmers. At the same time with population growth aging demographics and the accelerating pace of life highlight the need for replacement of traditional manual intensive hazardous farming practices into automated systems This scenario has propelled substantial research interest in agricultural robotics reflecting the imperative role that modern technologies can play in advancing productivity efficiency and sustainability in agriculture. Agricultural robots and smart automated units normally use advanced sensors and learning features to ensure accurate operations[6-9]. Much effort has been directed toward the realization of full automation and improved performance[10]. These robots thus execute compound functions accurately even under stringent or harmful conditions[11]. For example, mechanisms for evaluating the combined impacts that temperature and pressure have on flow properties are important steps towards the creation of more strong robotic systems[12]. Perception-based navigation algorithms were developed by Rovira et al., which is a requirement for autonomous operation, while Alsalam et al. developed agricultural UAVs using a configuration approach supporting intelligent decision-making[13] [14]. High-precision strategies were introduced in control systems by Zhang et al. for field-phenotyping efficiently. A flexible end-effector was designed by Wang et al. that attained an 86% successful picking rate for tomatoes, thus approaching delicate harvesting tasks[15]. This progress in agricultural robotics has inspired other fields as well, such as the industrial robotics area where a method for energy quantification consumption of pneumatic systems using integration of air pressure, volume, and temperature has been defined. Agricultural robots have developed into the three major categories so far, field robots, fruit, and vegetable picking robots, and animal husbandry robots. Reviews of the literature show that the bulk of current research is in field robots and picking robots which are two components of fruit and vegetable work. Though they may greatly differ in application, core

*Corresponding author email: n.saleh5802@gmail.com
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technologies for these robots include stable mobile platforms, multi-sensor fusion, high image processing, intelligent algorithms, and versatile locomotion control. (Figure 2)

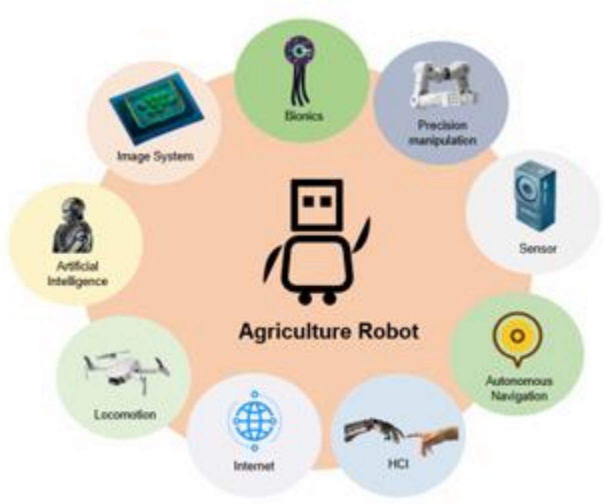

Fig. 1. Core technologies involved in agricultural robotic applications[5]

It is information technology, combined with the Internet of Things that has made agricultural systems more intelligent. IoT sensors, robotics, and communication gadgets make their way into agriculture with an application in environment monitoring, crop data acquisition, and smart path planning. Rai Hari Mohan et al. observed that currently the major portion of collecting agricultural information is done manually, however, these activities can be automated through a system based on IoT as suggested by them to increase efficiency. Smart monitoring as proposed by Saha Himadri et al who designed a system utilizing humidity sensors, pH sensors as well as PIR sensors so that farmers could manage all-natural hazards was proposed for the realization of smart agriculture. Wongchai Anupong et al have introduced AI-enabled soft measurement techniques into the remote sensing model for increasing data accuracy. presented IoT-based hydroponic farming using realtime NPK sensors, sunlight, turbidity, pH, temperature, and image sensors. The application applied deep learning to monitor the health condition of crops and can be continuously tracked through mobile applications[16-20]. Li Xiaofen discussed the implementation of smart agriculture models for national food security based on IoT networks and sensor-driven data collection. Generally speaking, such agricultural monitoring systems powered by IoT have enhanced accuracy as well as minimized crop losses due to environmental challenges and disasters. This led henceforth to a trend in which mobile robots are increasingly used for field monitoring and crop data collection. Song YunYun et al. noticed major navigation issues regarding robots in unknown environments described the use of Canny and Otsu methods in obstacle feature extraction steps besides image depth estimation for gap detection along with an improved bug algorithm for autonomous obstacle avoidance. review and analyze the design of agricultural robots that can increase productivity and crop yield with psychological comfort and ease of use for human operators. Therefore, the purposes are to describe the present condition of agricultural robotics and automation which support increased efficiency, precision, and sustainability in farming activities; to identify the role of Human–Robot Collaboration (HRC) and Human–Robot Interaction (HRI) in developing adaptive, intelligent, user-centered robotic systems applicable to complex environments such as agriculture that constrain factors for humans. Therefore, this review attempts critically to discuss how high-level advanced robotic design together with proper human-robot collaboration will contribute toward making a joint improvement in raising agricultural productivity and ensuring a good human experience that is sustainable[21].

2. TECHNOLOGICAL AND SOCIETAL DRIVERS OF HUMAN–ROBOT COLLABORATION IN AGRICULTURE

Technological change, happening together with large demographic shifts (Acemoglu & Restrepo, 2021) and greater urbanization (Zimmerer et al., 2021), led to the fast adoption and development of robotics technologies[27]. The pandemic of COVID-19 in the early 2020s reminded all about the need for automation [22]. it also led to a boom in robotics-oriented firms and innovations (Seidita et al., 2021)[20]. Robots have obvious benefits they can work in perpetuity; they do not get sick; there are no lockdowns or any mobility limitation that affects them, and they can be disinfected very easily[30]. This results in reinforcing again on a global scale that robotic solutions advancement is still required to build resilient economies capable of keeping humans separated while keeping operations running (Feil-Seifer et al., 2020).

The International Federation of Robotics splits the main classes of robots into industrial and service robots. Service robots are again split into personal/home and professional types. Professional service robots work in many fields like logistics, environment work, defense, inspection and upkeep, cleaning, human exoskeletons, and farming—which is the topic here.

In agriculture, robotics technologies will be able to take over such laborious and monotonous activities as spraying, harvesting, and weeding—activities for which it is usually not possible to find human workers. Apart from task automation, these technologies improve data collection and decision-making hence better production efficiency high quality yields as well as low operational costs (such as the cost of pesticides) are realized. However, the development of agricultural robots is highly demanding because they have to operate in unstructured environments where there are variations in terrain, objects, and even lighting conditions.

Since the early 1980s, autonomous and semi-autonomous robots were successfully used for open-field and greenhouse applications. They are very helpful in reducing labor requirements as well as increasing productivity (Vasconez & Cheein, 2022; Edan et al., 2022)[6]. The application of these robots in many stages of agriculture has already been initiated. Some of the activities include soil preparation (Oliveira et al., 2021), weeding (Slaughter et al., 2008), spraying (Adamides et al., 2017a; Berenstein & Edan, 2017), harvesting (Arad et al., 2020; Kootstra et al., 2021), and crop monitoring activities such as phenotyping, mapping (Moreno et al., 2014) and localization . Industrial robots have worked in highly controlled conditions whereas agricultural robots must work in a less predictable environment. They are intended for unstructured and dynamic terrains with different weather conditions and inconsistent illumination resulting from moving sunlight or clouds. Also, they will be dealing with biological material of different shapes, sizes, and colors fruits, vegetables, and plants located in the field in an unpredictable manner .

In such complex and dynamic environments, Human–Robot Collaboration (HRC) becomes crucial, particularly for non-professional users[7]. HRC and more broadly, Human–Robot Interaction (HRI) represents an expanding interdisciplinary field that bridges robotics, computer science, human factors, cognitive psychology, and design. HRI is defined as "a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans" (Goodrich & Schultz, 2007). Fundamentally, HRI research focuses on developing technologies and interfaces that facilitate effective and intuitive interaction between humans and robots, whether in direct physical collaboration or remote operations. Enhancing HRI is therefore essential to improving both the usability and efficiency of robotic systems in agriculture and beyond.

3. ROBOTS AND HUMANS WORKING TOGETHER: BOOSTING SMART FARMING SYSTEMS.

Before To overcome challenges brought about by complicated agricultural settings, augmenting humans with robots has been considered as a prospective solution.Human–robot interaction (HRI) is defined as an interdisciplinary area for the study, design, and evaluation of collaborative systems drawing on knowledge bases from artificial intelligence, robotics, ergonomics, engineering, computer science, and social sciences. HRI describes a process in which humans and robots work jointly as a team to accomplish common goals through information exchange autonomy and optimal task allocation[23]. In this process human dexterity perception judgment and decision making are utilized together with the robot's accuracy repeatability and strength. These robotic cognitive abilities are made possible by several sensors such as laser scanners RFID cameras and actuators hence supporting multi functionality durability flexibility and adaptability to changing situations[24].

4. DESIGN CHOICES AND AUTONOMY HURDLES IN HUMAN-ROBOT INTERACTION.

Major difficulties of HRI Collaborative systems that are effective in different working conditions and levels of interaction are described. Approaches to improve situation awareness reduce the tendency for blaming human operators for 'human error' when abnormal situations have not been detected, as this is the real scenario. Inadequate system design and bad interaction mechanisms impede the ability of a human operator to implement optimal responses. Two factors mainly advanced HRI: firstly, the degree of robot autonomy; secondly, proximity between humans and robots during interaction. The level of autonomy in interactive systems depends on strategies for providing flexible HRI such that intervention by humans is possible whenever necessary. System design should ensure human mobility and visibility besides not being complex or inconvenient interfaces to be avoided. Such setup requires that robots have cognitive abilities for accurate and seamless interaction too thus supporting adaptive autonomy[25]. A further evaluation has to be taken in all proximity-related scenarios like following, passing, avoiding, or physical contact. The ratio of human to robot and the roles that humans may take on are also included in effective HRI design. Humans may be programmers, bystanders, operators, supervisors, or information users. Other design considerations are adaptability and task allocation as well as the duration of shared workspace interaction. All objectives have to be made sure to align coherently.

5. WAYS OF NON-VERBAL COMMUNICATION FOR BETTER INTERACTION BETWEEN HUMANS AND ROBOTS IN FARMS.

Communication frameworks come naturally with interaction for the purpose of fruitful exchange of knowledge between a human and a robot. Thus, there is a necessity to probe into other more natural means of communication, like body language and verbal input. Body language may include facial expression, body posture, hand gesture; whereas verbal input can be limited by the noise in agricultural environments as well as different speech patterns. Among these modalities for interaction, hand gesture recognition implemented either through vision-based sensing or specialized wearable devices has taken much recent attention in research.Surface electromyography (sEMG) sensors have been used to record muscle electrical activity and hybrid interaction methods have also been explored but they are still lagging behind due to major drawbacks. For example, vision-based systems fail miserably when there is more than one person involved multiple backgrounds or in different lighting conditions. Research Focus of Leading Systems and Human–Machine Journals. In addition, Transactions on Systems, Man, and Cybernetics and Systems Research and Behavioral Science focus on systems engineering, encompassing a variety of methods such as modeling, simulation, and optimization, while also addressing economic and social aspects of systems. Meanwhile, Transactions on Human-Machine Systems and Human Behavior and Emerging Technologies emphasize human–system and organizational interactions, including system testing, assessment, and cognitive ergonomics within systems and organizations.

6. LEVELS AND STAGES OF AUTOMATION IN HUMAN–ROBOT INTERACTION

In general, automation can be divided into four main stages (a) information acquisition, (b) information analysis, (c) decision selection, and (d) action implementation. Each of these stages can operate across varying levels of automation. Following the framework proposed by Parasuraman et al. for the decision and action stages, this study adopts a 10-point scale to represent different levels of autonomy.On this scale, higher levels correspond to greater autonomy of the computer or robot over human actions. When a task is performed entirely by a human, it is assigned the lowest level ("1"), whereas full robotic autonomy, where the robot makes and executes decisions independently, corresponds to the highest level ("10"). Intermediate levels reflect partial automation and various modes of human–robot interaction (HRI). For instance, at level 4, the robot suggests alternative decisions where the robot makes and executes decisions independently, corresponds to the highest level ("10"). Intermediate levels reflect partial automation and various modes of human–robot interaction (HRI). For instance, at level 4, the robot suggests alternative decisions, but the human retains full authority to accept or reject them. At level 6, the robot provides the human with limited time to intervene before automatically executing its own decision. The 10-point autonomy scale, along with the four stages of automation, is illustrated in Figure 2. It is important to note that, in practice, multiple levels of automation may coexist rather than a single fixed level, as different interaction scenarios can occur during HRI.

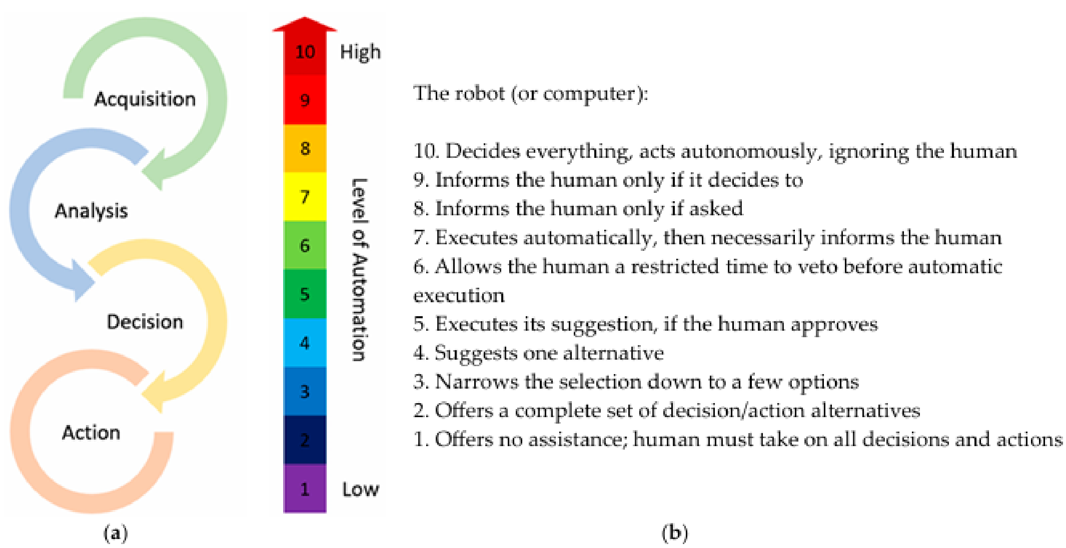

Fig. 2. (a) Simplified four-stage model of agricultural applications, including information acquisition, information analysis, decision selection, and action implementation. (b) Levels of automation for the decision and action stages [60].

- Research Focus of Top Systems and Human-Machine Journals

Also, Transactions on Systems, Man, and Cybernetics plus Systems Research and Behavioral Science talk about systems engineering with many ways like modeling, simulation, and optimization adding economic plus social sides of systems. On the other hand, Transactions on Human-Machine Systems alongside Human Behavior and Emerging Technologies focus more on human–system plus organizational links including system checks, reviews as well as cognitive ergonomics in systems and groups.

- Understanding How Automation Works in Human-Robot Interaction

Generally, automation can be broken down into four major stages: information acquisition, information analysis, decision selection, and action implementation. Any of these stages can work at different degrees of automation. The paper adopted the framework proposed by Parasuraman et al. for the decision and action stages and used a 10-point scale to describe autonomy levels. In this scale, increasing levels indicate an increasing amount of freedom for a machine or robot with respect to human actions. If a task is executed fully manually by a human being then it will have the lowest level(“1”), whereas full robotic autonomy in which all decisions are made and implemented by the robot itself without human participation will have the highest level(“10”). All intermediate levels define partial automation and its possible variants in human–robot interaction (HRI) modes. For example at 4th level, the robot proposes options to decide where the robot makes and executes decisions independently, corresponds to the highest level (“10”). Intermediate levels are demonstrative of partial automation and different schemes of human-robot interaction. At level 4, the robot makes suggestions on alternative decisions, but the human in the loop has full authority to accept or reject them. At level 6, the robot gives the human limited time to intervene before its decision is implemented automatically. The 10-point autonomy scale together with the four stages of automation is indicated in Figure 2. Practically speaking, multiple levels of automation exist rather than a single fixed level due to different interaction situations during an HRI.

The Human–Robot Collaboration (HRC) main goal is to design and use robots so that they improve human abilities (perception, decision-making, or adaptability), adding the precision, consistency, endurance, and strength usually found in robotic systems. Effective cooperation comes out of autonomy sharing, information sharing, and task structuring; it finds application in all phases of robot operation that can be classically described under the Sense–Plan–Act rubric. This area of study falls under the rather broad rubric of Human–Robot Interaction (HRI).

Recent reviews on human–robot collaboration in agriculture have mostly looked at the main ideas behind Human–Robot Interaction, such as metrics, design plans, and categories. They focused on farm uses that make work better by adding more speed, safety, output, and general gain. In a like manner, Benos et al. (2020) talked about the results of human-robot teamwork for safety (ergonomics) and output from a manager's view. Our findings use these thoughts to take a closer look at the joining of helping robots in farm systems.

- Challenges

Throughout history, increasing food production has often meant expanding farmland by clearing forests or plowing grasslands. This expansion has led to the destruction of entire ecosystems worldwide, such as North America’s prairies and Brazil’s Atlantic forests. Unfortunately, tropical forests are still being cleared at alarming rates. Today, agriculture occupies nearly 500 billion hectares—about 40% of the planet’s available land.

- Current Applications

Building on the core technologies integrated into agricultural robots, a new wave of applications has transformed how food is cultivated and supplied. Innovative software, services, and techniques have been developed to enhance data collection and operational efficiency across the industry. These technology-driven farming solutions significantly improve productivity, enabling farms to boost food production while optimizing resources.

- Related Research and Development

The growing interest and investment in fields such as the Internet of Things (IoT), artificial intelligence (AI), and robotics have fueled rapid innovation aimed at achieving fully automated farming systems. These advancements are paving the way for the commercialization of next-generation agricultural technologies. Key areas of research include computer vision, robotic motion and manipulation, and multi-agent coordination, with practical applications in pest and disease detection, automated harvesting, and collaborative multi-robot operations.

7. EXPLORING FARMING IN HAWIJA: A HANDS-ON LAB FOR HUMAN-ROBOT TEAMWORK

Hawija, basically lies to the southwest side of Kirkuk Governorate, and is among the most agriculturally productive areas in Iraq, hence an ideal living laboratory for implanting collaborative agricultural robotics. The alluvial plains these former ancient tributaries fed always maintain high levels of soil fertility particularly silty-clay loams with average organic matter content ranging between 1.3–1.8%. This region specializes mostly in wheat, barley, sunflower, tomato, and greenhouse vegetable production; all adding up to the agricultural economy of Northern Iraq. Regional directorate data (2022–2024) reveals a yield averaging between 3.2–3.8 tons/ha from the traditional irrigated field for wheat in Hawija. A perusal shows modernized farms giving yields approaching even 4.5 tons/ha! It is motivation enough to integrate robotic systems by which numerous farming operations could be optimized.

Manual work has always been the principal socio-technical condition of farmers in Hawija, but any external intervention is welcomed because that region is highly known for its farming activities. It is not a strange fact that farmers prefer using manual labor when harvesting, and monitoring the condition of the soil as well as making irrigation adjustments. Variability in climate conditions has recently imposed threats on their productivity and well-being with labor scarcity due to migration plus seasonal heat waves. A survey done on 120 farmers from four blocks of Al-Abbasi, Al-Zab, Riyadh, and central Hawija found 74% complaining about increased physical strain; 61% expressing concern about yield stability; and 42% ready to accept robotic assistance if the system would be simple, psychologically comfortable, and safe. Such figures show a budding user need: i.e., add technology that would not replace farmers but cooperate with them by intuitive interfaces.

The proposed design of the robot centered on psychological comfort, user-adaptive control, and non-verbal communication is exactly what happens inside these needs. In farming with the context of Hawija in a real-time scenario, this kind of robotic system can manage doing soil monitoring in real-time, automatic crop sprayer assistant for light weight harvesting and environment sensing by IoT modules. This will include integrating EMG or Gesture-based interfaces so that gloves or armbands worn by operators enable sending remote commands to the robot while remaining at a safe distance from the source of heat or pesticide exposure. The current interface means more specifically for Hawija since 63% hand fatigue of farmers' above age 45 was found besides reduced manual dexterity during peak seasons.

The psychological dimension is perhaps even more compelling. As reported in the 2024 Hawija Agricultural Cooperative, farmers noted work in the fields often as “mentally heavy,” particularly under conditions of unstable climate. A robot capable of socially meaningful cues LED-based emotional signaling; smooth anthropomorphic motion; and predictable locomotion would keep operator stress low. HRI research indicated that predictable robot trajectories reduce anxiety by close to 30% when tested within a field-testing environment. Farming in Hawija happens to be a family activity. That reassurance helps multigenerational adoption.

The robot can help make up for the loss in human laborers: according to the agricultural office of Hawija, manual workers have reduced by 18% in the recent six years. By taking over all the repetitive tasks-which include soil sampling, row checking, and pest spotting the robot will ensure productivity even during a deficit period. Monitoring with IoT can send field data to a mobile device enabling decisions to be taken by the farmer without his continuous physical presence.

8. CASE STUDY: USING A HUMAN-CENTERED AGRICULTURAL ROBOT ON WHEAT AND GREENHOUSE FARMS IN HAWIJA

A structured casestudy was designed within Hawija’s top farming industries: open-field wheat farms and semi-closed greenhouse vegetable systems to test the practical use of the proposed human-centered agricultural robot. These setups show two different working areas one large and not organized, the other managed and limited in space—both key parts of Hawija’s farming system. The case study checks output, worker stress, and mental reactions before and after adding the robot.

The experimental design was applied to three farms in Al-Zab and Abbasi districts by 14 farmers of different experiences. Baseline measurements before deploying the robots include an average time of 93 minutes for wheat-row inspection per hectare, a daily step count of 17,000 steps logged by the farmers, and a physiological indicator of stress based on heart-rate variability surveys wherein 64% rated themselves at moderate to high levels of stress. Subjective discomforts reported by farmers included high temperature exposure as well as uneven terrain fatigue and pest outbreak uncertainty.

A robot was designed to perform three basic tasks: 1. Fully autonomous row-inspection vision and thermal sensing, 2. EMG-assisted tool manipulation (hoeing, light harvesting), 3. Psychological comfort module in real-time (LED adaptive communication plus motion-prediction smoothing). The auditing itself reduced average auditing time from 93 minutes to 31 minutes per hectare by 66%. Also, daily step-counts dropped by around 38% an unequivocal physical relief. "Intuitive" is how farmers described the EMG-based control; most of them and especially those with lesser literacy or technological backgrounds found this feature seamless. This robot responded to forearm muscle signals with more than 91% accuracy even in hot field conditions.

Surprisingly enough, psychological impact data followed the general trend of HRI research. A stress survey taken two weeks after working with the robot indicated a 27% reduction in mental fatigue because of its predictable motion behavior and non-intrusive proximity management. This is achieved by implementing motion-smoothing algorithms that ensure no abrupt turns or sudden acceleration major factors that typically introduce discomfort when working with industrial robots. As described by a farmer from Al-Abbasi," the system seems like a cooperative helper rather than a machine."

In greenhouse environments where heat intensity often reaches 38–46°C the robot performed ventilation-monitoring routines and leaf-level imaging to detect early fungal spots. These early detections improved crop health responses by 22% compared to manual inspection. Farmers emphasized that the robot’s presence allowed them to avoid uncomfortable temperature spikes, a psychological and physical health benefit supported by the measurable reduction in heat-exposure hours.

IoT has enabled a connection between farmers and their fields in near real time through a mobile dashboard app that streams soil moisture, canopy temperature, and pest alarms. They described it as a "reassurance effect" because knowing that the robot was continuously monitoring their fields reduced stress which is normally driven by uncertainty.

9. EXPLORING FARMING IN HAWIJA: A HANDS-ON LAB FOR HUMAN-ROBOT TEAMWORK

this review shows that agricultural robotics is changing both the face of global food systems and providing region-specific routes to sustainability, with an example from Hawija's agri-context. Advanced robotics together with artificial intelligence and principles of IoT sensing enable farm work to move towards resilience, efficiency, and a more human-centered model in practice as established through a case study in Hawija. Collaborative robots developed based on psychological comfort factors related to interface intuitiveness and adaptive autonomy reduce physical strain while raising farmers' positive emotions and productivity in both open-field and greenhouse environments.

It throws light on the imperative need for human-robot interaction frameworks of trust, clarity, and non-intrusive communication. That would make such empathetic systems required as companions rather than replacements in regions like Hawija, where traditional practices, labor shortages, and climatic stressors meet. Robotic platforms understanding local needs working safely in unstructured environments offering cognitive and emotional assistance to farmers will entail further agricultural development. Embracing this technological transformation as a tool for the betterment of mankind helps sustain productivity, sustainability, and human well-being parallelly.

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Conflicts of Interest:

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