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New technical and operational solutions for the use of drones in Agriculture 4.0.

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CHAPTER 1

General Introduction

1. Introduction

Future Modernization and innovation are deemed essential to resolve the existing global challenge. Nowadays, among the most challenging problems around the world are global population growth, global warming, climate change, and food security, therefore farmers need to increase their yields by about 50 percent to be able to feed the world by 2050 when the world's population will reach 9.1 billion, 34 percent higher than today (FAO, 2009; Botta et al., 2022).With this population growth, the amount of cultivable land shrinks and there is an increased demand for food (Egea et al., 2022); labor shortage and climate change play limiting factors in satisfying this urge in need for agricultural products. Concepts in modern agriculture like proximal monitoring, sustainable and precision agriculture help to alleviate the pre-mentioned urge. To enhance agricultural production from available arable land, one possibility is to invest in technology to meet the global demand for food (Mehla and Deora, 2023). Precision Agriculture (PA) is an essential element of the modern agricultural revolution that aims to improve food productivity in balance with the increment of the global population whilst reducing resource waste (Gopalakrishnan et al., 2022). Several platforms of the agricultural revolution are aimed at generating new concepts around sustainability, food production, energy, and agricultural technologies.

Traditional agriculture relies on using heavy machinery that causes an increase in soil compaction of arable lands due to an increase in soil bulk density. This could lead to a reduction of yields and field trafficability as well as an increase in fuel use (McGeary et al., 2022; Lagnelöv et al., 2023). A heavy machine could be replaced by UGVs without an increase in labor costs, therefore decreasing by 71.5% the environmental effects from 270 to 77 kg CO_2eq ha^{-1} as well as the labor cost by 33 % from 385 to 258 € ha^{-1} (Lagnelöv et al., 2023).

Recently, there has been a spurt in the evolution of Information Systems (IS) in varied social science fields. IS are a somewhat recent discipline in the field of social science and takes advantage of other mature disciplines like organization, management, engineering, and computer science (McGeary et al., 2022).

The IS field presents many approaches for analyzing the intention to implement information technologies, attitudes, and perceptions about these technologies. Numerous methodologies derive from the Theory of Reason Action (TRA), which proposes that attitude or individual's beliefs could explicate behavior, and the Theory of Diffusion which indicates that innovation's adoption is reliant on the user's perception of the innovation itself (Adrian et al., 2005). Venkatesh et al., 2003, stated that TRA is one of the most important and prominent theories of human behavior, and has been utilized to foresee a broad range of behaviors (Venkatesh et al., 2003).

The cycle of precision agriculture involves different stages found in Fig. 1, the first is data collection which consists of monitoring of local weather conditions, mapping and measuring within the field spatially variable parameters of soil and crop (data collection); the second is interpretation, by mapping of spatially variable rate crop input applications; and lastly spatially variable rate crop input applications.

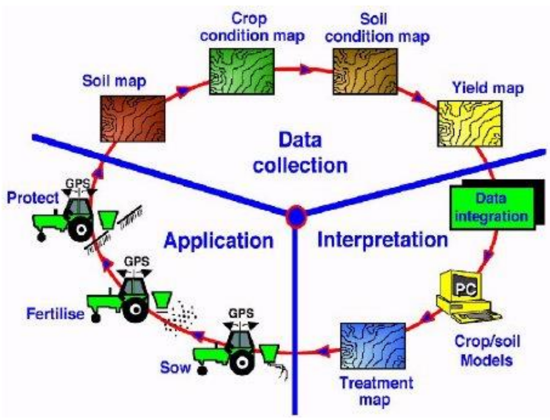

Figure 1 Precision agriculture cycle (Comparetti, 2011).

To execute precision agriculture, several tools are needed, a satellite positioning system, for detecting exactly any position to geo-reference any measured field parameter and, any crop input rate position that should be applied; sensors, for measuring soil and crop field parameters; devices, for scheduling and observing spatially the applications of the crop input rate variables; software, for creating the maps and also for interpretation of the data; lastly soil and crop simulation models, for recognizing the spatial variability reasons within the field, to correct the crop input rates from the next growing seasons.

The most common definition of PA is presented by Pierce and Nowak (1999): ”Precision Agriculture is the application of farming strategies and methodologies to do the right thing, in the right place and at the right time”, while data and technologies detect and decide what is Agriculture 4.0 is said to have started around the early 2010s, with low-cost and improved sensors, actuators, microprocessors, nanotechnology, high-bandwidth cellular communication, cloud computing, smart tools, satellites, IoT, remote sensing, and proximal data gathering and artificial intelligence (AI) (Dung et al., 2017; Clercq et al., 2018; Ravikumar, 2022).

Information and communication technologies (ICT) play an important role in agriculture. From helping with day-to-day work and administration to advanced techniques of precision agriculture which help reduce costs and increase productivity (Micevsk, 2018). With ICT, farmers can be updated with recent information about agriculture, weather, new varieties of crops, and new ways to increase production and quality control, planning the type of crops, following good agricultural practices for cultivating, harvesting, post-harvesting, and marketing their produce. It also has the great potential to widen the marketing horizon of farmers directly to the customers or other appropriate users for maximum benefit. Farmers may connect directly with many users and may get information about current prices for their goods. ICT technologies can strengthen farming communities by widening the networking and collaborations with several institutes, NGOs, and private sectors (Singh et al., 2017).

Nowadays with connectivity pressing forward, new technologies are available like GPS precision-guided tractors, sensor-based water irrigation systems, pest surveillance from the air, smart livestock monitoring along with farmers hooked up to Big Data.

According to M. Strohbach et al. (2016), Big Data storage technologies act as an input for the formation of a cross-sectorial roadmap for the expansion of big data technologies in a range of high-impact application domains. Also, particularly address the volume, velocity, or variety challenge and do not fall in the category of relational database systems. A relational database is a kind of database that provides and stores access to data points that are related to one another (Oracle, 2023), and data are stored in the form of a set of tables, and columns (Galgonek and Vondrášek, 2023).

The use of unmanned vehicles and connected analytics has great potential to support and address some of the most pressing problems faced by the agricultural sector in terms of access to actionable real-time quality data. Sensor networks based on the Internet of Things (IoT) are increasingly being used in the agricultural sector to meet the challenge of harvesting meaningful and actionable information from the Big Data generated by these systems (Sylvester, 2018).

The next figure (figure 2) shows a 'data chain' for precision agriculture, which explains best the development of a dataset.

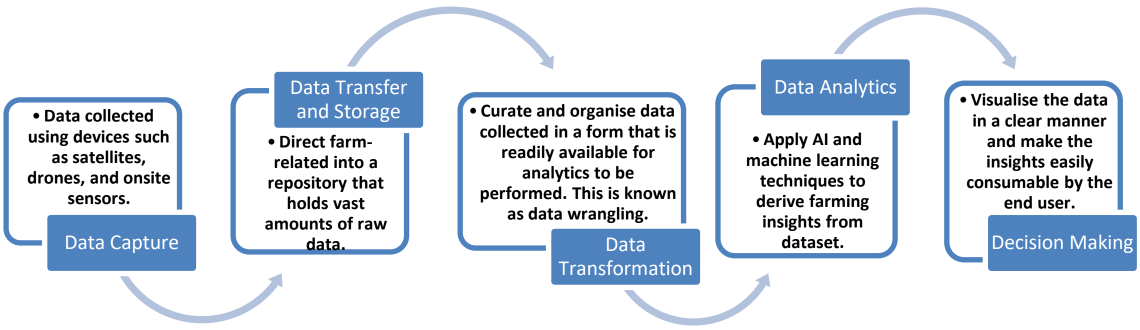

Figure 2 The Big Data for precision agriculture (UNDP, 2021).

A crucial point is to continuously apply security principles and data privacy, for instance, storage limitation and data minimization.

Data Acquisition is the process of collecting, sorting, and cleansing data before it is placed in a data storage warehouse or any other form of storage on which data analysis could be executed. Data Storage is the perseverance and management of data in a scalable way that satisfies the requirements of applications that necessitate fast access to the data (Curry, 2016).

Additional challenges with data analytics and big data for precision agriculture include bandwidth constraints and data fragmentation. Bandwidth constraints illustrate the task of running machine learning algorithms in the cloud with limited internet connectivity, especially in rural and less developed areas. Data fragmentation refers to the issue of combining data across various equipment (sensors, drones, etc.) in an interoperable and usable format (UNDP, 2021).

Using a mono-purpose drone isn't always cost-effective, because of the complexity of the agricultural system englobing the farm size, grown crops, and orchard typology it may be useful for a group of nearby farms and surely for large farms. From here the adoption of precision agriculture will depend on the availability and the affordability for the farmers, this is described in Figure 3, explaining the 5 A's for technology access.

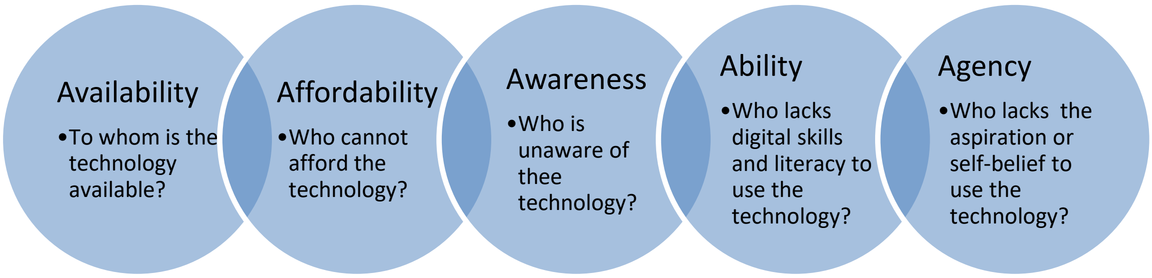

Figure 3 The five A's of technology access (UNDP, 2021).

Drones have been used in the last few years with the will to augment agricultural efficiency, especially by reducing labor-force (Ravikumar, 2022). Collaborative robotics has been one of the most important developments in the industry of robotics throughout the past years [20].

The cooperation between autonomous ground and aerial vehicles (UGVs and UAVs) could lead to noticeable improvements in informed management by executing in-field tasks in a time-effective and precise way (Ceccarelli et al., 2022). Unmanned ground vehicles are the terrestrial type of drones also known as UGVs are used for several uses like crop harvesting, soil sampling, mechanical weeding, irrigation management, and precision spraying to meet the requirements of precision agriculture (Botta et al., 2022). The Unmanned Ground Vehicles (UGVs) are becoming increasingly popular, especially for on-field monitoring and operational activities. The first reported UGV was tested for military purposes in 1921, while the first scientific studies for agricultural applications have been conducted over the past two decades. UGVs are modifiable ground robotic platforms that could be equipped with tracks, wheels, cameras, sensors, robotic arms, and other extensions for agricultural practices. Moreover, these ground robots can run automatically and/or be operated remotely.

Some companies and researchers developed multipurpose robotic platforms that could be customized and used for many kinds of productions. The complete robot is composed of a main platform and modules including wheels, cameras, sensors, cargoes, and one or more energy units.

1.1. Unmanned ground vehicles

Drones are usually referred to as unmanned aerial vehicles (UAVs) while a "drone" is effectively any unmanned robot including unmanned ground vehicles (UGVs) which are the subject of this study.

In the broadest sense, a UGV is "any piece of mechanized equipment that moves across the surface of the ground and serves as a means for carrying or transporting something, but explicitly does not carry a human being" (Douglas, 1995). Carlson in 2004 defined a UGV as "a ground-based mechanical device that can sense and interact with its environment". UGVs might be categorized by their types such as mode of locomotion, intended operating area, and type of control system (Nguyen-Huu et al., 2009). One possible UGV taxonomy based on three modes of locomotion of mobile robots is wheels, crawler track, legs, and articulated body (Hirose, 1991).

Unmanned ground vehicles started on August 3, 1903, when the engineer Leonardo Torres-Quevedo presented a vehicle named "TELEKINO" that could be directed from a certain distance (Everett, 2015). At a later stage, between 1939 and 1940, unmanned tanks called Teletanks were used in the Winter War (Fletcher, 1994). In addition to these uses, UGVs could be used in space applications, civilian and commercial applications, manufacturing, mining, supply chain, emergency response, and agriculture.

UGV structures are not the same and vary from one to another, in general, a UGV comprises the following parts (Nguyen-Huu et al., 2009):

- Sensors: to perceive its surroundings, and therefore, permit controlled movement.
- Platform: to provide locomotion, power, and utility infrastructure for the robotic system.
- Control: control systems affect the level of autonomy and intelligence of the UGV.
- Human-machine interface: it depends on how the UGV is controlled. It could be a remote control and/or a monitor control panel.
- Communication: communication is essential and happens between humans and UGVs or between UGVs themselves (herd of UGVs). The communication could be via fiber optics or radio links.
- System integration: the synergy of the UGV depends on the choice of system-level architecture, sensors, configuration, and components. A well-designed UGV would be self-reliant, fault-tolerant, and adaptable, which increases the autonomy level.

1.1.1. Unmanned ground vehicles in precision agriculture

A very important concept is precision agriculture which is based on measurement, monitoring, and decision-making approaches to improve the decision support for farm management. Due to recent advances in communication, information processing technologies, and sensors (Berger et al., 2023), UGVs are playing a crucial role in agriculture for inspection (Carbone et al., 2018), sensing (Milioto et al., 2018), pest control (Gonzalez-de Santos e al., 2017), and harvesting (Pereira et al., 2017), among others. Autonomous systems are a promising choice for safely performing precision agricultural activities constantly (Bechtsis et al., 2019).

Lately, farmers have been adopting PA using different kinds of technology like field sensors, information systems, advanced machinery, satellite data, informed management, and global navigation systems adapted to agricultural machines to increase yields, facilitate work, and reduce inputs (Gebbers and Adamchuk, 2010; Karydas et al., 2023). Many precision agricultural technologies (PATs) have been developed in the last few decades, including unmanned aerial and ground vehicles (Neupane et al., 2023). PATs are based on a resource-efficient and very precise approach, therefore having an important ability to deliver further sustainable agricultural production and to increase agricultural productivity. PATs could also help current or common trends in agricultural exploitations like organic and family farming. Even with the benefits and significance of PATs, former research has reported rare adoption and low acceptance of these technologies amongst farmers. These reported results are explained due to the focus of previous studies on the economic variables, and effects of farmer and farm characteristics. Previous results show that PATs are less adopted by less educated and older farmers especially in small farms because land fragmentation and small-sized lands avoid the achievement of satisfactory economies of a certain scale for the implementing technologies. It was perceived that poor returns and high investments showed meaningfully lower PAT adoption; previous studies showed that the barriers that keep from the adoption of Smart Farming Technologies (SFTs) were high cost and lack of clarity regarding SFTs added value and cost-benefit. Adopting a new technology is limited by the economic benefit factor, applying innovations and technologies may be rejected by users who go back to original, traditional practices even though the benefits of new technologies have been noted (Caffaro et al., 2020).

In dangerous agricultural lands, UGVs could be used in agricultural land mines which are caused by mine pollution causing an explosion and usually blowing off a foot or a leg (Andersson et al., 1995; Strada, 1996); floodplains danger exists, and people are victimized because they are not aware of it (Beuchert, 1963), landslides (Sociedad et al., 2021), landgas which are formed by the conversion of landfills into agricultural lands leading to destruction and injuries due to methane gas explosion (Pivato et al., n.d.; Williams and Aitkenhead, 1991), lands with extreme temperatures (Sun et al., 2019), and others.

1.2. Agriculture 4.0

Rudimentary undeveloped agriculture has been called Agriculture 1.0, it dates to its beginnings about 10,000 years ago, until the 1920s, it required physical strength, animal traction, and manual labor. This kind of agriculture required a lot of labor and, consequently, constrained the size of the cultivated lands and was primarily concentrated on subsistence, making few profitable surpluses. Its succeeding era states the beginning of a more tech-intensified agriculture, called Agriculture 2.0, ranging from 1920 to 1990 with the adoption of technological packages, for example, fertilizers, machines and improved varieties, and other kinds of technologies became more prevalent (Borém and de Paula Corrêdo, 2022). Agriculture 3.0 pointed out mechanization and the use of technology like the global positioning system (GPS), software, and intelligent machinery to enhance productivity levels. To better automate and augment agricultural productivity while decreasing pollutants and agricultural inputs, a new approach is considered (Polymeni et al., 2023, Silva et al., 2023).

Agriculture 4.0 is a new approach to farm management and precision agriculture using technology. The term "Agriculture 4.0" was used at the World Government Summit by experts in 2018, as a movement where technology meets farming, automated equipment is introduced to a wide array of Internet of Things (IoT) sensors to measure soil moisture and vehicles to keep track of crops (Clercq et al., 2018). Agriculture 4.0 includes different technologies combining a set of sensors, information systems also known as IS, improved types of machinery, and informed management to optimize production by reporting for inconsistencies and ambiguities in an agricultural system (Mammarella et al., 2021). It is about connectivity, smart agriculture, or digital farming, as well as the integrated internal and external networking of farm operations.

The evolution of Agriculture 4.0 occurs at the same time as similar evolutions in the industrial world, where it is marked as Industry 4.0. Hence, the term Agriculture 4.0 is often used in farming. In terms of definitions, Agriculture 4.0, in analogy to Industry 4.0, stands for the integrated internal and external networking of farming tasks. This means that information in digital form exists for all farm sectors and processes; communication with external partners such as suppliers and end customers is likewise carried out electronically; and data transmission, processing, and analysis is automated. Agriculture 4.0 paves the way for the next evolution, including the present operation without direct human and system-based devices that can make decisions automatically (Dung et al., 2017).

It’s a new path toward farm management and precision agriculture (PA) using technology, including sensors, smart tools, satellites, the IoT, remote sensing, and proximal data collection.

Agriculture 4.0 will no longer have to depend on applying fertilizers, pesticides, and irrigation through the entire field, farmers will be using the minimum quantities (fertilize specific areas of the farm, or even individual plants) or even removing them from the supply chain (Clercq et al., 2018). Rovers’ presence on the field gives high accuracy of the provided data supporting farm management and enabling the automation of agricultural activities.

1.3. Technology Acceptance and Estimation Method

The lack of user acceptance has been an obstruction to the success of new technology (Davis, 1993). Information systems (IS) researchers have proposed intention models based on social psychology as a probable theoretical foundation for research on the elements of user behavior (Davis et al., 1989).

The Technology Acceptance Model (TAM) primarily introduced by Davis in 1986 continues to be the most extensively accepted theoretical model in the information science field. Tam is based on the Theory of Reasoned Action (TRA) first developed by Fishbein and Ajzen in 1975, as attitude paradigm technology. TAM helps predict and describe users’ behavioral intentions concerning information systems. Behavioral intention is the most direct precursor of technology use, according to the TAM, and is also a predictor of actual behavior (Straub et al., 1995; Yu et al., 2023). TAM speculates that two beliefs perceived usefulness (PU) and perceived ease of use (PEOU) primarily relieve acceptance behaviors (Davis et al., 1989). It proposes that adoption and application usage can be projected based on the factors of PU, PEOU, and attitude toward using (ATU) (Davis, 1987).

According to Davis et al., (1989), PU is the potential of an individual’s subjective probability that using a technology can increase their job performance. While PEOU refers to the extent to which the individual expects the target system to be free of effort.

PEU also has a beneficial and significant influence on PU. PU and PEOU, were created by synthesizing expectation theory, self-efficacy theory, etc. (Yu et al., 2023) and factor analyses suggest that PU and PEOU are “statistically distinct dimensions” (Davis et al., 1989).

Davis et al. (1989) also suggest that TAM assumes that technology usage is determined by behavioral intention (BI) which is determined by the user’s attitude toward using (ATU) the technology, and PU with relative weights estimated by regression:

$$BI = ATU + PU \qquad (1)$$

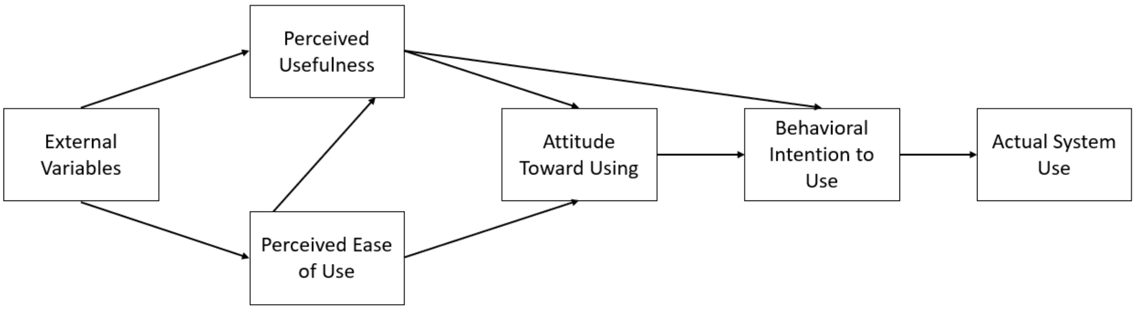

Figure 4 Technology Acceptance Model (TAM) (Davis et al., 1989)

TAM can predict or explain factors that affect the use of technology, and also it tries to explain the behavior of the technology itself (Straub et al., 1995; Yu et al., 2023).

The ATU-BI relationship already represented in equation (1) implies that all else being equal, individuals tend to form intentions to react toward which they have a positive effect (Davis et al., 1989). Even though the direct effect of a belief such as the PU on BI runs counter to TRA. The PU-BI relationship also in equation (1) implies that individuals will form intentions toward behaviors they believe will increase their job performance.

Previous IS search contains empirical evidence in favor of the ATU-BI and PU-BI relationships seen in equation (1).

The TAM has demonstrated to be able to explain technological acceptance in various fields, including information systems for digital banking (Gurendrawati et al., 2023), informatics in health (Walle et al., 2023), apps for social networks (Alshurideh and Al Kurdi, 2023), internet banking services (Thuy et al., 2022), autonomous vehicles (Liu and Liu, 2023), digital technology in education (Lin and Yu, 2023), mobile tourism apps (Ba et al., 2023), and self-driving cars (Bhardwaj et al., 2021), etc. TAM was also applied in the application of smart farming technologies (SFTs) by farmers i.e., drones, autonomous machines, and agricultural robots (Caffaro et al., 2020).

1.4. Objectives of the Thesis

The main objective of the thesis was to study technical and operational solutions for the use of new SFTs like UGVs in the context of Agriculture 4.0. The scientific knowledge regarding UGVs, the farmer's acceptance model, and the evaluation of performances of a specific terrestrial drone were evaluated.

The thesis includes six chapters: a general introduction, a bibliometric review, an assessment of the UGVs acceptance model, an evaluation of the rover in the field, a chapter about the specifications of the used drone and its usage in the field, and, finally, a general conclusion.

The first chapter (Chapter 1) of this thesis is the general introduction, and it highlights the history of unmanned ground vehicles (UGVs) and Agriculture 4.0 through time on one hand. On the other hand, it shows the technology acceptance and estimation method evolution, usage, and briefing.

The succeeding chapter (Chapter 2) describes in detail the specifications of the XBOT used in this research along with its different uses (bioclimatic sensors and autonomous mode).

Chapter 3 shows a bibliometric study concerning unmanned ground vehicles, in this study the evolution throughout the time of the term "UGV" or other similar terms. The findings help to show the concern and interest of the scientific community in unmanned ground vehicles in a 10-year timeframe.

Chapter 4 is based on the preliminary field studies of the CrossBOT (XBOT) rover. In these experiments, energy and fuel consumption were calculated. On one hand, the XBOT was attached to a mower, and the cut efficiency was calculated. On the other hand, the XBOT was attached to a tiller and, the granulometry (particle size distribution) as well as the bulk density of the soil were calculated. Speed tests were done on the XBOT while driven on the minimum, medium, and high speed; the same tests were carried out once using the mower and another time using the tiller.

Chapter 5 is based on the technology acceptance model; it studies the farmers' acceptance of unmanned ground vehicles. This experiment investigates farmer's perceptions, beliefs, attitudes, and adoption intentions of using UGVs in agriculture. The model is based on scientific literature and therefore the survey was developed to know which factors influence the intention to use UGVs and eventually support farming activities.

Finally, a general conclusion with the main findings of the thesis was presented in Chapter 6.

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CHAPTER 2

CROSSBOT (XBOT) Drone Specifications and Uses

1. Introduction

1.1. XBOT technical specifications

XBOT-0018 named CrossBOT is a robot that can operate inside plantations, and which carries out measurements of ambient temperature, air humidity, soil temperature, CO_2 concentration in the air, light intensity measurements (full spectrum, infrared, visible), fluorescence measurements using a portable fluorimeter positioned on an automatic telescopic guide on board the robot.

The Robot has two modes of operation:

- Manual
- Autonomous, recalling a previously stored path.

XBOT machine is equipped with the following sensors to perform soil analysis:

a. Sensor for measuring temperature and humidity RHT03 to carry out measurements of ambient temperature and air humidity. The temperature is expressed in degrees Celsius, the humidity in percentage.

b. Sensor for measuring soil temperature MLX90614, the temperature is expressed in degrees Celsius.

c. MG811 sensor for detecting CO_2 concentration to carry out measurements of CO_2 concentration in the air. The CO_2 values are expressed in voltage levels (mV) as the sensor requires a preliminary calibration in the environment of use.

d. TSL2561 sensor to carry out measurements on the light intensity including full-spectrum, infrared and, visible. The light intensity values are expressed in lux.

1.2 Illustration of the robot and description of its parts

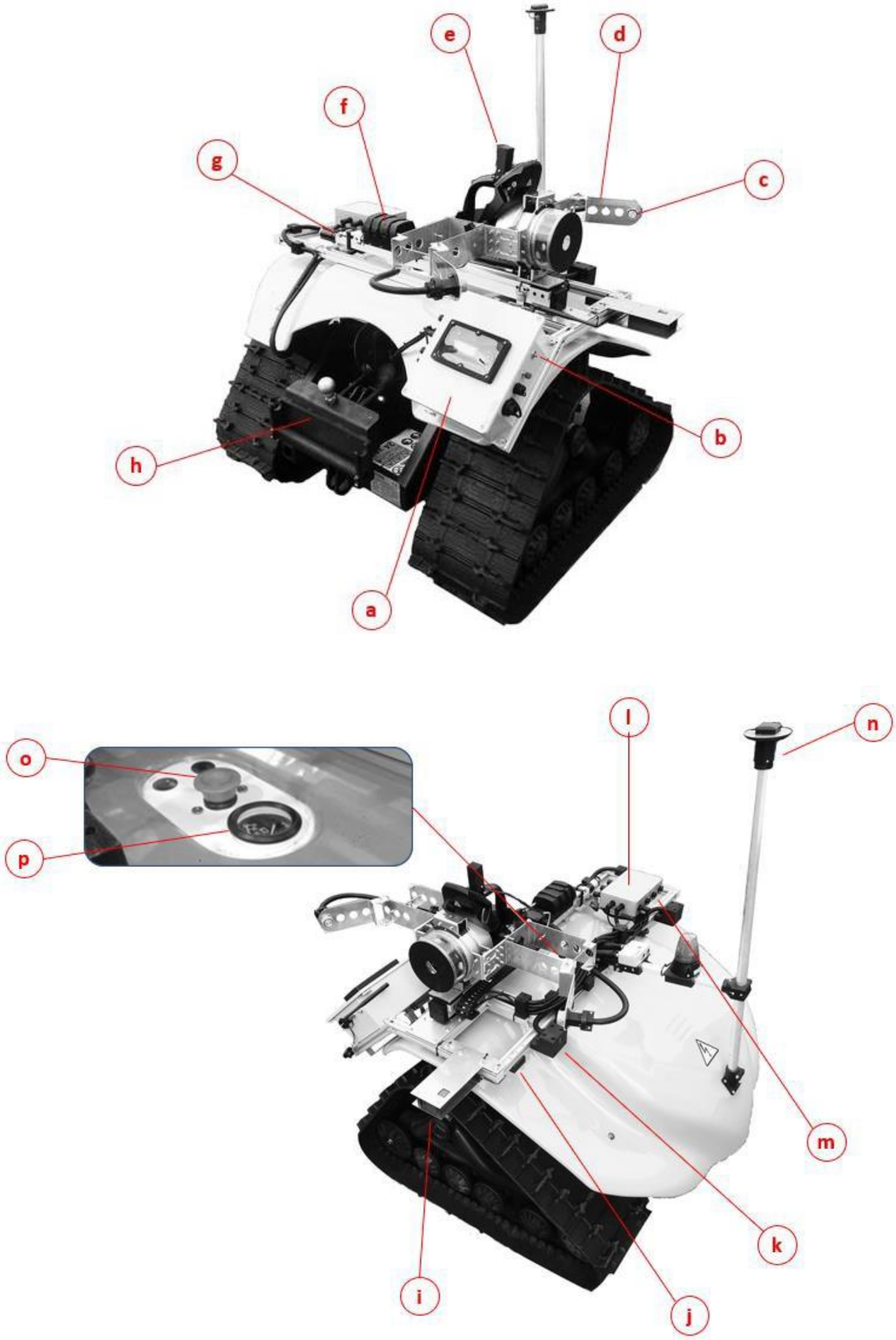

Figure 1: Description of the parts of the robot

Figure 2: Description of the accessories of the robot

Item and description parts of XBOT-0018 in Figure 1 and Figure 2.

a) On-board computer with display and keypad.
b) On-board computer on / off switch.
c) Ultrasonic sensors for cluster identification.
d) Support for Fluorimeter.
e) Linear actuator to exert adequate pressure on the acquisition button supplied with the Fluorimeter.
f) Fluorimeter battery holder.
g) Motorized telescopic guide with 600 mm stroke suitable for outdoor use for fluorescence measurements, complete with end stop, powered at 24 VDC.
h) Lift arm.
i) Sensors of: Air humidity, Air temperature, Ground temperature, and Brightness.
j) CO2 sensor.
k) Ultrasonic sensors with a control unit (USi-UP Slave "Mayser").
l) Control unit for sensors and actuators.
m) Auxiliary sockets 24V.
n) GPS antenna.
o) Emergency mushroom button.
p) Analog voltmeter indicating the battery status.
q) GPS base station equipped with control unit and antenna.
r) GPS base station power supply battery (6V 4.5Ah lead acid battery).
s) Battery charger for GPS base station (SAP code: CARICAT.ALCAPOWER.AP2612C).
t) Futaba remote control, model T6K (s/n B90154858).
u) Robot Charger (24V-30AH-AGM (s/n: 2402147)).
v) Battery charger side connector to recharge the Robot.
x) AGM 12V 220Ah battery side connector for recharging.
y) Robot AGM 12V 220Ah battery.
z) Antennas for Robot and GPS base station.

2. Operation of the robot

The XBOT Robot can operate according to two working methods manually and autonomously.

2.1. Manual method

With the manual method, the robot can be used manually, for its handling and the manual start of the environmental and punctual measurements in the field and on the plants, using the radio control. The measured values include ambient temperature, air humidity, soil temperature, CO_2 concentration in the air, and light intensity measurements (full spectrum, infrared, visible). Furthermore, simultaneously with the mentioned measurements, the robot also carries out fluorescence measurements on the plant, using a portable fluorimeter positioned on a telescopic guide on board the robot.

2.2. Autonomous Driving Method

With the autonomous driving method, the robot carries out the operations of driving and measuring environmental values and plants in a completely automatic way. This working method involves an initial learning phase, in which the robot memorizes the paths to follow, and subsequently executes them in complete autonomy. During Autonomous Driving, the system will acquire data from the environmental sensors installed on the platform every 30 seconds. Furthermore, there will be an additional time interval necessary for the telescopic guide to extend, upon automatic command of the robot, until it identifies the plant near the fluorimeter itself, due to two ultrasonic sensors. Once the measurement is complete, the robot returns to its rest position, and it continues to run along the path in progress.

The autonomous driving method consists of two modes of operation:

1. REC mode, in which an operator, via a remote control, instructs the machine on the path to follow, correlating the movements to the geographical position in which it was carried out. The operator can memorize up to 99 routes, recalling them according to work requirements.
2. AUTO mode, in which an operator, after having selected the previously stored path, can have it replicated by the robot automatically and in total safety. The decision-making

takes place through the analysis of the vehicle status, the analysis of the stimuli coming from the outside, the analysis of the path, and performing the motion control and the control of the actuators. In this operating mode, the system will interrupt its run, acquiring data from the sensors installed on the platform and associating them with the GPS coordinates. Because of the ultrasound sensors installed on board the platform, the robot reacts to external stimuli, allowing it to stop promptly in the event of obstacles along a path. To be able to start a route automatically, at least one route must have been previously recorded.

For both the manual and autonomous guided methods, with the robot standing still, the operations to be performed to start the measurements with the activation of the telescopic tool follow the following time sequence:

a. Lengthening of the telescopic tool until the ultrasonic sensors (Figure 1 - c) detect an alarm zone and in any case not beyond the maximum stroke of 600 mm.
b. The way of the tool is interrupted and then blocked when one of the following two events occurs:
    i. if the telescopic tool (Figure 1 - g) has reached the limit switch (maximum extension).
    ii. if the anti-collision (Figure 1 – c) sensors do not detect an alarm zone.

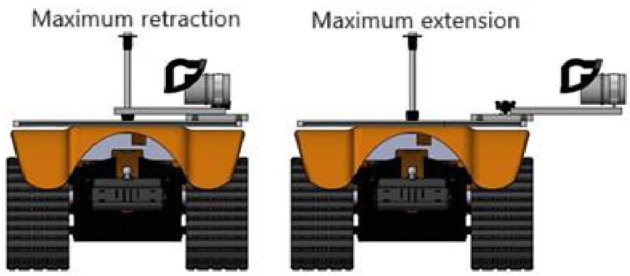

Figure 3: Description of the telescopic tool of the robot

c. The linear actuator (Figure 1 – e) is powered to exert a suitable pressure on the acquisition button supplied with the fluorimeter to start the acquisition of the relative measurement.

c. (continued)

The data is stored in the internal memory of the instrument itself, not in the robot's memory or on the USB storage device.

d. The rod of the linear actuator (Figure 1 – e) is retracted after the time required for acquiring the measurement.
e. After a short time, the telescopic slide returns to the rest position (fully retracted).

At the end of the measurements, it is possible to save the paths followed by the robot and the measurements made on a mass storage device. With the backup operation, a copy of all the data acquired by the robot is made on a USB device.

3. XBOT bioclimatic sensors

3.1. RHT03

Digital relative humidity and temperature sensor RHT03, as known as DHT22. DHT22 is a digital sensor that is easily implemented. This type of sensor is on the inside made up of a capacitive sensor and a thermistor (Cerdan and Andrade-Arenas, 2022) that are responsible for the detection of the humidity and temperature of the object and where the object is (Robson et al., 2021). The main characteristics of the DHT22 sensor are shown in Table 1.

Table 1 Characteristics of the DHT22 sensor (Cerdan and Andrade-Arenas, 2022).

Model	DHT 22
Power supply	3.3 -6 VDC
Operating range (humidity)	0 – 100 % RH +/- 2%
Operating range (temperature)	-40 -80ºC +/- 5ºC
Resolution	Humidity (0.1%RH) Temperature (0.1ºC)

The DHT22 sensor has a digital output called "single-bus" with high precision and accuracy regarding measurement (Mardiyanto et al., 2019). Since it is connected to an 8-bit computer chip it makes it easy to calibrate it, also it has very good stability. Calibrating the sensor is very precise and the calibration data is stored in the OTP-type memory program work (Cerdan and Andrade-Arenas, 2022). The sensor is represented in Figure 4.

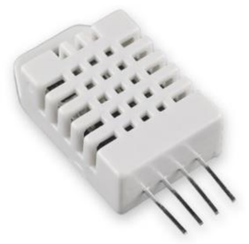

Figure 4 Humidity and temperature sensor RHT03.

3.2. MLX90614

MLX90614 is a non-contact infrared body temperature sensor, using an infrared-sensitive thermopile detector. It has a low power consumption, a small size, and a non-contact measurement. This sensor is aimed to measure a targeted object's temperature by absorbing the emitted infrared rays. It has two sensing elements for ambient and object temperatures with a wide measurement array of −70 °C to 382.2 °C, with an accuracy of ±0.5°C. It also incorporates a signal processing IC that delivers a calibrated digital output for both temperature values over an I2C interface (Gudipalli et al., 2023; Islam et al., 2023). The field of view of this sensor is around 5°, so it is very appropriate for calculating highly accurate temperatures with a wide array of temperature readings (Umiatin et al., 2022). The sensor is represented in Figure 5.

Figure 5 MLX90614 infrared temperature sensor (Meenakshi et al., 2022)

3.3. MG811

MG811 CO_2 (Carbon Dioxide) sensor is provided with a thermocouple, which measures the concentration of gas molecules more precisely. It uses Analog-to-digital conversion (ADC) to transmit data. The sensor gathers the voltage changes by generating a small voltage proportionally to the amount of CO_2 gas existing in the air exposed to the internal element and transfers the voltage values to the microcontroller (MCU) through the onboard ADC channel (Pan & Wang, 2021). MG811 sensors can detect the presence of CO_2 gas between 350-10000 ppm (Shahane and Godabole, 2016; Amaliya et al., 2021) MG811 works on a solid electrolyte cell principle and is highly sensitive to CO_2. MG811 has a large measuring array of 300ppm to 10000ppm. MG811 has an analog output of 30~50mV, and the operating array of the sensor is -4°C to 50°C (Shahane and Godabole, 2016). The sensor is represented in Figure 6.

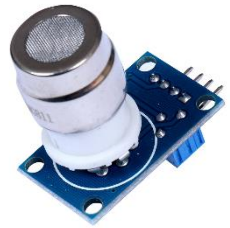

Figure 6 MG811 carbon dioxide sensor module

3.4. TSL2561

The TSL2561 (Figure 7) is manufactured by AMS-TAOS, it is a light-to-digital converter that converts light intensity to a digital signal. The device joins two photodiodes, one broadband (visible plus infrared) and the other infrared-responding photodiode (Geeroms et al., 2015). This radiance sensor is a progressed computerized light sensor, ideal for use in a broad array of light circumstances (More et al., 2020). This sophisticated light sensor uses infrared and visible light sensors to work as the human eye as it can measure both very small and very large amounts of light (Kanakaris et al., 2019). This sensor contains both infrared and full-spectrum diodes (Beyaz and Gül, 2022).

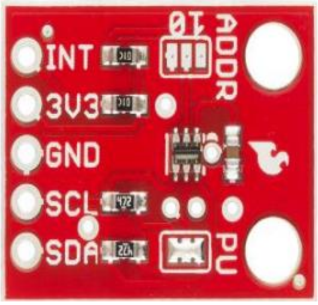

Figure 7 TSL2561 sensor (Beyaz and Gül, 2022)

It's appropriate for the usage of low-power data logging systems of about 0.5 mA when it is active and less than 15 uA when in power-off mode consequently increasing battery life and offering optimal viewing during a range of lighting conditions (Beyaz & Gül, 2022)

Table 1 Specification of TSL2561 sensor (Nurjannah & Alfata, 2020; Beyaz & Gül, 2022)

Temperature scale [°C]	-30 to 80
Power supply [V]	3.3 - 5
Light ranges [lux]	0.1 - 40000
Low supply current max [mA]	0.6
Voltage scale [V]	2.7 - 3.6

The outcome of the sensor circuit measurement is two digital values, one implying information on both infrared radiation and visible light, and the other giving information on infrared radiation only (Hrbac et al., 2013).

4. Conclusions

XBOT is a versatile, robust, and powerful ATV skid-steering tracked mobile robot that can run autonomously and manually, it could be used for a large variety of applications in the fields. The 2×2 all-terrain tracks allow the rover to run on various types of terrain and its arm can haul a mower and tiller, making the work easier, simply by controlling the drone with the remote control. XBOT is considered a light machine, weighing 400 Kg, that doesn't cause evident compaction of the soil. Its batteries last between 2 to 3 hours per a 6-hour recharge, which allows enough time for any field activities. The extraction of the sensors' stored data is made thru the USB interface. Finally, this robot has proven to have good capabilities and features, further studies are recommended to experiment with it more.

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CHAPTER 3

Unmanned Ground Vehicles in Agriculture: A Bibliometric Review

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https://dspace.uevora.pt/rdpc/bitstream/10174/30608/3/AgEng2021_Proceedings.pdf.

Simple Summary

Familiarizing with new technologies does not always lead to quick adoption, especially in the agricultural sector. Unmanned ground vehicles (UGVs) operate while in contact with the ground and without a human presence onboard. UGVs could be used where it is inconvenient and dangerous to have the presence of a human operator. UGVs are being developed for civilian, military, and agricultural use to perform various activities. Several platforms are available on the market for commercial use. A bibliometric study was carried out regarding UGV or similar synonyms on three different scientific websites. The results help to show within the timeframe the interest of the scientific community in these platforms along with the subject areas, document types, and main counties involved in these publications. As well, another bibliometric study took place regarding the main UGVs available in the market for commercial use in agriculture, the results show the technical specifications of each platform, as well as the number of publications found.

Abstract

Robotic technologies in agriculture have seen rapid evolution throughout the years. Among these technologies, Unmanned Ground Vehicles (UGV) are becoming increasingly popular, especially for on-field monitoring and operational agricultural activities. The introduction of this technology in the field, implemented with specific sensors and components, provides high-accuracy data in line with the precision agriculture principles. Moreover, UGVs may reduce human workload and improve work quality, enabling the automation of agricultural activities. These advantages, increasingly documented in the scientific literature, encounter a lack of reviews on UGVs applied for agricultural purposes. This paper aims to improve the body of knowledge about the application of UGVs in agricultural contexts. Detailed analysis of the interest of the academic community available on Web of Science, Scopus, and IEEE Xplore databases was undertaken by testing 12 different keywords. In this study, the features of the UGVs available in the market were also evaluated. The results showed that, among the several keywords utilized, the main outcomes were found for the terms “Rover” and “Unmanned Ground Vehicles”. Across the three scientific search platforms, the studies conducted in this topic area were mostly found as “conference papers”. Considering the world

distribution of the results for the keywords that included the term “Agriculture”, the countries mainly involved were found to be the United States, Italy, India, and Spain. Finally, this paper presented the current challenges and forthcoming trends within the introduction of UGVs in agricultural farms.

Keywords: Rover, Precision Agriculture, Agricultural Engineering, Robotic platform, UGV.

1. Introduction

An Unmanned Vehicle is a device that operates without a human presence on board, autonomously using artificial intelligence, or operated remotely by a human. Unmanned vehicles could be aerial or grounded; the Unmanned Aerial Vehicle (UAV) could fly above obstacles, cross faster, and cover a wider area that might not be accessible for the Unmanned Ground Vehicle (UGV). While the UGV could inspect more accurately and closely than the UAV (Tran et al., 2020). These unmanned vehicles could coordinate and function with each other or stand-alone. These vehicles could be identified with several terms and acronyms other than UGV. According to Scopus, the term "UGV" first appeared in a scientific search in 1974, whereas "rover" appeared in 1896. Other terms newer terms like "agricultural robot" in 1982, "ground robot" in 1994, and "unmanned ground vehicle" in 1991. UGVs are used in space applications, civilian and commercial activities, as well as for defense and emergency response, for example, during the 2020 pandemic of coronavirus, UGVs were used in Tunisia to enforce new COVID-19 restrictions (Project Ploughshares, 2020). Throughout time, the use of "UGVs" has been gaining ground for several agricultural and farming practices, ranging from pruning and inspection, disease detection to precise spraying of fertilizers, pesticides, and insecticides (Fotio Tiotsop et al., 2020; Karthik et al., 2018). Other activities that could be accomplished with the use of UGVs are cutting fruits (Rakshitha et al., 2017), mowing (Broderick et al., 2014), field scouting, weed control, harvesting (Quaglia et al., 2019), as well as monitoring animals (Roure et al., 2018; Usher et al., 2015). Depending on their application, these autonomous platforms could be equipped with simple or advanced sensors and equipment such as video and thermal imagers, visible and near-infrared cameras, LIDAR, robotic arms, and agricultural tools (Bao et al., 2019; Milella et al., 2019; Srisuphab et al., 2019; Wendel and Underwood, 2017).

This paper aims to improve the body of knowledge about the application of UGVs in agricultural contexts. Detailed analysis of the interest of the academic community available on Web of Science, Scopus, and IEEE Xplore databases was undertaken by testing 12 different keywords. In this study, the main characteristics of the UGVs available in the agricultural domain were also evaluated.

2. Materials and Methods

Unmanned vehicles seemed to show an increase of concern in the scientific community. To study the literature concerning these platforms this study has been structured in two main parts: the first one describes and highlights the trend of topics searched for keywords related to UGVs, and their relationship with agriculture; the second one focuses on the characteristics of UGVs used in agriculture and available in the market as well as the countries involved in the scientific research. In this study, Scopus, Web of Science, and IEEE Xplore have been chosen as they represent the most reliable scientific databases to analyze the main items for a specific set of keywords. Scopus is one of the largest scientific databases of peer-reviewed scientific – literature journals, conferences, and book proceedings. Web of Science's platform provides access to different kinds of indexes comprising regional and multidisciplinary citations; specialist subjects; patent family; and scientific data sets. Whereas IEEE (Institute of Electrical and Electronics Engineers) Xplore digital library is a resource for technical and scientific publications in computer science, electrical engineering, and electronics. On one hand, a search has been carried out on abstract and citation databases such as Scopus, Web of Science (WoS), and IEEE Xplore on two levels. The first one was for a set of keywords related to the term UGVs, while the second one related to the term UGVs and "agriculture", specifically: UGV, UGV and agriculture, Unmanned ground vehicle, Unmanned ground vehicle and agriculture, Robot platform, Robot platform and agriculture, Ground robot, Ground robot and agriculture, Ground robot platform, Ground robot platform, and agriculture, Rover, Rover and agriculture.

The analysis has been carried out including different criteria involving: the number of publications per keyword over the years (per year/contribution trend/publication trend); the subject areas (subject area); and the document type (document type). All the data concerning the "per year/ publication trend" have been searched for the time frame 2009-2020 due to the increasing interest in these topics in the last years. The most considerable subject areas, obtained for each keyword searched, have been selected for the data analysis. Anyway, the subject area related to the agricultural area has been always included in the results, to show the magnitude of the data obtained.

The data related to the document type has been selected considering the most representative type of document indexed (articles, journals, conference papers, etc.) according to the available time frame covered by each scientific database (Scopus 1896-2020, Web of Science 1985-2020, and IEEE Xplore 1872-2020).

The total number of publications per country was identified for the Scopus database considering the whole years' coverage and putting together all the data obtained for all keywords with the term agriculture. The results have been presented in a Map Chart to determine the countries most involved with scientific research in this topic area. Market research has been carried out to identify the UGVs available for agricultural application. Features and characteristics of the available UGV have been analyzed to define the main aptitude of these technologies. Moreover, the interest of the scientific community in the application of effectively available UGVs in agriculture has been analyzed using the data gathered from Scopus, Web of Science, and IEEE Xplore.

3. Results and Discussion

3.1. Total number of publications

The number of publications available was much higher for the keywords not including the term "agriculture". The results obtained from the three scientific databases showed that the highest number of publications were associated with the keywords "rover" followed in order by "robot platform", "UGV", "unmanned ground vehicle", "ground robot" and finally "ground robot platform". Figure 1 shows the percentage of the total number of publications per keyword according to the three scientific databases.

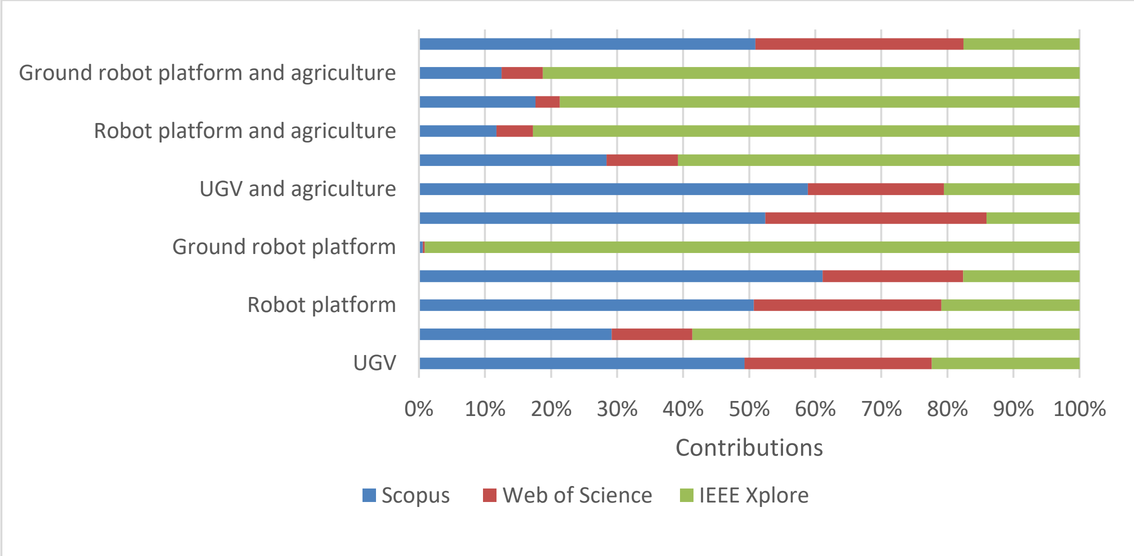


Figure 1 Percentage of the total number of contributions per keyword(s) according to Scopus, Web of Science, and IEEE Xplore.

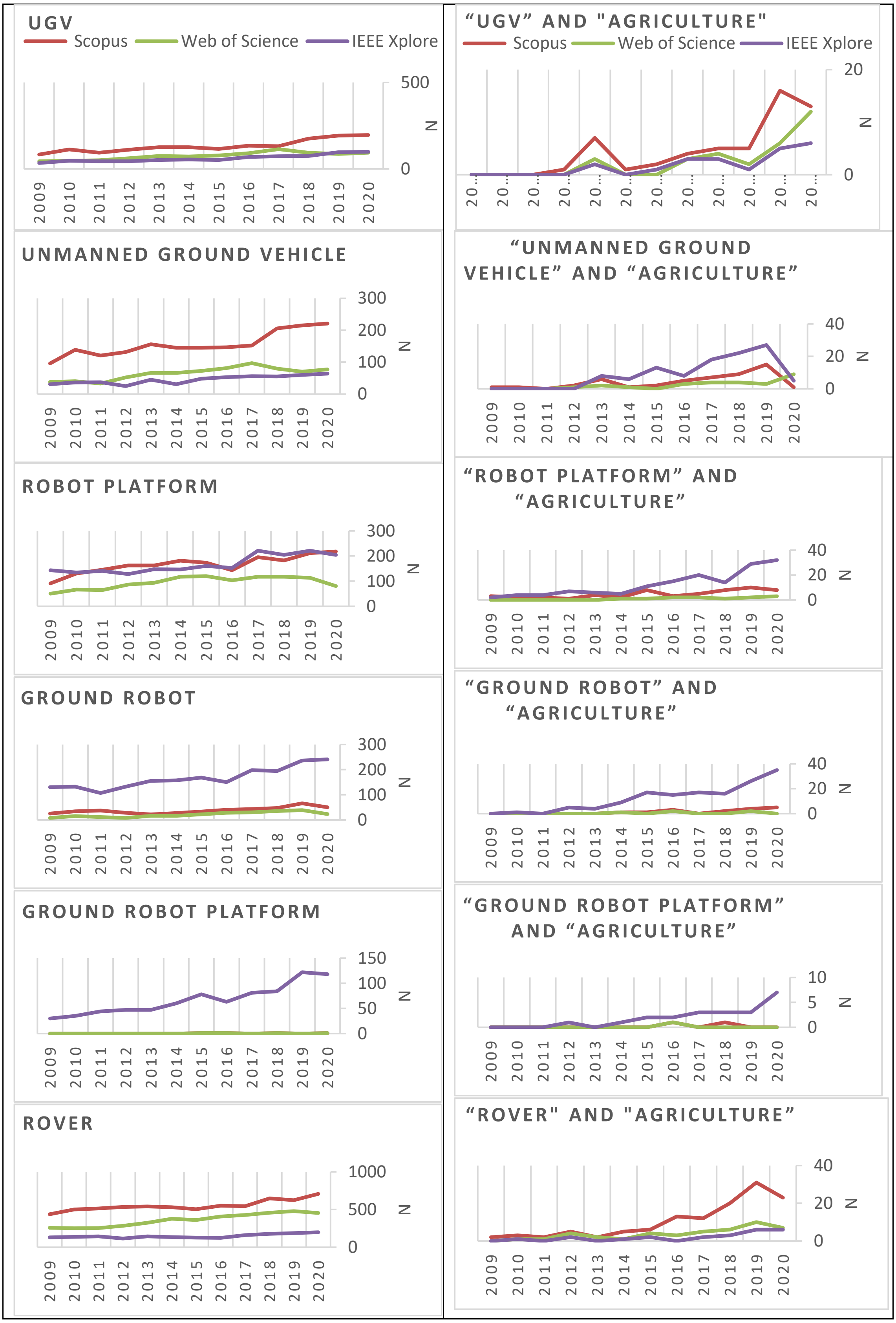
IEEE Xplore shows the highest number of contributions when compared to Scopus and Web of Science for the following keywords: "unmanned ground vehicle and agriculture"; "robot platform and agriculture"; "ground robot and agriculture"; "ground robot platform and agriculture"; "ground robot platform"; "unmanned ground vehicle". For the overall keywords analyzed, the results underlined that Scopus found the highest number of contributions compared to WoS. Table 1 represents the percentage of publications when the searched keywords are associated with the term "agriculture" within the results obtained when searching for the same keywords alone. Scopus and WoS held the highest percentage for the keywords "ground robot platform and agriculture". On Scopus, the second-highest percentage came for "Ground robot and agriculture" with 3.82%, followed by "UGV and agriculture" and "Unmanned ground vehicle and agriculture" with an average of 3%. On WoS, the second-highest percentage of 2.71 came for "Unmanned ground vehicle and agriculture" followed by "UGV and agriculture". On IEEE Xplore, the highest percentage of 59.12 came for "Ground robot and agriculture" where 107 publications out of 181 included "agriculture", and the second-highest percentage of 16.46 came for "Robot platform and agriculture". Unpredictably, the "Rover" keyword with the highest number of publications had the lowest percentages on Scopus, WoS, and IEEE Xplore when the keyword search was associated with agriculture, 0.92%, 0.89%, and 1.18% respectively. These results showed that the main outcomes were found for the keywords, not including the term “agriculture”, underlining that the scientific community is mostly oriented on studies related to other aspects (e.g. technical issues, design, and development, path planning, etc.) rather than on-field agricultural applications.

Table 2 Percentage of the contributions per keyword associated with agriculture compared to the keyword(s) search alone in the three different scientific databases.

Keyword(s)	Scopus	Web of Science	IEEE Xplore
UGV and agriculture	3.03	1.84	2.33
Unmanned ground vehicle and agriculture	2.99	2.71	3.18
Robot platform and agriculture	0.96	0.81	16.46
Ground robot and agriculture	3.82	2.28	59.12
Ground robot platform and agriculture	50.00	50.00	1.90
Rover and agriculture	0.92	0.89	1.18

3.2. Number of publications per year

Figure 2 highlights the yearly number of results on each of the three scientific databases per keyword. The results were arranged into 2 columns, showing the publication trends, over the last 11 years, of the 12 keywords investigated, containing or not the term agriculture. Overall, an increase from 2009 to 2020 has been found for all the keywords investigated. The highest growth was found for the “Ground Robot” and “Agriculture” keywords on IEEE Xplore showing an increase of 35 times. The results obtained show how the keywords that did not include the term agriculture already had a consistent presence of published scientific articles in the past years. Moreover, observing the keywords that also included the term agriculture, there was a considerable increase in the number of publications, mostly in the last 5 years.


UGV
Scopus
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“UGV” AND "AGRICULTURE"
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GROUND ROBOT
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“GROUND ROBOT” AND “AGRICULTURE”
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GROUND ROBOT PLATFORM
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“GROUND ROBOT PLATFORM” AND “AGRICULTURE”
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ROVER
1000
500
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N
2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
“ROVER" AND "AGRICULTURE”
40
20
0
N
2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020

Figure 2 Yearly number of contributions per keyword(s) and per keyword(s) associated with "agriculture" according to Scopus, Web of Science, and IEEE Xplore (N = number of publications).

3.3. Number of publications per subject area

This section will show the number of publications of the keyword(s) alone, then annexed in the search with “agriculture” across the three scientific databases. For the “UGV” keyword, agriculture and related fields represent 0.49% of total subject areas on Scopus, while in WoS 0.41% which both came last among other areas, and in IEEE Xplore none is found. As for "UGV" and "Agriculture" keywords, agriculture and related fields represent 11.39% of total subject areas on Scopus, while in WoS 22.72% which is the lowest in their categories, and in IEEE Xplore 30.55% which came equally as “mobile robots” subject area. For “Unmanned Ground Vehicle” agriculture and related fields came last and represent 0.53% of total subject areas on Scopus, while in WoS and IEEE Xplore, none were found. As for "Unmanned Ground Vehicle" and "Agriculture" keywords, agriculture and related fields represent 12.24% of total subject areas on Scopus, while in WoS 20% which is the lowest in their categories, and in IEEE Xplore 34.01% which came second after “autonomous aerial vehicles” subject area. For the “Robot platform” keyword, agriculture and related fields came last and represent 0.77% of total subject areas on Scopus, while in WoS and IEEE Xplore, none is found. As for "Robot platform" and "Agriculture" keywords, agriculture and related fields represent 11.76 % of total subject areas on Scopus found third after “engineering”, while in WoS it’s 10% which was found last in its categories, and IEEE Xplore 52.04 % which came first. For the “Ground robot” keyword, agriculture and related fields came last and represent 0.55% of total subject areas on Scopus, while in WoS and IEEE Xplore, nothing is found. As for " Ground robot " and "Agriculture" keywords, agriculture and related fields represent 15.79% of total subject areas on Scopus, while in WoS 28.57% which is the lowest in their categories, and in IEEE Xplore 24.54% which came first among the subject areas. For the "Ground robot platform" keyword, agriculture and related fields are found on any platform. As for the "Ground robot platform" and "Agriculture" keywords, agriculture and related fields were found in the first subject area and only on IEEE Xplore representing almost the half of total subject areas by 47.62%.

Table 3 Number of publications per subject area across Scopus, WoS, and IEEE Xplore for the selected keywords.

Database	Subject area	" UGV"	" UGV" and " Agriculture"	" Unmanned Ground Vehicle"	" Unmanned Ground Vehicle" and " Agriculture"	" Robot platform"	" Robot platform" and " Agriculture"	" Ground robot"	" Ground robot" and " Agriculture"	" Ground robot platform"	" Ground robot platform" and " Agriculture"	" Rover"	" Rover" and " Agriculture"
Scopus	Engineering	1,484	27	1,828	34	1,527	12	547	17	4	2	6,478	33
	Computer Science	1,299	31	1,506	36	1,604	14	512	15	2	2	2,733	32
	Mathematics	659	12	787	16	487	4	197	5	1	1	939	7
	Agricultural and Biological Sciences	17	9	22	12	28	4	7	6	0	0	602	9
	Earth and Planetary Sciences	37	2	35	1	17	0	10	0	0	0	3,134	5
Web of Science	Engineering electrical electronic	445	2	374	0	463	3	84	1	1	0	1,040	0
	Robotics	416	7	328	6	556	3	106	3	1	1	893	7
	Automation control systems	343	3	280	2	411	3	71	2	2	1	679	0
	Computer science artificial intelligence	289	6	222	5	407	3	56	1	1	1	726	0
	Agriculture	5	5	0	4	0	1	0	2	0	0	0	6
	Engineering aerospace	33	0	0	0	0	0	6	0	0	0	1,170	0
	Engineering	0	0	0	0	0	0	0	0	0	0	0	16
IEEE Xplore	Agriculture	0	11	0	67	0	102	0	100	0	10	0	18
	Mobile robots	458	11	1130	31	524	68	125	53	445	7	736	9
	Remotely operated vehicles	435	7	1165	23	0	12	18	18	120	4	79	2
	Autonomous aerial vehicles	151	7	1958	76	0	23	38	42	168	4	0	0
	Robot vision	138	3	422	21	187	26	64	32	176	2	174	3
	Path planning	137	4	383	11	118	16	41	16	94	2	233	0
	Humanoid robots	0	0	0	0	125	0	0	0	34	0	0	0
	Planetary rovers	0	0	0	0	0	0	0	0	0	0	1,236	5
	Mars	0	0	0	0	0	0	0	0	0	0	512	1

For the "Rover" keyword, agriculture and related fields came last and represent just 4.65% of total subject areas on Scopus, where it is only found on this platform. As for "Rover" and "Agriculture" keywords, agriculture and related fields represent 12.16% of total subject areas on Scopus and came third, while in WoS 16.67% which is the lowest in their categories as well and in IEEE Xplore 54.54% which came first among the subject areas, this could be explained by the interest in publishing documents having agriculture, agricultural machinery, horticulture, crops, and agricultural robots as subject areas on IEEE Xplore.

3.4. Distribution of publications per document type and Country

This part highlights the total number of publications, of each keyword tested, per document type. The results illustrated that, across the three scientific databases, about 75% of the publications were published as conference papers, while only 25% were published as articles or review papers. IEEE Xplore held the highest number of contributions published as conference papers (90%). The keywords “Ground robot platform” including or not the term agriculture showed 100% of publications as conference papers in Scopus and WoS databases. The keywords “Rover” also when associated with the term agriculture, held the highest contribution as articles compared to the other tested keywords in Scopus and WoS.
Figure 3 shows the number of publications per Country for the keywords including the term agriculture according to the Scopus database.

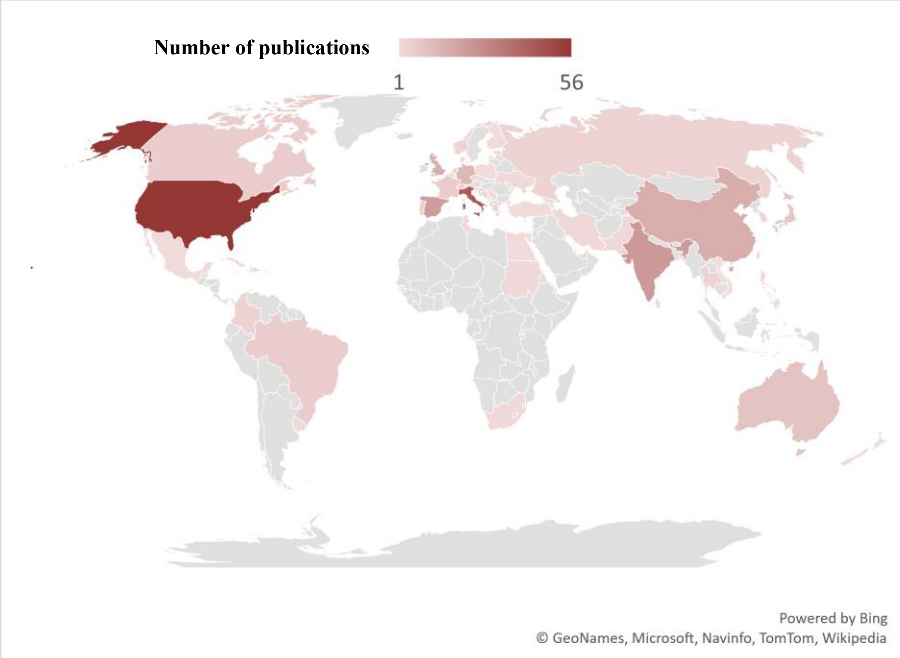

Figure 3 Number of publications per country for the keywords including the term agriculture according to Scopus.

These all-time results for the selected keywords show the highest interest found in the United States with 56 publications, followed by Italy with 44 publications, India (23), Spain (22), China and the United Kingdom (16), and Germany (13). A total number of 42 countries follow the previous list with fewer publications ranging from 9 to 1.

Most of the countries involved in scientific research having the highest number of publications belong to countries with developed economies, except India and China according to the United Nations' country classification in 2020.

3.5 Technical specifications and key studies indexed on agricultural domain UGVs

Table 3 shows the main features of the analyzed agricultural UGVs which largely differ from each other. One of the first features that most distinguishes these robots is the dimensions. The biggest UGVs were found to be Bonirob, Thorvald, and Robot Dino, reaching up to 3000 mm of width, while Robot OZ was the smaller one. Regarding the traction system, all the UGVs were equipped with 4-wheel drive except the XBot which was found to be an all-terrain tracked robot. The maximum working speed ranged between 1.8 to 18 km/h. the overall UGVs analyzed were powered by batteries, where

Bonirob was also equipped with a fuel generator, while Vitirover was furnished with photovoltaic solar panels.

The main topics studied across Scopus, WoS, and IEEE Xplore for the agricultural domain UGVs are discussed below. Husky robot held the highest number of references (32) followed by Bonirob (12) and Thorvald (5). Clearpath's Husky platform has been developed in agriculture with an autonomous driving systems using state estimator with multi-rate sampled data collected by an onboard sensor (Jin et al., 2019). The accuracy of posture detection was improved with a specific Kalman filter (Lin et al., 2018) while driving it indoors and outdoors on several surfaces (Dogru and Marques, 2018). Franco et al. (2019) embedded a new algorithm for visual paths, while Gopi et al. (2017) worked to develop a prototype for gesture-based communication between untrained humans and mobile robots. Husky robot has been widely used for monitoring activities in polluted and contaminated soils (Akhil et al., 2019; West et al., 2019), for localization, mapping, and planning (Abdul-Rahman et al., 2019; Lenac et al., 2017; Wang et al., 2013).

Table 4 Main features, power, performances, and communication of the agricultural domain UGVs.

	Robot	XBOT	BONIROB	VITIROVER	WARTHOG	HUSKY	THORVALD	ROBOTNIK	WEEDING ROBOT OZ	WEEDING ROBOT DINO	VINEYARD ROBOT TED
Main Features	Dimensions (L x W x H) [mm]	1250 x 1266 x 723	2800 x 2400 x 2200	750 x 390 x 290	1520 x 1380 x 830	991 x 671 x 370	1500-1750 x 1000-3000 x 825	720 x 614 x 417	130 x 47 x 83	2500 x 1400 – 1800 x 1300	450 x 142-185 x 200
	Ground Clearance [mm]	350	-	-	254	127	Variable	-	7	-	-
	Weight [Kg]	500	1100	20	280	50	180	65	150	800	1700
	Traction system	All Terrain Tracks	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive	4 Wheel Drive
	Max Payload [kg]	350	150	-	272	75	250	65	90-300	-	-
	Max Speed [km/h]	3	5.4	1.8	18	3.6	5.4	10.8	1.8	4	4
	Climb capacity	< 40°	-	< 8.53°	< 45°	< 45°	-	< 45°	< 5.71°	-	-
Power Performances	Total Power [W]	4800	-	~20	192-480	192	2000	2000	-	-	-
	Power Options	Battery Pack	Battery Pack, Fuel generator	Solar panel + battery pack	Battery Pack	Battery Pack	Battery Pack	Battery Pack	Battery Pack	Battery Pack	Battery Pack
Communication	Communication Interface	USB, RS-232, Wi-Fi, Ethernet, CAN bus, RC pulses	USB (6 ports outside, up to 14 ports inside), WiFi (2.4 & 5 GHz), Bluetooth 4.0	-	Ethernet, USB, Remote Control, Wi-Fi	-	I/O ports and CANbus	WiFi 802.11 n Internal: USB, RS232, GPIO y RJ45	Communication with user via text message	text message communication with anti-theft tracking device	communication via SMS and anti-theft tracking device

The main research topics studied with the use of Bonirob, an autonomous robot for plant phenotyping, deals, in the first stage, with mapping of plant diseases based on spectral imaging information, navigation, and plant-sensors also using a 3D LIDAR (Ruckelshausen et al., 2009; Rahe et al., 2010; Weiss et al., 2010; Wunder et al., 2011). Moreover, Peveling and Schulze (2011) presented a sensor system based on Ultra-Wideband-RADAR which can evaluate the properties and dimensions of the plants. Another work illustrated how the Bonirob system was employed for the task of mechanical weed control in organic farming and the determination of soil parameters (Michaels et al., 2012; Scholz et al., 2016). To evaluate which configuration can be used to distinguish root plants and weeds through the use of specific sensors, images were acquired with the autonomous field robot Bonirob (Haug and Ostermann, 2015a-b; 2016; Knoll et al., 2016). Lastly, Fleckenstein et al. (2017) studied the path planning problem for the BoniRob agricultural robot with adjustable relative wheel positions to increase the navigation capabilities. Thorvald platform was developed as a versatile and modular robot for a wide variety of agricultural operations such as seeding, weeding, and harvesting. It can carry a large variety of tools and is lightweight so that it can operate during wet periods without being stuck or damaging the structure of the soil (Grimstad et al., 2016). Moreover, Grimstad and From (2016, 2017a, 2017b, 2018a, 2018b) presented detailed studies on the characteristics of the hardware and software components of the Thorvald II mobile robotic platform.

4. Conclusions

The present bibliometric review illustrates the literature evolution of Unmanned Ground Vehicles and their application in the agriculture domain. This study showed an increasing interest in the scientific community with the topics related to autonomous robots in agriculture throughout the time (2009 - 2020), where the main findings are reported as follows:

- The keyword that was most used was “Rover” including or not the term “Agriculture” compared to the other keywords tested;

- Across the three scientific databases utilized in this study, the main results were found in the subject area related to Engineering fields;

- Analyzing the number of studies developed on these topics, the document type most published was the conference paper (75%) rather than articles or reviews;

- The all-time results for the selected keywords, which included the term agriculture, showed that the highest interest was found for the United States followed by Italy and India;

- The main characteristics of the UGVs implemented in the agricultural context highlight a high variability in terms of size, weight, and max speed, while the main traction system and power source adopted were the 4-wheel drive and the battery pack, respectively.

In conclusion, this bibliometric review aims to motivate and promote the interest of the scientific community towards the design, development, and application of autonomous robots in the agricultural sector. These technologies represent a valuable opportunity for farms to implement precision agriculture practices in their production system.

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CHAPTER 4

Implementation and Assessment of an Autonomous Ground Vehicle (AGV) for On-Field Agricultural Operations

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Abstract

In the last few decades, many studies have focused on the development and implementation of autonomous ground vehicles (AGV) and teleoperated mobile robotic platforms capable of carrying out agricultural tasks (soil preparation, crop treatments, harvest) with limited or no human intervention. The AGVs are emerging technologies where the availability of scientific findings that clearly state the overall benefits deriving from their implementation in the agricultural sector are still limited. Thus, this study aims to customize a commercial AGV for specific use in agriculture and test its operating capabilities on-field to perform agricultural tasks coupled with different implements. The electric-tracked AGV used in this study was a compact rover (1.30 x 1.05 m) powered by lead-acid batteries. The AGV was coupled with a rotary flail mower and a rotary tiller. Both implements were self-powered by an endothermic engine. Considering the performance of AGV coupled with implements, cutting efficiency (CE%), soil clumping, and bulk density ($g.cm^{-3}$) were assessed with the towed load. Furthermore, the energy consumption (kWh) in performing on-field tasks was measured. The driving performance tests allowed monitor the forward speeds where the maximum speed value corresponded to 0.77 m s^{-1}. Moreover, the forward speed was significantly influenced by the towed load but not by the usage time. The CE was 36.81% on average, and the rotary tiller operations improved soil characteristics. The results of this study contribute to the implementation and usage of AGV in agriculture to perform specific on-field tasks. The study provides an overview of the use of an electric autonomous ground vehicle to support farmers in field management in safer conditions and with low environmental emissions.

Keywords: Unmanned ground vehicle, Robot, Weed control, Soil tillage, Sustainable agriculture.

1. Introduction

The agricultural sector has been faced with many challenges related to the environmental impacts of anthropogenic farming practices. The increasing demand for world food production has been supported over the years by the improvement of the agricultural sector. Thanks to the introduction of new machinery e.g., tractors, automatic milking machines, and new management strategies e.g., genetic improvement, and the use of fertilizers, it has been possible to increase production yields [1, 2]. Nowadays, the agricultural sector has the potential and responsibility to mitigate the environmental impacts of GHG emissions through sustainable actions and management strategies. This goal could be pursued with conservative approaches while improving yields and preserving soil fertility [3]. Furthermore, the introduction of smart technologies could be a powerful support tool for farmers to achieve this goal. The combination of precision agriculture practices, digital farming technologies, and robotic solutions could provide answers to these challenges as well as reduce the farmers' manual labor demand and increase their welfare [1,4]. In the last years, many studies and manufacturers have been focused on the development and implementation of agricultural robots, autonomous ground vehicles (AGV), and teleoperated mobile platforms capable of carrying out agricultural tasks i.e., soil preparation, crop treatments, weed control, and harvest with limited or no human intervention [5,6]. Despite AGVs and robotic solutions have been studied and tested in the agricultural context, equipped with sensors, or implements, ready-to-market AGVs for farming applications are still rare. Moreover, AGVs are emerging technologies where the availability of scientific findings that clearly state the overall benefits deriving from their implementation in the agricultural sector are still limited. Additionally, despite the large quantity of robots applied in industry, few robots are effectively used by farmers as support for their activities [7]. Many challenges affect the implementation of AGV in the farming context since agricultural robots should operate in a dynamic and unstructured environment frequently producing insufficient results caused by integral uncertainties, unspecified operational settings, environmental conditions, and randomness of events [8]. Using robots in agricultural activities is complex because they must deal with living products like leaves and fruits creating high variability of parameters that would affect the robot's behavior, many of which cannot be controlled a priori [9].

This study aims to evaluate the performances of a tracked compact rover with autonomous navigation coupled with different implements accomplishing agricultural tasks in orchards and vineyards.

2. Materials and Methods

The AGV used in this study was produced by the Italian company “Niteko S.r.l.” and was a fully electric tracked rover. The AGV was remote-controlled and was improved to perform autonomous navigation in the field. This AGV was 130 cm wide and 105 cm long, with rubber tracks of 33 cm each (Fig. 1), and powered by two lead acid batteries (200 Ah, 24 V). The components of the autonomous navigation system are real-time kinematics (RTK) GPS, composed by a receiver on the rover (u-blox, ANN-MB-00) and a base antenna to correct the signal. Moreover, the AGV was equipped with two ultrasonic bumper sensors as a security system to detect objects in front of the AGV, stopping it in case of obstacle detection (i.e., vine stock). The performances of the AGV coupled with towed implements were measured during on-field operations as well as the stand-alone AGV performance. The implements used are a rotary tiller (140 kg) and a flail mower AT120 (230 kg) produced by the “GEO Agric S.r.l” (GEO ITALY s.r.l., Italy). The working widths are respectively 90 cm and 120 cm, as well as the gasoline engine power of 4.8 kW and 11.8 kW for the tiller and mower. The performances of the AGV towing implements were measured during soil and weed management operations in the iter-row of the vineyard and in the open field.

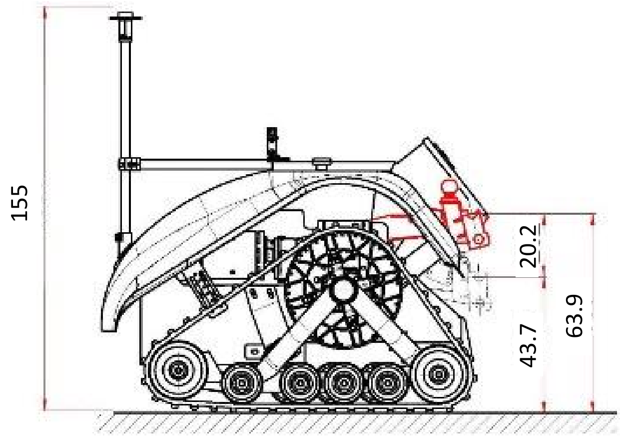

Fig. 8. Technical drawing of the customized autonomous ground vehicle (AGV) used in this study. Dimensions are in cm.

1.1 On-Field operation tests

The performances of the stand-alone AGV (Fig. 2a), and the AGV coupled with the rotary tiller (Fig. 2b), or with the flail mower (Fig. 2c) were tested. Specifically, the forward speed (m s^{-1}) and the energy uptake (kWh) to perform specific operations were considered. In addition, the influence of different towed weights on the performance of the AGV was investigated. The weights considered were the stand-alone AGV (W0), the rover coupled with rotary tiller (W140), and the rover coupled with the flail mower (W230). The forward speed was calculated by registering the time (s) to move the rover in a determined path of 100 m. The working efficiency of the towed implements was measured considering the tilling capacity of the AGV coupled with the rotary tiller as well as the cutting efficiency of the AGV coupled with the flail mower.

Fig. 2. Customized autonomous ground vehicle (AGV) and implements used in this study with different configurations. a) Stand-alone AGV, b) AGV coupled with rotary tiller, and c) AGV coupled with flail mower.

The tilling tests were done to evaluate the performance of the AGV while towing a tiller. The test simulated the operation of soil preparation for sowing. In plots of 1500 m^2, bulk density (g cm^{-3}) and amount of clumps (%) with different diameters were measured to evaluate the quality of the soil processing. The soil samples collected were six before tilling and nine after tilling. For the bulk density, a cylinder of a known volume of 130 cm^3 was used [10,11], whereas to quantify the amount of clumps, two sieves with mesh sizes of 6x6 cm and 2x2 cm were used. The amount of clumps was measured weighing the total and residual fraction of each sieve. The humidity (%) of the soil samples was measured by weighting the samples before the drying process in an oven at a temperature of 105 °C until the weight of the sample became constant [11].

The mowing test was done to evaluate the performance of the AGV while towing a flail mower. Specifically, the cutting efficiency (%) was assessed. The data were collected in two different experimental plots during the winter season. A total of nine samples were randomly collected before mowing, to characterize the weed (height and diameter), and twenty-seven samples were collected after mowing. The sampling was randomly made inside each subplot using a 50x50 cm wood square. The cutting efficiency (CE) was determined using Eq. (1) and considering the ratio between weed dry matter (g) cut by a single passage of the flail mower towed by the AGV and the total biomass dry matter [12,13]. The amount of cut weed was determined by the difference between the weed collected before mowing (DW_{pre}) and the residual weed uncut by the flail mower (DW_{post}) and collected using scissors.

$$CE = [(Dw_{pre} - Dw_{post})/ Dw_{pre}]*100 \quad (1)$$

Furthermore, the autonomous on-field navigation performances of the AGV were monitored. The autonomous navigation of the AGV was stressed to evaluate the capability of this system to autonomously navigate into the vine row. The data were collected in a vineyard with a slight slope of 0.4% in the forward direction of the row. The inter-row of the vineyard was not tilled but had spontaneous weed growth that homogeneously covered the soil. A total of five tests were conducted from April to May to collect data on the positions of the AGV.

3. Results and Discussion

Table 1 shows the results of the relationship between AGV towed weight (W0, W140, W230) and AGV performance in terms of forward speed (m s^{-1}). The maximum forward speed registered was 0.77 m s^{-1} considering the W0. Moreover, the results indicate that the towed weight has a significant effect on the forward speed of the AGV. The speed of W0 is higher than the speed of W140 and W230. Although the load tends to reduce the AGV's speed, differences in the order of 0.04 - 0.06 m s^{-1} are scarcely observable in practical terms on the field. However, this could have a different impact with implements of a higher load of more than 300 kg, which may impact the AGV traction performance as well as the battery life and engine performances [14].

Considering the AGV towing capacity for a long time (2 hours), it was observed that there are no significant differences in the forward speed and therefore in the performance of the AGV's electric engine. The speed remains constant from the start to the end of the test for all loads considered. Furthermore, Table 1 reports the results of the AGV performances considering the energy absorption of the engines during the on-field trials. It was observed that the weight has no significant effect (*p-value* = 0.736) on the total amount of energy uptake by the AGV. Further analyses are needed to investigate if higher weight (more than 300 kg) could influence the total energy uptake of the AGV engines as well as the overall performance of the AGV.

Table 5. Average forward speed (m s^{-1}) and energy uptake (kWh) of the AGV considering different towed weights (kg). Values within rows with different superscript letters are statistically different (*p-value* < 0.05).

		Towed weight		
		W0	**W140**	**W230**
Speed (m s-1)	Max	0.77^{a}	0.74^{b}	0.71^{b}
	Mean	0.57^{a}	0.54^{b}	0.52^{b}
Energy (kWh)	Max	4.69^{a}	4.10^{a}	3.63^{a}
	Mean	3.09^{a}	2.75^{a}	2.70^{a}

Fig. 3 shows the results of the tillage tests where an improvement of the seedbed was achieved. The clumps with higher sizes (between 2 cm and 6 cm) decreased after tilling the soil. In addition, the clumps with sizes higher than 6 cm were significantly reduced between pre- and post-tillage. Hence, the AGV showed the capability of towing a tiller to improve the soil quality regarding the subsequent sowing operations. Concerning bulk density of the soil, a reduction between pre-tillage and post-tillage of 1.02 g cm^{-3} and 0.92 g cm^{-3}, respectively, was observed.

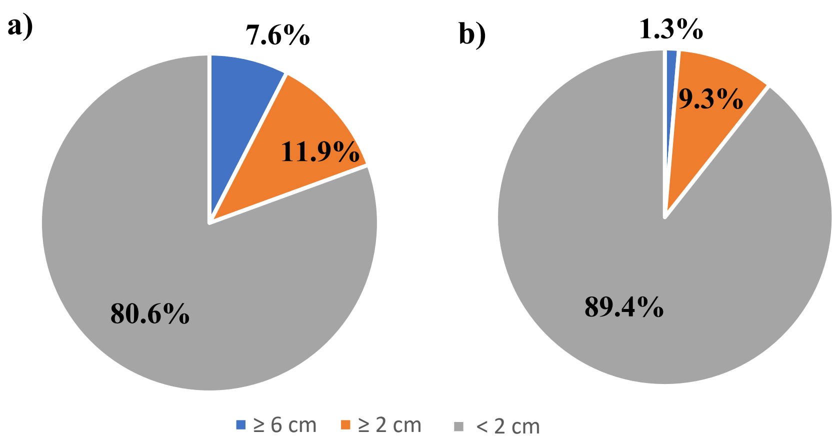

Fig. 2. Results of the tillage test performed with the AGV and rotary mower. a) Distribution of soil clumps according to size in the pre-tillage. b) Distribution of clumps post-tillage with the AGV average forward speed of 0.54 m s^{-1}.

These results underline how the system composed of AGV and rotary tiller provides a possible solution for managing the soil in vineyard inter-row or in areas where conventional tractors may not be able to pass due to their excessive sizes reducing also soil compaction than heavy tractors [15].

The experimental plots of the mowing test were characterized by spontaneous vegetation on average with a dry matter content of 169.8 ±46.65 g m^{-2}. The average height, average minimum, and average maximum of the weeds were 16.77±8.94 cm, 10.47±4.71 cm, and 33.81±6.87 cm, respectively. Whereas the average diameters, average minimum and average maximum of the steams were 0.27 ±0.2 cm, 0.11 ±0.02 cm, and 0.42 ±0.2 cm, respectively. The cutting efficiency of the flail mower towed by the AGV was on average 36.81±10.22% in comparison with the total removal of the weed. This indicates how more than half of the weed biomass was not removed by a single passage of the AGV and mower. In other studies in which the agricultural robots' performance of weed removal was evaluated, an efficiency of more than 90% was observed and of 65% in the management of the vineyard inter-row [16,17]. Moreover, a specific study on weed management in globe artichoke, showed that a small autonomous mower achieved a higher weed control effect, lower energy consumption, and lower cost compared to the conventional system, suggesting the suitable implementation of these autonomous mowers in horticultural crops [18]. Despite the weeding removal efficiency result lower than 50%, the amount of residual weed does not represent a negative aspect, especially if farmers want to maintain a cover crop to avoid soil erosion.

In Fig. 4 are reported the coordinates registered by the AGV during autonomous navigation tests in the vineyard row. It was observed a deviation between the GPS points for the different replicates of the same path that are not overlayed as expected. This indicates that some errors occur in the autonomous navigation in comparison with the reference path. Nevertheless, the deviations from the reference path are not very large the coefficient of determination (R^2) was high (Fig. 4). Moreover, the root mean square error is 53 cm. These deviations or errors may occur because of oscillation of the GPS antenna placed on the AGV during path recording caused by the vibrations of the AGV itself and the consequent trajectory adjustment automatically made by the AGV system software during autonomous navigation. Despite these errors, the autonomous navigation allowed the AGV to move inside the vineyard row which in this case has a width of 2.5 m. The autonomous navigation system plays a critical role in AGVs. Research indicates that maintaining the correct route in agricultural settings poses significant challenges and allows different autonomous driving performances [19,20]. In addition, the measured forward speed of the rover in autonomous navigation was on average 0.21 m s^{-1}, thus the rover needs 3.5 minutes to complete a single vineyard row of one hundred meters and this should be carefully considered when planning the AGV activities as this time could influence the operation management.

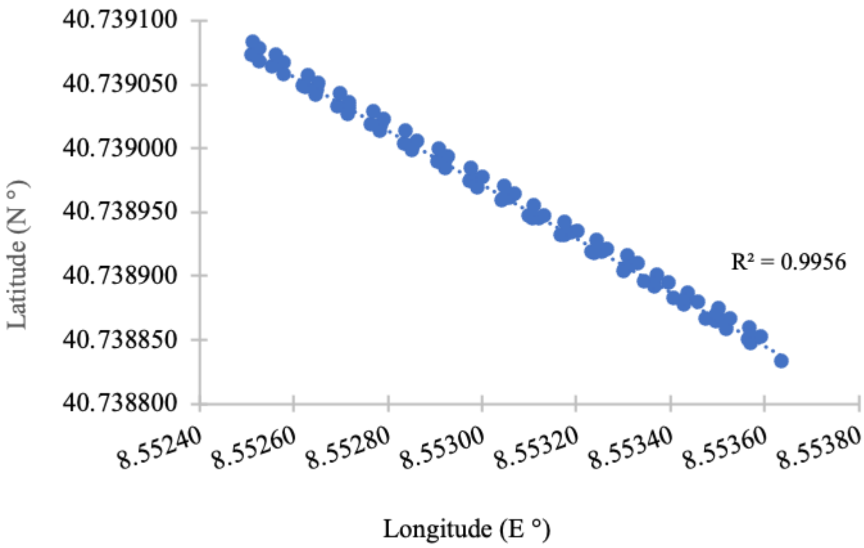

Fig. 3. Latitude (North decimal degrees) and longitude (East decimal degrees) measured by the AGV antenna during autonomous navigation in the vineyard row.

4. Conclusions

Autonomous robotic weed control systems hold promise for the automation of this task [21,22]. Robotic technology may also provide a means of reducing agriculture's current dependency on herbicides, improving its sustainability, and reducing its environmental impact [23]. In this study, the implementation of a commercial rover with Real Time Kinematic - GPS system was presented. Furthermore, the performances of the autonomous ground vehicle were measured by considering different configurations to accomplish agricultural tasks. Specifically, the AGV was coupled with a rotary tiller and a flail mower for soil and weed management evaluation tests, respectively. The results demonstrated the AGV's capability to efficiently tow implements up to 230 kg and 11.8 kW engine power for soil tillage and weed control.

The AGV coupled with the implements showed promising operative performances both in the vineyard inter-row and in the open field. Autonomous navigation tests were positive, indicating an acceptable accuracy in the autonomous movement of the AGV in the vineyard, with errors in the order of 53 cm. The AGV was able to complete the path within the 2.5 m inter-row of the vineyard without hitting the vine rows. In the future, further studies will focus on the improvement of the autonomous navigation system as well as on the evaluation of the towing capacity and traction of the AGV. Moreover, other implementations of the AGV would be focused on the use of different batteries (i.e., lithium) to power the electric engines and evaluate the performance of the system.

Conflict of Interest

The Authors declare no competing interest.

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CHAPTER 5

Analysis of Factors Affecting Farmers' Intention to Use Autonomous Ground Vehicles

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Abstract

In recent years, new autonomous ground vehicles (AGV) have been developed for the agricultural context to assist farmers and automate agricultural processes. Although there has been a high advancement in the development of AGV, this technology is not yet widely used on farms. Several factors may affect farmers' willingness to adopt an autonomous ground vehicle. Therefore, this study aims to investigate the factors that influence farmers' intentions to use AGV in agricultural activities. Based on previous studies that examine technology acceptance in the agricultural context, a model was developed. Based on the Technology Acceptance Model (TAM) an extended version of the TAM was used including the Attitude of Confidence, Personal Innovativeness, Job Relevance, and Perceived Net Benefit. Sixty-eight farmers from various countries, mainly from Lebanon and Italy, completed a questionnaire to assess their intention to use AGV. The surveys' answers were analyzed using partial least square structural equation modeling. The results of the measurement model indicated that all variables were valid except for the attitude of confidence. The structural analysis showed that personal innovativeness had a positive effect on perceived ease of use, while job relevance and perceived ease of use had a positive effect on perceived usefulness, which positively influenced attitude toward using AGV and perceived net benefit. It was also found that attitude and perceived net benefit had a positive effect on the farmers' intention to use AGV for field activities. Finally, the model outcomes underlined that neither farm size nor farmers' education level had any influence on their intention to use AGV in agriculture.

Keywords: Unmanned ground vehicles, Technology acceptance model, Robot, Agriculture, Agricultural robot, PLS-SEM

1. Introduction

In the twenty-first century, one of the significant challenges that humanity faces is to meet the rising demand for food while reducing wasted resources. Between 2005 and 2050 the worldwide food demand is expected to increase between 60 and 110%, meaning that there is a crucial need to adopt and apply precision agriculture management techniques [1]. Agriculture is one of the main factors in reducing poverty and helps improve food security for around 80% of the world's impoverished people living in rural areas [2]. A crucial component of agriculture is irrigation water, which plays a vital role, especially in arid and semi-arid regions. Unfortunately, its availability is dwindling mainly because of population growth and climate change [2,3]. Globally, around 70% of the total fresh-water resources are used in the agricultural sector [4] where irrigation has a share of 85% of the total water used in agriculture, generating about 40% of the total food production [1]. In addition to irrigation, fertilizer application can significantly increase crop yield, but it may also cause environmental pollution and soil hardening [5,6]. Moreover, there is a global decline in arable-cultivated lands and a shortage of water resources. Therefore, optimizing fertilizer and irrigation strategies would help crop yield as well as save resources, reducing production costs, and protecting the environment. Precision agriculture (PA), also known as information-based management of agricultural production systems, was introduced in the mid-1980s to provide appropriate treatment at the right time [7]. PA is an agricultural management approach based on the collection, processing, and analysis of individual data to support management decisions on estimated variability. It enables farmers to make specific management decisions in both time and space to improve resource use efficiency, productivity, quality, profitability, and sustainability of agricultural production [8]. PA aims to reduce production inputs used in agriculture while improving overall the quality and quantity of agricultural productivity [7,9].

Recently, new Autonomous Ground Vehicles (AGV) have been developed for the agricultural context to assist farmers and automate agricultural processes. An AGV, also known as an Unmanned Ground Vehicle (UGV), is an autonomous or semi-autonomous terrestrial vehicle capable of performing specific operations supported by the RTK-GPS system that allows autonomous navigation in the field. Different vehicles have been developed with different dimensions, i.e., compact vehicles or large tractors, and different operating capabilities, i.e., towing implements, tilling, weeding, or spraying thanks to the implemented tools. Agricultural machinery manufacturers are developing a wide range of AGVs moving towards the use of electric engines and high-efficiency machines. In addition, the AGV market can be segmented based on various criteria including size, locomotion system, and purpose of use. UGVs can be used for several agricultural and farming practices, ranging from pruning, inspection, and disease detection to precise spraying of fertilizers, pesticides, and insecticides [10,11]. Other activities that could be accomplished with the use of UGVs are cutting fruits [12], mowing [13], field scouting, weed control, harvesting [14], mapping, collecting soil and crop samples [15], monitoring animals [16,17] and irrigation [18]. AGVs are promising technologies that could mark new agriculture characterized by automatic and autonomous systems. UGVs have the potential to provide a more sustainable agricultural production, which could aid in addressing the current challenges in agriculture. Although there has been a high advancement of AGV also for the agricultural context, this technology is not yet widespread on farms. In addition, several factors may affect farmers' willingness to adopt an autonomous ground vehicle.

Therefore, this study aimed to investigate the factors that influence farmers' intentions to use AGVs in agricultural activities by using an extended Technology Acceptance Model (TAM) framework. Several studies are found related to the application of TAM for evaluating farmers’ acceptance intention of specific smart technologies or precision agriculture technologies [19-21]. However, a limited number of studies have focused on the acceptance of unmanned ground vehicles in agriculture [22].

2. Technology acceptance model (TAM) Theoretical Background and Hypotheses

A model for technology acceptance was developed by Fred Davis in 1985 to explain the relationship between user motivation and actual system use. The model suggests that the user’s motivation to use the system is influenced by an external motivation that includes the features and capabilities of the actual system. Davis also extended the model

(Technology Acceptance Model) to include three motivation factors that are depicted in Fig. 1: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and attitude toward using [23].

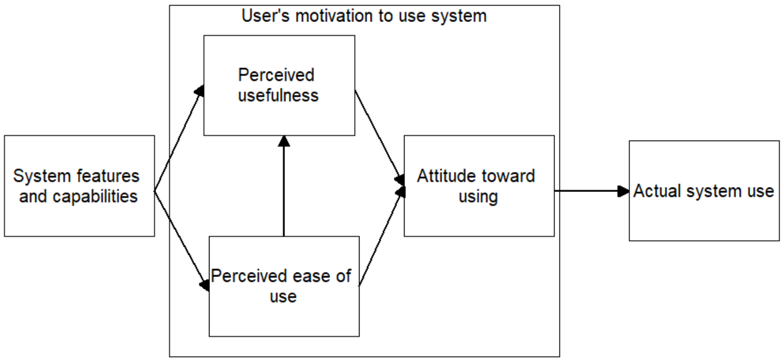

Fig. 9. Conceptual model for technology acceptance including TAM [20] (modified by the authors).

According to Davis [24], PU is defined as the extent to which a user believes that using the system will enhance job performance, while PEOU is described as the degree to which a user perceives that using the system is effortless. Both factors affect the user's attitude towards the system, which is a crucial element in determining whether the system will be accepted or rejected.

The TAM structure asserts that these factors determine a person's intention to use technology and, finally, the actual adoption. In addition, a system that is high in PU can lead the user to believe in the existence of a positive use-performance relationship [24]. Moreover, Adrian et al. [21], studied the influence of farmers' perceptions of adopting precision agriculture technologies using this method. According to TAM, a potential user is more probably to use a certain technology if he or she perceives it as useful [21]. Therefore, to analyze these aspects the following hypotheses were proposed:

H1: Perceived usefulness will influence the intentions to implement and use UGVs.

H2: Perceived usefulness will influence the attitude toward using UGVs in agriculture.

According to Davis in 1989 [24], if users don't realize an application that would fairly improve performance, they're not likely to use it, whereas Michels et al. [25] explained that a person who recognizes using technology as effortless also recognizes the technology as more helpful. As suggested by the TAM model, a farmer who sees using UGVs as simple has a higher intent to use them for agricultural practices. Additionally, if the farmer feels that the information given by the UGVs is helpful for the on-farm operations, there will be a higher intention for him or her to use a UGV. Furthermore, if a farmer believes that utilizing a UGV is simple, he or she also sees this tool as more helpful. Davis [24] also found mild proof that the PEOU could impact the intention to use (ITU) a technology through perceived usefulness. The following hypotheses were proposed for evaluating that:

H3: Perceived ease of use will impact the perceived usefulness of UGVs.
H4: Perceived ease of use will affect attitude toward using UGVs in agriculture.

As already stated, as easily as the user finds the technology to use, he or she will find it useful and will most probably adopt it [21]. Meanwhile, ATU of technology is a construct used in research for the measure of the positive or negative feelings of a certain user about the application of the target behavior. Attitude outlines a user's behavioral intention to use technology [26]. This is analyzed by the following hypothesis:

H5: Attitude toward using will influence the intention to use (ITU) and adopt UGVs, respectively.

In 2005, Adrian et al. [21] added a latent variable called attitude of confidence (AOC) in the extended TAM for adopting precision agriculture technologies. This variable was placed as "Precision agriculture technologies provide a vast amount of information and require new skills in using information systems" [21,25]. The farmer to use this information must acquire new skills, therefore the latent variable "confidence subscale" measures "the confidence of a producer to learn and use precision agriculture technologies" [21,25]. Experimental findings have demonstrated that the AOC, particularly the person's attitude to having the ability to use and learn technology, affects the perceived ease of use [21]. In addition, AGV provides large amounts of information for the farmers; to collect and use this information efficiently, the farmer requires new skills, like transforming the online data into maps to guide specific fertilizer applications. Thus, a positive effect of the AOC on the ITU of AGV, and PEOU is considered [25] and it was evaluated in this study by the following proposed hypotheses:

H6: Attitude of confidence in using UGVs in agriculture has a positive effect on the perceived ease of use of UGVs.
H7: Individuals' attitude of confidence toward learning and using UGVs will affect their perception of the usefulness of these tools.
H8: Attitude of confidence in using UGVs in agriculture has a positive effect on the intention to use UGVs in agriculture.

Job relevance (JR) is the degree to which the technology applies to the user's job [23,27]. A farmer may see that the UGV fits the tasks within the farm, he or she will see the UGV as more useful and later will have a higher intention to use it [25]. Consequently, the subsequent hypotheses are investigated in this study:

H9: Job relevance of UGVs in agricultural activities has a positive effect on the perceived usefulness.
H10: Job relevance of UGVs in farming or agriculture has a positive effect on the intention to use and implement UGVs.

Adopting precision agriculture shows that some demographic factors could affect the adoption of the technologies and the technology profitability including tenure, location, farm size, age, farming experience, education, access to information, off-farm occupation, credit, and cultivated crops [21,28]. Education level (El) affects the adoption of the technology, the highest the educational level is, the earliest the technology is adopted. Among adopters, computer use is common due to higher educational degrees. An increasing age lowers the probability of adopting technology because of factors fundamental to the aging process or the lowered probability of payback from a reduced planning perspective over which projected benefits can accumulate [28,29]. Thus, this study analyzed the following hypothesis:

H11: Education level will affect the intentions to adopt UGVs.

Moreover, farm size (Fs) plays a crucial role in adopting farming technologies such as AGV [29]. Applying AGV needs a large investment in time, capital, and the learning process. This investment requires costs in transactions and information which will prevent small farms from investing in these technologies. Thus, this study analyzed the following hypothesis:

H12: Farm size will impact the intention to adopt UGVs.

Perceived net benefit (PNB) is the user's belief that the technology will offer him or her a benefit of more value than its cost. Within our study, this factor included the advantage of using AGV over current traditional practices considering the economic cost involved in implementing and adopting the technologies. Within the questionnaire, five items included the benefits of AGV: increased profits, increased yields, the cost-effectiveness of AGV, reduced costs, and information for more adequate decisions [21]. A farmer who perceives the potential net benefits when using AGV will be more likely to adopt them rather than a farmer who does not perceive the net benefit of these technologies. PNB is directly affected by perceived usefulness because PNB includes intrinsic usefulness [21]. Therefore, the subsequent hypotheses are investigated in this study:

H13: Perceived usefulness will affect the perceived net benefit of UGVs.
H14: Perceived net benefit will affect the intentions to use and adopt UGVs.

Personal innovativeness (PI) is a factor that describes the interest or willingness of a person to try new technology and determines a positive influence of the innovativeness of farmers to accept AGV postulated in hypotheses H15 and H16 as shown in Fig. 2. It is also hypothesized that personal innovativeness influences factors related to the farm where the farmer works or to the farmer himself [30]. These aspects are analyzed in this study by the following proposed hypotheses:

H15: Farmer's personal innovativeness influences positively the perceived usefulness of UGVs.

H16: Farmer's personal innovativeness influences positively the perceived ease of use of UGVs.

Fig. 2 allows us to better comprehend the adjustments and extensions made to the basic TAM along with the additional variables: personal innovativeness, attitude of confidence, job relevance, educational level, and farm size.

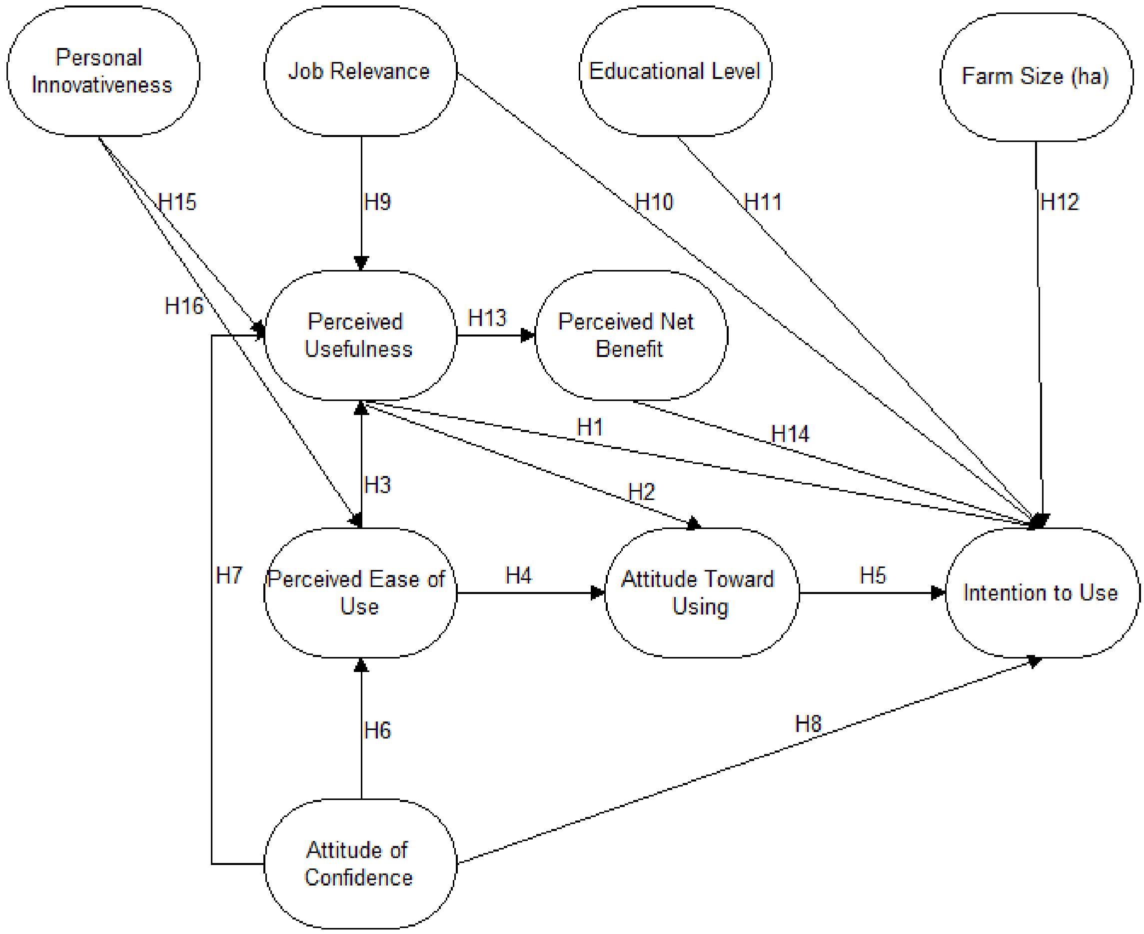

Fig. 10. Illustration of the proposed research model for UGVs' acceptance by the farmers. H1, H2… Hx = hypothesis to test.

3. Materials and Methods

3.1 Survey design and analysis

This study involved a total of 68 farmers from different countries who answered the submitted questionnaire. The first part of the survey concerns general questions, where the farmer provides sociodemographic (i.e., age, gender, education level) and farm-related information, i.e, size of the farm (ha), type of tractors used, and type of farm (arable farm, hay farm, orchard). Then, in the second section of the questionnaire, the farmers were asked to assess 31 randomized statements (items) for the estimation of the extended TAM. The items serve as the indicators to estimate the corresponding latent variables and were measured by using a five-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; and 5 = strongly agree). To guarantee a reliable knowledge base about UGVs among the participating farmers, a one-minute, educational video on how UGVs work, and the probable extent of application were presented at the start of the questionnaire. All the items considered in this study were identified from proper literature and adjusted to match the context of this study about the use of autonomous ground vehicles in agriculture. The items used in the survey to assess the variables are presented in Table 1.

The questionnaire was originally developed in English and then translated into Italian and Arabic to spread out the sample of this survey. Moreover, before diffusing the questionnaire, it was pretested and implemented using Google Forms. For recruiting participants, several channels were used, such as e-mailing several farmers' associations and publishing the survey's link on the social media pages of many agricultural-related groups, alongside private contacts. To have complete-answered surveys, key questions have been set as mandatory, therefore there would be no incomplete datasets.

3.2 Statistical Data analysis and quality criteria

The data collected with the questionnaires were analyzed using the partial least square-structural equation modeling (PLS-SEM) technique. PLS-SEM includes different multivariate statistical methods (factor analysis, multiple regression) that allow simultaneous inspection of the relationship between observed variables and latent variables as well as among latent variables. PLS-SEM is a nonparametric variance-based SEM that was selected since is less restrictive than other approaches which require normally distributed data and perform well also with a small sample size.

The model was analyzed using a two-step approach. First, the measurement model was inspected to test the relationship between the items and the latent variable. The quality criteria of the model considered were standardized factor loading (FL), average variance extracted (AVE), composite reliability (CR), and Cronbach's alfa. These quality criteria must accomplish a specific threshold that for FL, CR, and Cronbach's alfa is greater than 0.7, whereas AVE must be greater than 0.5 [27, 28]. In addition, the discriminant validity (DV), which indicates how different latent variables are from another one, was determined using the Fornell-Larcker criterion [29]. In the second step, the structural model was evaluated to test and determine the causal relationship between the latent variables. The developed model was tested by using standardized path coefficient (β) and t-statistics. The relevance and significance of the indicators are validated using a bootstrapping procedure with 5,000 subsamples. The "SEMinR" package in R software was used to perform the analysis.

3.3 Measures

The scale was developed from the literature review and previous studies. Table 1 presents the indicators correlated with the model constructs.

Table 6. References and indicators used.

Item	Statement	Reference
Factor "Perceived usefulness of UGVs in agriculture" (PU)		
Pu1	I think that with the help of UGVs, I will contribute to environmental protection with a more targeted application of fertilizer and pesticides and reduce production costs	[25, 34]
Pu2	I think using the UGVs, will increase on-farm productivity and income	[25, 35]
Pu3	Using the UGVs would enhance effectiveness on the on-farm job (mowing, tilling, spraying, and monitoring)	[36]

Pu4	Using the UGV would make it easier to do my on-farm job (mowing, tilling, spraying, and monitoring)	[25]
Pu5	I would find the UGV helpful in my on-farm job (mowing, tilling, spraying, and monitoring)	[25]
Factor "Perceived ease of use of UGVs in agriculture" (PEOU)		
Peou1	I think learning to use UGVs would be easy for me (piloting with remote control, setting autonomous mode, and using implements like a mower and tiller)	[25]
Peou2	I would find it easy to get the UGV to do what I want it to do (piloting with remote control, setting autonomous mode, and using implements like a mower and tiller)	[36]
Peou3	It would be easy for me to become skillful at using the UGV to perform specific on-field activities (mowing, tilling, spraying, and monitoring)	[36]
Peou4	I would find the UGV easy to use (piloting with remote control, setting autonomous mode, and using implements like a mower and tiller)	[36]
Peou5	Using UGVs (piloting with remote control, setting autonomous mode, and using attachments like a mower and tiller) seems understandable to me	[25]
Peou6	Learning to use UGVs (piloting with remote control, set autonomous mode, using attachments like a mower and tiller) is no problem for me	[25]
Factor "Attitude of confidence in using UGVs in agriculture" (AOC)		
Aoc1	I think I am not the type of farmer who is good at working with UGVs and other digital instruments	[25]
Aoc2	I don't think I would use UGVs since their use seems too complicated for me	[25]
Aoc3	I am no good with new technologies in precision agriculture	[21]
Factor "Job relevance of UGVs in agriculture" (JR)		
Jr1	Usage of UGVs is of high relevance for several operational procedures on my farm and field	[25]
Jr2	Usage of UGVs is important for my on-farm job	[25]
Jr3	Usage of UGVs is appropriate for my on-farm job and for my security	[37]
Intention to use UGVs in agriculture (ITU)		

Itu1	Assuming I have a UGV and the relative implements, I intend to use them for spraying, mowing, tilling and monitoring	[27]
Itu2	I will always try to use a UGV within my farm and/or field	[35]
Itu3	If I have a UGV, I will use it more often	[35]
Factor "Attitude toward using UGVs in agriculture" (ATU)		
Atu1	Using the UGV for mowing, tilling, spraying, and monitoring is a good idea	[36]
Atu2	The UGV makes work more interesting	[36]
Atu3	I would like to work with the UGV for mowing, tilling, spraying, and monitoring	[36]
Factor "Perceived net benefit of UGVs in agriculture" (PNB)		
Pnb1	I believe the use of UGVs can increase profits	[21]
Pnb2	I believe the use of UGVs can increase yields	[21]
Pnb3	I believe UGVs can provide information for better decision-making	[21]
Pnb4	I believe UGVs are cost-effective	[21]
Pnb5	I believe the use of UGVs can reduce production costs	[21]
Factor "Personal innovativeness of UGVs in agriculture" (PI)		
Pi1	I think I would like to explore on-field applications with the UGV (mowing, tilling, spraying, and monitoring)	[30]
Pi2	I enjoy being around people who are using and exploring new agricultural technologies like the UGV	[30]
Pi3	I often seek information on new agricultural technologies like the UGV	[30]

4. Results

4.1 Sample description and descriptive results

The study had 68 participants, of whom 75% were male and 25% were female: most of them were from Lebanon 67% and the rest were from Italy, India, Iran, Jordan, Kenya, Kyrgyzstan, Pakistan, Palestine, South Africa, Trinidad and Tobago, Turkey, Uganda, and the United States of America. The average age range was 25 - 34 years (29%)

followed by 35 – 44 years (28%), and 39% of the participants had a college degree. More than half of the applicants (52%) had a land less than 5 hectares of arable land, 42% of crops like wheat or vegetables, and 33% of fruit- or nut-producing trees. Only 12% of the participants don't use a tractor for earthworks, while 25% of the participants use utility tractors and 19% a two-wheel tractor.

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4.2 Measurement model analysis

Before performing measurement model estimation, the multivariate normality distribution of the data was checked by computing multivariate skewness and kurtosis coefficients, which indicate the nonnormal distribution of the data. Therefore, considering the reduced sample size of the study and the nonnormality of the data a PLS-SEM technique was used. The results are evaluated using the two-step approach. The first step was measurement model testing to assess the relationship between the observed variables (items) and the corresponding latent variables (factors). In addition, convergent validity and internal consistency were evaluated by computing Cronbach's alfa, composite reliability (CR), and average variance extracted (AVE).

After the preliminary estimation of the measurement model, the items with a factor loading lower than 0.7 were removed (Pu1, Pu5, Peou1, Peou2, Pnb1, Pnb3, Aoc2, Aoc3) as these items' results were not enough correlated with the corresponding latent variables. Moreover, the AOC Cronbach's alfa resulted under the 0.7 threshold, thus this factor is removed from the model. The measurement model analysis, without low-loading items and AOC construct, was performed again and the descriptive statistics for items and factors are reported in Table 2. The mean value for the overall constructs is 4.01, which indicates that the respondent positively perceived the use of AGV for agricultural on-field activities.

Table 7. ***Measurement model analysis with reliability and validity index for items and constructs. Descriptive statistics with mean and standard deviation (SD) are reported for each item.***

Construct/Item	Mean	Loadings[a]	Cronbah's alfa	CR[b]	AVE[c]
Perceived usefulness (PU)			0.873	0.922	0.798
Pu2	4.162	0.860			
Pu3	4.412	0.891			
Pu4	4.206	0.928			
Perceived ease of use (PEOU)			0.881	0.918	0.738
Peou2	4.088	0.906			
Peou3	4.309	0.817			
Peou4	4.176	0.862			
Peou5	4.088	0.848			
Job relevance (JR)			0.785	0.870	0.691
Jr1	3.985	0.830			
Jr2	3.471	0.834			
Jr3	3.471	0.829			
Attitude toward using (ATU)			0.835	0.901	0.752
Atu1	3.471	0.866			
Atu2	3.471	0.838			
Atu3	3.985	0.896			
Perceived net benefit (PNB)			0.834	0.900	0.751
Pnb2	4.029	0.882			
Pnb4	3.941	0.862			
Pnb5	4.044	0.855			
Personal innovativeness (PI)			0.739	0.851	0.656

Pi1	4.250	0.843			
Pi2	4.338	0.809			
Pi3	3.971	0.775			
Intention to use (ITU)			0.825	0.895	0.741
Itu1	4.206	0.854			
Itu2	3.926	0.896			
Itu3	4.250	0.832			

[a] Standardized factor loadings

[b] Composite reliability

[c] Average variance extracted

Considering the readability and validity of the new measurement model (Table 2), all standardized factor loadings were higher than 0.7 and significant ($p < 0.001$), indicating a high correlation between items predicting the corresponding construct. Moreover, Cronbach's alfa, CR, and AVE of each construct were higher than the indicated thresholds, further confirming satisfactory convergent validity and internal consistency (Bagozzi and Yi, 1988; Nunnally and Bernstein, 1994). The results of the discriminant validity are reported in Table 3 where no issues were observed among factors as the square root of AVE always exceeds the correlation between factors.

Table 8. ***Discriminant validity result considering the Fornell–Larcker criterion. The square roots of AVE are on the diagonal values (bold) and the correlation is on the off-diagonal values.***

	PU	PEOU	ATU	PNB	JR	PI	ITU
PU	**0.893**						
PEOU	0.698	**0.859**					
ATU	0.842	0.672	**0.867**				
PNB	0.762	0.545	0.833	**0.866**			
JR	0.623	0.422	0.671	0.654	**0.831**		
PI	0.665	0.704	0.796	0.711	0.674	**0.810**	
ITU	0.749	0.623	0.853	0.821	0.708	0.777	**0.861**

4.3 Structural model analysis

The structural model analysis allows for the investigation of the relationship among latent variables (constructs) of the model by estimating expected directional associations among variables. The summary of the hypothesis testing results was reported in Table 4, whereas the analysis of the relationship between the constructs is shown in Fig. 3, reporting standardized parameter estimates for the path coefficients and the statistical significance of each hypothesized path.

Table 9. ***Results from the structural model.***

Hypothesis	Results
H1: Perceived usefulness → Intention to use	not supported
H2: Perceived usefulness → Attitude toward using	supported
H3: Perceived ease of use → Perceived usefulness	supported
H4: Perceived ease of use → Attitude toward using	not supported
H5: Attitude toward using → Intention to use	supported
H6: Attitude of confidence → Perceived ease of use	-
H7: Attitude of confidence → Perceived usefulness	-
H8: Attitude of confidence → Intention to use	-
H9: Job relevance → Perceived usefulness	supported
H10: Job relevance → Intention to use	not supported
H11: Educational level → Intention to use	not supported
H12: Farm size → Intention to use	not supported
H13: Perceived usefulness → Perceived net benefit	supported
H14: Perceived net benefit → Intention to use	supported
H15: Personal innovativeness → Perceived usefulness	not supported
H16: Personal innovativeness → Perceived ease of use	supported

Considering the tested hypothesis, seven results were statistically significant ($p < 0.05$, $p < 0.001$) and six results were not supported (not statistically significant). It was not possible to test hypothesis 6, hypothesis 7, and hypothesis 8 due to the deletion of the AOC factor. Whereas it was observed that the intention to use (ITU) autonomous ground vehicle (AGV) was directly influenced by the farms' attitude toward their use (ATU) supporting hypothesis 5, and by perceived net benefit (PNB) supporting hypothesis 14.

Moreover, both PNB and ATU were influenced by perceived usefulness (PU) supporting hypothesis 13 and hypothesis 2, respectively. Whereas PU did not affect farmers' intention to use AGV since hypothesis 1 was not supported as well as farm size (hypothesis 12) and education level (hypothesis 11). Hypothesis 3 that perceived ease of use (PEOU) influenced PU was supported, but PEOU influence on farmers' attitudes was not supported (hypothesis 4). The factor of farmers' personal innovativeness (PI) only influences PEOU supporting (hypothesis 16) and not PU (hypothesis 15). Finally, job relevance (JR) had a direct effect only on PU (hypothesis 9), but not on the intention to use AGV (hypothesis 11).

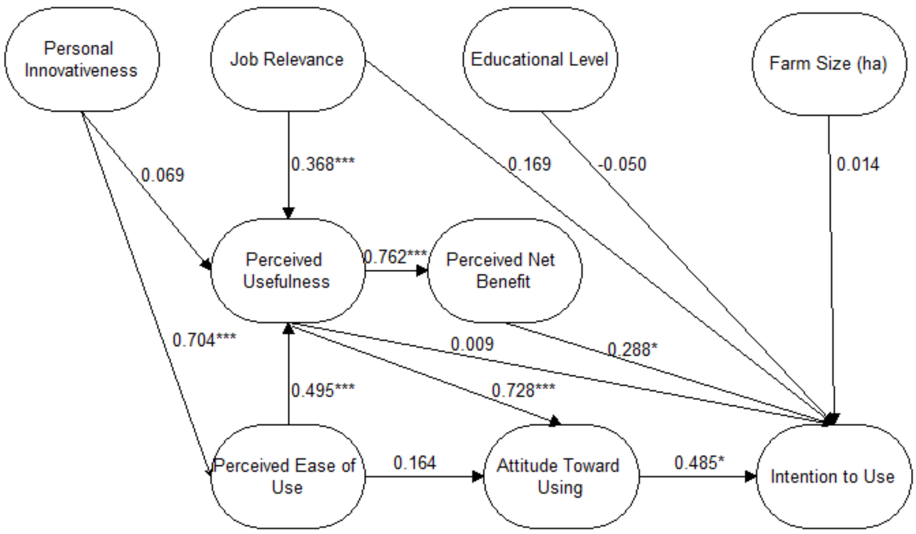

Fig. 11. The structural model analysis results with the hypothesis tested. Standardized parameter estimates for path coefficients are reported (****p* < 0.001; ***p* < 0.01; **p* < 0.05).

5. Discussion

In this study, a theoretical model was developed using the TAM to comprehend farmers' acceptance of autonomous ground vehicles in agriculture. The results showed that perceived usefulness (PU) and attitude toward using (ATU) AGVs positively affected the intention to use (ITU) and adopt UGVs in agriculture. Hence, based on the study findings, H2 was supported by the original and extended TAM structural models which is consistent with the findings of Rezaei et al. [32]. The construct of ATU had a significant positive impact on the ITU of UGVs in agriculture (supporting H5). This observation is consistent with the findings of many empirical studies in the setting of TAM-relevant research [26,34,38-40]. The study suggested that farmers who perceive AGVs as useful for their activities are more likely to have a positive attitude toward this technology which will lead him or her to use it. However, none of the variables PU, JR, EL, and FS directly affected the ITU of UGVs in agriculture where the hypotheses H1, H10, H11, and H12 were rejected respectively. Despite the potential assistance provided by UGVs in various operational tasks, a farmer's ITU of UGV tends to be lower, a finding that contradicts the results obtained by Michels et al. [25]. Our results also showed the acceptance of hypotheses H3, H9, H13, and H14, which suggested that PEOU has a positive effect on PU, which, in turn, positively impacts PNB, leading to the intention to use and adopt UGVs in agriculture. Both PEOU and JR had a positive effect on PU, meaning that farmers who perceive an AGV as easy to operate and suitable for their work will find this technology useful. PU affected PNB, which also had a positive impact on ITU indicating that a farmer perceives the AGV to be a beneficial investment, which makes them more likely to use it. Additionally, farmers who perceive AGVs as cost-effective are more likely to use them.

Specifically, PEOU is involved with the nature of a job and concerns the fundamental characteristics of technology, including clarity, flexibility, and ease of use. As the operation of technologies like UGVs gets easier, farmers tend to develop positive perceptions of their usage. When farmers are knowledgeable and confident in the robot's use, they are more likely to develop positive attitudes towards it.

This study also revealed a significant relationship between JR and PU. According to our results, farmers perceive an AGV as more useful if they recognize that its various functions are relevant to several on-farm tasks. This indicates that when the AGV provides relevant activities to farmers, it develops a sense of trust in the technology, leading to better perceived usefulness, as shown in previous studies [25,34]. Farmers who revealed the usefulness of using and learning unmanned ground vehicles and perceived a net benefit from using these robots showed a greater tendency to adopt these technologies [21].

The rejected hypothesis 15 suggested that PI did not directly affect PU, and thus did not impact the intention to use, as demonstrated in H1. Thus, PU is not correlated with the willingness of the farmer to try AGV.
Finally, the results supported hypothesis 16, suggesting that PI positively influences PEOU. According to these findings, innovative farmers with a positive attitude toward technology tend to appreciate and find useful the implications of unmanned vehicles in agriculture. Furthermore, such farmers might be more experienced in selecting suitable types of UGVs for their fields [42].

5.1. Limitation of the study

This study about the farmers' intentions to use unmanned ground vehicles in agriculture, tried to broaden the sample of respondents by including farmers from different countries around the world, differently from Rübcke von Veltheim et al., [22] that involve only German farmers. However, this may lead to greater differences as they may have different economic conditions and agricultural farm structures. In any case, the main limitation of this study lies in the small number of responses, and therefore cannot reflect the entire farm's panorama. A larger and more balanced sample among different countries and including more female farmers would certainly be desirable for future research. Another limitation is the fact that farmers do not currently use AGVs on their farms and therefore do not fully know what the real application of these vehicles could be.

6. Conclusions

This study used an extended Technology Acceptance Model to investigate the factors that influence the diffusion of autonomous ground vehicles in the agricultural domain. There is limited research on the acceptance of AGVs, a technology that can support farmers' activities and reduce the environmental impact of the agricultural sector. The novelty of this study was that it developed a survey in three different languages, Arabic, English, and Italian, expanding the dataset by considering both countries with emerging economies and countries with more stable economies. Furthermore, the study considered several factors such as educational level and farm size. In addition, external variables, including the attitude of confidence, personal innovativeness, and job relevance, were added to comprehend their impact on the attitude toward using AGVs and to provide a more comprehensive understanding of the factors that affect farmers' acceptance and adoption of technology. The research has confirmed the reliability of the TAM framework in describing intentions to adopt autonomous vehicles for farm activities. All the considered variables were validated during the analysis of the measurement model, except for the attitude of confidence, which was removed to improve the model fit. The results showed that the intention to use the AGV was directly affected by attitude towards its use and perceived net benefit, and indirectly influenced by personal innovativeness, job relevance, perceived usefulness, and perceived ease of use. These findings highlight that understanding farmers' attitudes and perceptions is important for the successful spread and implementation of AGVs in agriculture. Benefits and cost are key factors influencing the adoption decision. Therefore, efforts should be made to enhance farmers' understanding of the economic benefits and improve their perception of the effectiveness of using autonomous vehicles to accomplish on-farm tasks.

The study suggested that to spread and implement the usage of smart farming technologies such as AGVs among farmers, a farmer must believe that the AGV will provide more benefits than its cost and must feel positive about using this kind of technology.

Future research could focus on the efficiency and cost-effectiveness of using AGVs in farming practices to reduce costs and improve time management.

Conflict of Interest

The Authors declare no competing interest.

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CHAPTER 6

General Conclusions

Concluding Remarks

This thesis discussed new technical and operational solutions for using autonomous ground vehicles (AGVs) in Agriculture 4.0. XBOT is the drone used in our experiments in the field, different criteria were tested to highlight the efficiency of this robot. In addition, on the one hand, research was carried out to know the evolution in time of scientific articles related to “AGV”, on the other hand, another research highlighted the rovers most studied by the scientific community. Furthermore, farmers’ perceptions toward the use of unmanned ground vehicles (UGVs) in agriculture were also considered.

Chapter 1 emphasized future modernization and innovations, plus the problems we are facing nowadays and in the future generations regarding population growth and food demand. It introduced what are the UGV and drew attention to their use in agriculture; plus, it highlighted Agriculture 4.0, and TAM.

Chapter 2 showed the characteristics of the XBOT in detail and focused on the bioclimatic on-board sensors which are RHT03, MLX90614, MG811, and TSL2561. These sensors can reveal respectively digital relative humidity and temperature, infrared body temperature, concentration of CO_2, and light intensity. Data was acquired from these sensors but could not be analyzed due to the lack of other on-field data to compare both and check for the sensitivity and reliability of the XBOT sensors.

The scientific literature in Chapter 3 reported the evolution in time for the interest of the scientific community in “unmanned ground vehicles” or similar terms. The growth noted through time, revealed the most common document types as well, subject areas, total number of publications, number of publications per year, and country. This study also revealed the technical specifications of the most studied UGVs by scientists as well as the number of publications per rover. The findings showed that the interest within the context studied increased across the 11-year timeframe, while the term “Rover” associated with or without the term “Agriculture” acquired the highest number of publications. The results showed that the publications were mostly conference papers in the engineering fields and within the United States. Husky was the most studied robot by scientists, and the most common characteristics found were the 4-wheel drive and the presence of a battery pack.

Chapter 4 underlined on-field agricultural operations using XBOT accompanied or not with a rotary tiller and/or a flail mower at 3 different forwarding speeds. Therefore, while using the tiller, bulk density was calculated to evaluate the quality of soil, while using the mower the percentage of cutting efficiency was assessed. In addition, the forward speed was also taken into consideration and calculated whether the AGV was used alone or with the mower or tiller. The findings indicated that the UGV is capable of towing implements up to 230 kg and 11.8 kW engine power for soil tillage and weed control. Regarding the autonomous navigation of the drone, the tests came positive with around 53 cm of errors. The AGV showed its capability to run autonomously in a 2.5 m vineyard without hitting the vine rows.

The fifth chapter focused on the acceptance level of farmers to use UGVs in their activities. The factors related to the intention to use AGVs were explored and evaluated through the Technology Acceptance Model (TAM). Several variables were considered in the model, such as “perceived usefulness”, “perceived ease of use”, “attitude of confidence”, “job relevance”, “intention to use”, “attitude toward using”, “perceived net benefit”, and “personal innovativeness” of UGVs in agriculture. The survey was conducted in three different languages, Arabic, English, and Italian. The scale and the relationship between the variables were investigated using the partial least square-structural equation modeling (PLS-SEM). The results obtained by the survey’s analysis showed that all the considered variables were validated during the analysis of the measurement model, except for the attitude of confidence, which was removed to improve the model fit. The results showed that understanding farmers’ attitudes and perceptions is important for the successful spread and application of AGVs in agriculture. Therefore, a farmer must believe that the UGV would provide extra benefits other than thinking about its cost, and he or she shall feel positive about using it.

Finally, developing AGVs for agricultural practices and spreading this technology shall be a promising future for farmers who wish to facilitate their work and use the latest technologies.

Future Prospective Works

In recent decades, there has been growing interest in unmanned land vehicles to increase agricultural productivity by reducing labor requirements. UGVs have been tested for various purposes including irrigation management, soil sampling, precision spraying, crop harvesting, and mechanical weeding. Combining improved technology of sensors with increased accessibility of various autonomous vehicle platforms will allow an opportunity for further research in the agricultural area. Future studies could include the economic feasibility of using these drones in small-scale holdings; the economic impact of utilizing such technology in agriculture, and finally the connection between the use of such technology on the quality of agricultural products. Whilst research into autonomous ground systems in the agricultural field has been performed, few commercial drones have been used by farmers. Furthermore, although most available UGVs in the market are used for research, developing these platforms can lead to commercially sustainable products in the next decades to deal with shortages in agricultural labor and foodborne illness considerations.