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Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots

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ABSTRACT

In a world that requires sustainable agricultural practices, quantitative plant-by-plant and field status monitoring can be advantageous to all farmers by optimizing their farm management. Autonomous robots, sensing technologies, and automated data analysis will play a key role. In the present article, we discuss three critical aspects of the incorporation of field robots in agriculture: 1) the main design specifications and economic aspects for Commercial Agricultural Robots (CARs) in terms of autonomous navigation (perception, localization, and kinematics); 2) the business models of agricultural robotics companies, which are compared to successful business models of robotic companies on the medical field; 3) the possibilities that CARs could bring, including the generation of big data about local food production and its impact on the local environment. Our analysis highlights the reasons that explain the low adoption of CARs in the current agricultural market. Finally, we reflect on the current distorted costs that consumers pay for food while the ecological footprints of food production and food delivery are neglected, and we encourage the discussion to promote sustainable food policies that support the establishment of robotic agricultural companies.

1. Introduction

The Food and Agriculture Organization (FAO) of the United Nations expressed in 2017 that there has been undeniable progress in reducing undernourishment rates and in improving nutrition and health levels, but also that in 2050 there will be a need of 50% more food compared to 2013 [1]. Regrettably, there is also evidence that scaled-up current food production leads to varied and significant harmful environmental consequences [2–4], such as the apparition of superweeds, the damage of farmland biodiversity, and the uncontrolled spread of pesticides by rain clouds.

This paper considers the EU region as an example of these needs and specific problems to solve. In 2013, the percentage of European farm holders of very small-sized farms, small-sized farms, and medium-sized farms was 40%, 29%, and 14%, respectively [5]. In such farms, known as Small and Medium-sized Farms (SMFs), two field management practices can be identified: 1) Precision Agriculture (PA), meaning to perform relevant crop measurements to collect on-site crop data to maximize the yield of food production while minimizing the use of fuel, herbicide, insecticide and nutrients; and 2) an agro-ecosystem way, meaning to consider and observe the strong ecological interactions that make plants grow (e.g., agroecology and agroforestry). The agro-ecosystem management underlies in an understanding of the local ecosystem services, acquired iteratively and holistically by farmers that live more in contact with nature. These farmers scarify fields to build resilience, employing old seeds varieties, indirect pest management techniques, and ancient weeding techniques due to their holistic understanding of biotic interactions in the field [6].

To the authors' view, the shortcomings of both approaches are the lack of comprehensibility. In our humble understanding of the topic, it is infeasible to measure everything relevant to crops and soils for a farmland with sufficient detail/resolution for PA [1]. Even if possible in an affordable way, it will be difficult for a person to make good use of this big data. On the agro-ecosystem approach [2], the infeasibility is to demand that farmers achieve a detailed understanding of farm ecosystems, which can be translated into field management actions that maximize both yields and sustainability (ecosystem preservation).

Therefore, as a solution to these weaknesses in field management, we study the feasibility of combining the best of these approaches using robotic solutions. The introduction of robotic systems in the crop fields enables highly repeatable systematic actions, such as selective mechanical weeding (which reduces the proliferation of superweeds) and health monitoring of crop and soil. In this paper, we term these robots as Commercial Agricultural Robots (CARs). Also, we use the term robotic com-

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panies to refer to companies that develop the technology, manufacture the robot or work with a 3rd party manufacturer.

However, the adoption of CARs by owners of SMFs implies facing a potentially high cost of technology integration. It is important to mention that common trends in the last decades have been the increase of the farms size, increase of automation levels and decrease of the amount of farmers and workers [7]. In such a scenario, most of the CARs are in use at the more resourceful farms, usually big and very big farms. Nevertheless, small, sophisticated and economically accessible robots could change this trend and make CARs available to smaller farms [8,9]; which is also important as farmers can use their immediately free time in new ventures (e.g., adding value to some or all of their production by transforming it into a local end-user product) or in expanding existing activities. In any case, the technology integration cost becomes critical [10] both for the profitability of the companies and for the farmers.

Other challenges for adopting CARs are maintenance and cost in terms of hardware and software, and the time span to assess the economic and environmental benefits of the robot and its performance. These activities are additional and very different from the traditional activities performed by most farmers; therefore, they surely may discourage the incorporation and use of CARs.

In terms of the adoption and sustainability studies to assess smart agricultural, an economic study [11] analyzed three different robotic weeding applications for the particular case of high-value crops and concluded that the cost of robotic applications was lower than the cost of conventional systems. Remarkably, the authors pointed out that sensors for precision localization and the small labor capacity of the vehicles were the main cost contributors, which may hinder the use of robots in low value crops. A recent and broader economic study [12] explained that estimating the use cost of CARs in arable land, similarly to conventional agricultural machinery, is by far inexact. The reason is the lack of the definition of critical operational parameters (inexistence of normative). Thus, they proposed a preliminary methodology to conduct an agricultural cost-benefit analysis when robotic systems are employed in arable farming.

The remaining of the paper has been structured as follows. Section 2 introduces techniques used by CAR to autonomously navigate across the farm. Section 3 develops a budget estimation for robots used in farms. Section 4 describes the business models adopted by agricultural robotics companies. Section 5 gives an analysis of successful business models of robotics companies. Section 6 outlines scenarios that may lead to sustainable farm production using ARs (Agricultural Robots). Finally, Section 7 concludes on the advantages of different ARs business models and the autonomous navigation strategies compatible with them.

2. Background: autonomous navigation for commercial agricultural robots

CARs need to perceive the environment, locate themselves and navigate through a crop field to perform specific tasks. Sensors and navigation strategies are two of the most crucial aspects for developing unmanned ground vehicles with autonomous capabilities. The needs in terms of sensors and cost vary greatly according to the type of environment (unstructured vs. structured environments) in which the robot will operate. Thus, the choice of sensors will have a significant impact on the unit's final cost and on the robot's navigation abilities.

In structured environments, a successful case is that of Automated Guided Vehicles (AGVs) [13]. For example, in automobile factories, autonomous or semi-autonomous trolleys move goods inside warehouses. These trolleys are tracked by AGV technology to operate on supportive infrastructure for self-localization in a predefined map. Supportive infrastructure implies the integration of simple magnetic tape tracks on the floor, wires under the floor emitting a magnetic signature, or landmarks across the factory to be identified by lasers. These navigation strategies, in structured environments, facilitate the navigation autonomy and safety of the vehicle with a smaller number of sensors. In agriculture, this kind of technology can be used for some tasks in greenhouses, but it is not directly applicable to outdoor and unstructured environments.

On the other hand, CARs can operate in outdoor and in unstructured environments. They typically use a Global Navigation Satellite System (GNSS) for localization in the field. Examples of such systems are GPS from the United States, GLONASS from Russia, BDS from China, and Galileo from the European Union. However, to enable long-term autonomy, it is desirable to have systems that do not rely exclusively on GNSS because of the signal shortage in parts of the fields and under the canopy. Non-GNSS-based localization techniques such as SLAM (Simultaneous Location And Mapping) in its different varieties [14–18] work well in various applications. Still, SLAM techniques are not well suited for agricultural environments where plants are located with regular, repetitive spacing and are intentionally grown to be as uniform as possible [19]. Therefore, robust localization in the field demands the simultaneous use of different techniques. The selection of the navigation strategy to be used in an unstructured environment is a crucial challenge in CARs development.

As required capabilities of self-localization and navigation may vary drastically depending on the field and application, the implemented design of the robot can impact the number and the type of sensor to endow the CARs. In fact, as the type and number of sensors increase, CARs can perform more complex tasks. For these reasons, the challenges of CARs arise from the difficulty of creating high-performance robots and specific navigation strategies while ensuring safety and legal requirements for autonomous operation [20].

The following section describes robot navigation strategies, kinematics, power train, and sensors used for self-localization and navigation in robots developed in research labs during the last few years to provide a technical baseline of agricultural robots. In addition, the cost of hardware components is given so that the total cost of CARs navigation hardware can be later estimated.

2.1. Features of agricultural robots for research

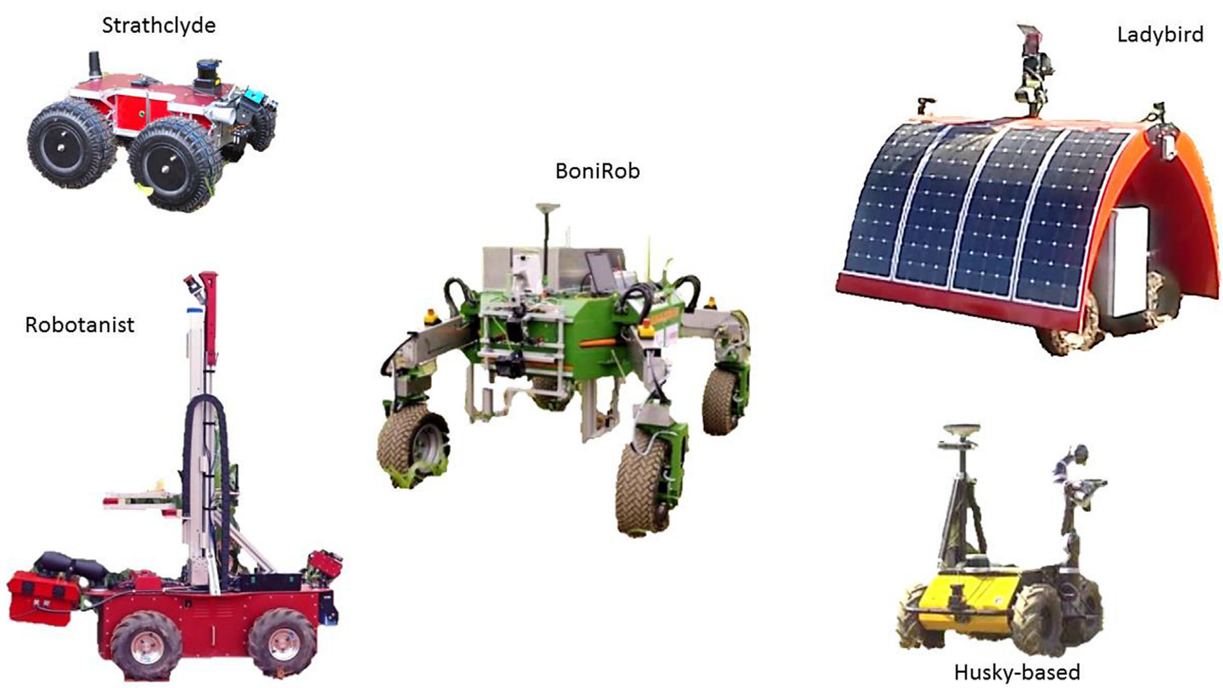
We considered six agricultural robots reported in the literature: Strathclyde [21], two Husky-based (GRAPE [22] and agRob [23]), LadyBird [24], Robotanist [25], and BoniRob [26]. They were chosen to give a wide and diverse technological baseline (showed in Scheme 1) for a future comparison to CARs.

As ROS (Robot Operating System) is being used for robot navigation and control on most robots, a brief introduction of this platform follows. Nowadays, general-purpose software for robot development is a reality after a decade of evolution. The Open Source Robotics Foundation (OSRF) maintains two combined open-source products called ROS and Gazebo. ROS is a robotics middleware composed of a large set of software libraries, conventions for data exchange between different processes, and data visualization tools. And Gazebo is a simulation tool to evaluate ROS-based robots in a 3D virtual environment.

The adoption of ROS in both research and industry settings is very significant. We mention that Tier-1 suppliers are successfully using it for rapid prototyping. While the manufacturing industry aims to integrate advanced versions of ROS (ROS-Industrial) in the final automated product [27]. Similar adoption was publicly initiated in the US military industry.

The navigation strategy of the six agricultural robots previously mentioned, which operate under ROS, are described below:

1. Strathclyde: It is a small rover prototype for a future agricultural robot developed by the University of Strathclyde [21]. The researchers assessed the localization error of the rover on navigation targets for different combinations of sensors. Its autonomous navigation capability was based on a generic motion model implemented on standard ROS libraries [28] and off-the-shelf hardware, such as a stereo camera, ultrasound range sensors, a scanning Laser Rangefinder (LRF), and an Inertial Measurement Unit (IMU). This



Scheme 1. Example of different agricultural robots developed for research purposes.

robot only uses standard ROS libraries to perform Visual Odometry (VO), SLAM, and global and local path planning, among other tasks. A GNSS receiver was employed as a first approximation of the rover location. Finally, they compared experiments conducted in the lab against outdoor ones, explaining the difficulties encountered regarding visual perception, particularly for the visual feature extraction in outdoor lighting.

2. GRAPE (Husky-based): It is a robot built with off-the-shelf hardware (i.e., including a Husky robot) elaborated for vineyard applications. In the EU project GRAPE, several navigation algorithms [22] were tested on the field to conduct plague control by using a rover equipped with a Light Detection and Ranging (LiDAR), a stereo camera, and a GNSS. They evaluated three SLAM algorithms (Gmapping from ROS [29], KartoSLAM [30], and Google's Cartographer [31]), two odometry estimators (robot_localization from ROS, and a custom ROAMFREE [32]), and the global planner move_base from ROS. The reported results were good in terms of autonomous navigation tasks. For the specific field application, the combination of Gmapping and ROAMFREE was the best one, as the ROS global planner needed an excessive inflation of obstacle boundaries. Such amount of inflation mislead navigation on very small obstacles such as weeds or long grass [33].
3. agRob (Husky-based): It is a robot designed to address the power consumption and path planning towards rechargeable stations located on steep slope vineyards. It was developed by the INESC institute and the University of Porto. Several algorithms implemented using ROS were evaluated for a vision-based docking system. They compared low computational algorithms, such as Virtual Force Field (VFF) and the Vector Field Histogram (VHF), combined with terrain heuristics (pre-processed charging trajectory and energy consumption maps) [23].
4. LadyBird: It was designed and built at the Australian centre for Field Robotics (ACFR), University of Sydney, in 2014. It is a modular and flexible system with a wide range of commercial and research applications, including phenotyping. The Ladybird can navigate autonomously over a pre-constructed map of the farm. The user specifies the rows that should be scanned, and a route network planner creates the path. The path is formed by segments and a trajectory controller is used to guide the robot along these path segments using a Real Time Kinematics (RTK) GPS and Inertial Navigations System (INS) [34]. The control system is also able to change autonomously between consecutive rows. The robot is equipped with front and rear facing LiDARs and a panospheric camera for crop detection and obstacle avoidance. An operator, located as far as 1 km from the LadyBird, can supervise it during autonomous operations and carries a fail-safe remote radio emergency stop unit that allows immediate revocation of control if either the red button is activated or radio contact is lost.
5. Robotanist: It is a robot developed at the Carnegie Mellon University to conduct image-based plant phenotyping autonomously in sorghum breeding fields [25]. The Robotanist is endowed with a GPS antenna located at the top of a mast to prevent occlusions as the plants grow taller. To achieve horizontal centimeter level accuracy, GPS carrier phase signals are transmitted to the robot from a base station located around 2 km away. The robot is also equipped with two planar LiDARs, one 3D LiDAR, two RGB cameras with full HD resolution, and an AHRS (Attitude and Heading Reference System) unit. This unit fuses the inertial data from the gyroscope, the accelerometers, and magnetometers using an Extended Kalman Filter (EKF) in order to obtain the 3D orientation of the sensor with respect to an Earth fixed coordinate frame. The navigation strategy of the Robotanist changes according to the sorghum growth stages. When the crop is short enough to allow a clear view of the satellite constellation from the GPS antenna, the navigation is performed by following GPS waypoints. Pure Pursuit [33], a path tracking algorithm, was used to perform the path following of a line between GPS waypoints. This method is not robust to GPS signal drops and it also does not consider obstacles on the path. However, obstacles are detected using the 3D laser sensor, even beneath the canopy. The robot integrates two ROS nodes to accurately determine its position. The first node corrects the GPS coordinates of the robot at the base frame (improving the accuracy of GPS positioning) using the orientation info from the AHRS and the relative poses of the GPS antenna, and the base coordinate frame of the robot. The second node calculates a current estimation of the robot pose (3D position and 3D orientation) and velocity relative to an Earth fixed coordinate frame

Table 1
Main features of agricultural robots used in research.

Robot name	Dimensions L x W x H [cm]	Weight [kg]	Kinematics	Speed [km/h]	Autonomy [h]	GPS based	Sensors (or hardware) used for navigation
BoniRob [26]	180–280 × 130–240 × 220 (1)	1100	Omnidirectional	1.5	24 (2)	Optional	3D LiDAR, Inertial sensor (IMU), RTK-GPS
GRAPE [22] & agRob [23]	99 × 67 × 39	50 – 125	Skid-steering	3.5	3	Yes	Stereo camera, 2D and 3D laser (LiDAR), GPS, IMU single antenna
Ladybird [24]	220–180–200 (1)	(?)	Omnidirectional	4.3	72 (3)	Yes	Stereo and panospheric cameras, 3D LiDAR, RTK GPS double antenna
Robotanist [25]	134 × 56 × 183	140	Skid-steering	2	8	Yes	Two 2D LiDAR, 3D LiDAR, RTK GPS, AHRS, RGB camera
Strathclyde [21]	82 × 52 × 38	15.5	Articulated	0.72	(?)	No	Stereo camera, 3D LiDAR, IMU, GPS

(1) With adjustable measures. **(2)** Without refueling, the power comes from batteries and a fuel-based generator. **(3)** Full operation during three workdays, with abundant solar radiation, without recharging. **(?)** Unknown.

using an Unscented Kalman Filter (UKF). The UKF is used to fuse the corrected GPS data and info from the AHRS and from encoders in the wheels.

6. BoniRob: It is a big agricultural robot comparable to the combination of a small tractor and its implement. It was developed by a collaboration between the Fachhochschule Osnabrück and BOSCH Deepfield Robotics to operate in arable land. A modular mechanical, electrical, and logical set of interfaces enable to incorporate different hardware modules according to the research applications. For example, different modules were implemented to conduct plant phenotyping, soil monitoring, weed control, and web-based communication [26]. The robot geometry can be modified to adapt to the track width and clearance of the crop field. BoniRob has four driving and auto-steering wheels, providing an important degree of maneuverability. Its autonomous navigation capability is based on the perceived information of a 3D LiDAR, which scans just in front of the robot path. The ground surface is extracted from the LiDAR data (3D Point Cloud) by computing the Hessian plane, so the rows of the land are identified from the transversal profile of the 3D point cloud. The rows detection strategy changes along the year; in winter, the transversal profile describes the rows corresponding to the tracks on the land, while in other moments of the year, the transversal profile describes the plant rows (e.g., maize). The localization is computed from odometry and inertial data with a Kalman filter, and the use of GPS is optional. Mainly, BoniRob moves over two rows of crop, the four steering enables the use of robust control to keep the robot centered above the rows. The navigation scenario uses semantic localization due to the limited number of expected scenarios that arable land presents (e.g., crop row, open field, side of the field, and row gap) and everything else is an error state. The second version of BoniRob adopted ROS as middleware but kept the critical part of the navigation task under a dedicated Real-Time Operating System (RTOS) [26].

To compare these six robots, their key technical features are summarized in Table 1. These features include dimensions, autonomy time, speed, sensors, etc. Except for the Strathclyde and the GRAPE-&-AgRob (husky-based), the research robots are relatively bulky (due to their considerable dimensions and weights), move on average 2.4 km/h (low speed), and have an energy autonomy on average of 27 h. In terms of navigation, they combine sensor technologies, such as LiDAR and IMU. Later in Section 2.2, a similar table summarizes the key features of CARs.

2.2. Features of commercial agricultural robots (CARs)

Agricultural robotics companies offer solutions for diverse applications such as herbicide spraying, lawn mowing, plant phenotyping, wine grape scouting, and pruning, mechanical weeding, and pick-and-place for plant pots repositioning (see some examples of CARs analyzed in Scheme 2). According to the specific agricultural task, each CAR has a particular kinematic, size, cost, energy, autonomy, and navigation technology. Listing all existing CARs is not possible, thus the analysis has been reduced to the features of 9 representative CARs introduced below in Section 2.2. It is worth mentioning that the number of considered CARs is limited to these 9 because for many other robots there is no public information, and manufacturers did not share detailed technical information of their products. This means that there is less information regarding technical features of CARs compared to the considered robots for research.

1. Ara [35] is a robot for the precise application of herbicide. It integrates a navigation system, sensors, a processor, a color camera, two arms, four wheels, solar cells, and self-charging batteries. In operation, the control algorithm identifies an invasive plant in real time through the images captured. Then, the processor estimates a position just above the plant, and moves one of its arms to this position for spraying a microdose of herbicide. This technology has the advantage of minimizing the waste of herbicide, reducing costs and pollution impact. Recently, the company has been commercializing Ara as an implement (without autonomous navigation); however, our analysis on the prior robotic system is valid.
2. Vitirover [36] is a technology for cutting all types of grass. In operation, this robot moves autonomously around a zone while mowing the lawn using rotating blades. Its navigation strategy makes use of a GPS and two separated IMUs, one located on the main electronics board and the other one on the tool holder. The GPS serves to delimit the region where the lawing is carried out. The robot establishes what to do by analyzing the rotation-translation-cap differences extracted from both IMUs. Its structure integrates two solar cells connected with batteries endowing it with the capability of self-charging. This robot is well suited for maintaining grass height in vineyard rows, tree rows, and grass-based playgrounds.
3. Oz, Ted, Bob, and Dino. The Naïo technologies corporation offers the four different CARs aforementioned [37]. Oz aims for weeding control and hoeing chores in all types of plants. This robot offers three different operation modes: manual, track, and autonomous. In manual mode, the robot is teleoperated. In track mode, it follows the user displacement along the field. In autonomous mode, Oz uses a LiDAR and some prior information of the field (i.e., length, width, and number of crop rows) to navigate between crop rows. Its structure integrates four wheels, a navigation system, sensors, and special tools for weeding and hoeing. In the case of the Ted and Dino robots, their target is weed control in vineyards and organic farms, respectively. Their mechanisms have four omnidirectional wheels and tools for weeding crop paths. On the other hand, Bob is a redesigned version of Oz with more autonomy and caterpillar tracks to cope with slopes and muddy terrains. It was developed to perform

Scheme 2. Commercial Agricultural Robots considered in the study.

tasks such as weeding and groundwork in vineyards and nursery gardens.

4. Myce-Vigne and Myce-Agriculture [38]: The company Wall-YE offers two CARs with different tooling: Myce-Vigne and Myce-Agriculture. Myce-Vigne operates for weeding, cutting, mowing, and hoeing on vineyards. While Myce-Agriculture addresses small plants on flat fields, being functional for seeding, sprinkling, weeding, and harvesting. Both robots have a visual-based navigation system, four wheels, solar panels to extend their autonomy in the field, and they contain a set of tools for different agricultural tasks.
5. Ibex2 [39] is a crawler-type CAR for autonomous weed control in grassland. This robot is under development in collaboration with Ibex Automation Ltd., the University of Lincoln, and the University of Leeds. Ibex2 integrates proximity sensors, cameras, and a GNSS system. From the manufacturer's comments, it is expected that this robot achieves commercial maturity in the near future.
6. HV-100 [40] is a robot commercialized by Harvest Automation that targets the floriculture industry. It is intended to move potted plants within plant nurseries or green-houses. Specifically, this robot is used for automating the tasks of pick-and-place plant pots at industrial level. Its navigation technology relies on LiDAR and infrared sensors. In operation, HV-100 [40] executes the tasks inside an area bounded by a reflective tape. The pick-and-place movements are based on robot training.
7. Thorvald started as a research project at the Norwegian University of Life Sciences and its second version [41] is currently commercialized by Saga robotics. It is a modular platform, available in three different versions: normal, compact, and research. The specific sensor and capabilities of the robot are adjustable according to the client's needs and budget. It can be delivered with four driving and steering wheels, and it is equipped with an IMU or AHRS unit, a LiDAR, and cameras. For specific tasks that require better precision in pose estimation, it is delivered with an RTK GNSS that provides centimeter level accuracy. In this case, preloaded maps are used for the navigation of the robot.
8. VineScout is an agricultural robot in process of industrialization, developed by the Agricultural Robotics Laboratory (ARL) at Universidad Politécnica de Valencia (UPV). This robot is designed to improve the quality of wine production by collecting big data on the vineyard, and then analyzing it on the field. When VineScout explores an area, the status of the plants is classified and displayed in high spatial resolution georeferenced maps (color-coded) [42,43]. Thus, enabling a selective harvesting that leads to produce normal and premium wine quality from the same field. Regarding the autonomous navigation strategy in the vineyard [44,45] it is achieved by the combination of ultrasound sensors, an instrumented Akermann steering, and stereo vision algorithms [46,47].
9. For FieldFlux [48] and RowBot [49], there is not enough information available to determine their navigation strategies, and their manufacturers did not provide it. Nevertheless, we conjectured the information of these two robots from visual inspection.

To summarize and to allow comparisons, Table 2 shows the main features of these CARs. Data correspond to the year 2021; note that these features may change over time.

3. Affordability of the different autonomous navigation strategies

To estimate the budget for navigation strategy, the market price of navigation sensors used in agriculture research robots is provided. Table 3 shows the model (or reference component), power consumption, and price of these components. Due to the price variability, Table 3 groups these sensors as low and high cost, including average values. The power consumption was considered because it may lead to an important increase in the overall cost: the greater the power consumption, the greater the capacity of the batteries.

3.1. Cost of sensors used in navigation by agricultural robot in research

The cost of sensors used for autonomous navigation has been estimated for the considered research robots. This cost derives from the sum of the hardware price involved in navigation tasks. The components of GRAPE, agRob, and Robotanist were obtained from the available hardware specifications, but for BoniRob, Ladybird, and Strathclyde these specifications are not provided, thus approximated values are used. Table 3 shows the cost of sensors used for autonomous navigation of these agricultural research robots. For all robots, we adopt the component cost based on the average price from Table A1 in Appendix A.

Table 2
Main features of available Commercial Agricultural Robots (year 2021).

Robot name	Dimensions [cm] L x W x H	Weight [kg]	Kinematics	Speed [km/h]	Autonomy [h]	GPS based	ROS based	Sensors used for navigation
Oz	100–130 × 40 × 60	110–150	Skid-steering	1	4	No	No	LiDAR, IMU
Ted	230 × 180 × 210	600–800	Omnidirectional	4	8–10	Yes	*(?)*	GPS, camera, LiDAR
Bob	130 × 45 × 90	250–300	Crawler	3	4–8	Option	*(?)*	Camera, LiDAR, (GPS)
Dino	250 × 140–180 × 130	600	Omnidirectional	4	6–8	Yes	*(?)*	RTK GPS, 2 cameras
IBEX2	100 × 80 × 80	250	Crawler	*(?)*	*(?)*	Yes	Yes	Cameras, LiDAR, GPS
MYCE Vine	150 × 86 × 80	80	Akermann, 4WD	1	10–12	Yes	No	GPS, 3 cameras
MYCE Agri.	200 × 60–200 × 160	100	4WD, 4WSteer	<1	20	Yes	No	GPS, 3 cameras
FieldFlux	210 × 280 × 230	300	Differential 3 wheels	1	8	Yes	*(?)*	RTK GPS, IMU
RowBot	120 × 55 × 160	*(?)*	Articulated steering	6	20 ***(2)***	Yes	*(?)*	GPS, RGB or IR cameras, LiDAR
Thorvald II	150 × 300 × 83 ***(3)***	180 ***(3)***	Omnidirectional ***(3)***	1.5	10 ***(3)***	Option	Yes	Cameras, LiDAR, IMU, (GPS)
Ara	220 × 170 × 130	130	Differential 4 wheels	1.5	Full autonomy (solar)	Yes	*(?)*	GPS, 1 color camera
VineScout	104 × 102 × 120	90	Akermann, 4WD	<2	***(2) (?)***	No	No	GPS, 1 stereo camera, ultrasound
Vitirover	90 × 47 × 115	18	Akermann, 2WD	0.84	Full autonomy (solar)	Yes	No	GPS, IMU
HV-100	52 × 69 × 54	45	Differential 4 wheels	*(?)*	4–6	No	*(?)*	LiDAR, Infrared

(1) Without refueling, the power comes from batteries and a fuel-based generator. **(2)** Powered by batteries and solar panels. **(3)** Several possible configurations. **(?)** Unknown - No information available nor provided by the manufacturer.

Table 3
Cost of navigation hardware for BoniRob, GRAPE-AgRob, Robotanist, Ladybird and Strathclyde.

Robot & weight range	Hardware component used for navigation	Cost [USD]
BoniRob (weight > 200 kg)	RTK-GPS Topcon HiPer Pro	2,900
	3D LiDAR FX6 Nippon Signal	3,625
	Inertial sensor (IMU) XSens MTi-10 series	1,440
	Total	**7,965**
GRAPE and AgRob (weight < 200 kg)	GPS (ref: Novatel OEMstar receiver)	1,995
	IMU (ref: XSens MTi-10 series)	1,440
	2D Laser (ref: Hokuyo UTM 30LX)	4,770
	stereo camera (ref: StereoLabs Zed)	449
	3D Laser (ref: Velodyne Puck Lite)	4,000
	Total	**12,654**
Robotanist (weight < 200 kg)	Two 2D LiDAR (ref: SICK TiM5xx and Hokuyo UTM-30LX)	2,826
	3D LiDAR (ref: SICK Visionary-T)	3,250
	RTK-GPS (ref: Novatel SMART6-L on L1 and WAAS)	1,300
	AHRS (ref: Xsens MTi-30)	1,500
	RGB camera (ref: IDS UI-5240CP-CHQ)	1,200
	Total	**10,076**
Ladybird (weight > 200 kg)	Stereo camera Point gray Bumblebee XB3	3,500
	Panospheric camera Point gray Ladybug 3	15,000
	3D LiDAR	3,625
	RTK GPS double antenna Novatel SPAN OEMV	8,700
	Total	**30,825**
Strathclyde (weight < 200 kg)	Stereolabs ZED stereo vision camera	449
	LiDAR Hokuyo UTM-30LX-EW	4,770
	GNSS single antenna	1,300
	Razor IMU	35,96
	Total	**6,555**

Table 3 shows the cost of agricultural research robots, focusing only on sensors used for autonomous navigation. This robot cost derives from the sum of the hardware price involved in navigation tasks. The components of GRAPE, agRob, and Robotanist were obtained from the available hardware specifications, but for BoniRob, Ladybird, and Strathclyde these specifications are not provided, thus approximated values are used. For all robots, we adopt the component cost based on the average price from Table A1 in Appendix A.

3.2. Estimated cost of commercial agricultural robots

As commercial companies usually do not provide information on the hardware used in their products, we estimated the cost of CARs navigation hardware based on the sensors indicated in Table A1. For this estimation, we calculated the average price of commercialized LiDAR, Camera, IMU/AHRS, among others. Using these values, the cost of each robot was derived similarly as in Table 3.

Thus, Table 4 shows the estimation of CARs prices classified as lightweight and heavyweight. We remark that this is an estimation (mean value) subject to variations. It can be observed that the hardware cost of a lightweight CAR is in the range of 1316 to 9312 USD with a mean for the considered robots of 3570 USD, and the hardware cost of heavyweight CARs is in the range of 6116 to 14,670 USD with a mean of 11,518 USD. As expected, the cost of hardware for navigation is lower for CARs than for research-oriented robots, which are often equipped with top-grade expensive hardware or hardware that also serves other purposes. It can also be seen that the cost of hardware for navigation still represents a significant cost of CARs; hardware

Table 4
Estimation of power consumption and cost of CARs navigation hardware**.**

Weight classification	Robot name	Hardware component used for navigation	Est. Power [W]	Est. Cost [USD]
Lightweight (weight < 200 kg)	Oz	LiDAR (2D. low price)	3.44	2,047
		IMU (low price)	0.043	16.33
		Total	**3.483**	**2,063**
	Bob	GPS (single antennal, low price)	3.5	1,300
		Camera (color, low price)	3	695
		(Laser) LiDAR (2D, low price)	3.44	2,047
		Total	**9.94**	**4,042**
	MYCE Vine	GPS (single antenna, low price)	3.5	1,300
		3 cameras (color, low price)	9 (3 W per camera)	2,085
		Total	**12.5**	**3,385**
	MYCE Agri	GPS (single antenna, low price)	3.5	1,300
		3 cameras (color, low price)	9 (3 W per camera)	2,085
		Total	**12.5**	**3,385**
	RowBot	GPS (single antenna, low price)	3.5	1,300
		RGB camera (color, low price)	3	695
		LiDAR (2D, low price)	3.44	2,047
		Total	**9.94**	**4,042**
	Thorvald II	GPS (single antenna, low price)	3.5	1,300
		RGB Camera (low price)	3	695
		LiDAR (2D, low price)	3.44	2,047
		IMU (low price)	0.043	16.33
		Total	**9.98**	**4,058**
	Ara	GPS (single antenna, low price)	3.5	1,300
		RGB Camera (low price)	3	695
		Total	**6.5**	**1,995**
	VineScout	SXBlue L1/L2 GNSS	5	7,495
		ZED stereo camera	1.75	449
		TrashSonar-WR ultrasonic sensors	0.059	100
		2D LiDAR (Ref: OMD8000-R2100-B16–2V15)	2.88	1,268
		Total	**9.69**	**9,312**
	Vitirover	GPS (single antenna, low price)	3.5	1,300
		IMU (low price)	0.043	16,33
		Total	**3.543**	**1,316**
	HV-100	LiDAR (2D, low price)	3.44	2,047
		4 Infrared sensors	0.040	60
		Total	**3.48**	**2,107**
Heavyweight (weight > 200 kg)	Bob	RGB camera (high price)	2.4	1,200
		(Laser) LiDAR (high price, 2D)	8.4	4,770
		GPS (single antenna, high price)	3.95	4,647
		Total	**14.75**	**10,617**
	IBEX2	RGB camera (high price)	2.4	1,200
		LiDAR (high price, 2D)	8.4	4,770
		GPS (double antenna, high price)	3.5	12,500
		Total	**14.3**	**14,670**
	FieldFlux	RTK-GPS (single antenna, high price)	2.9	4,500
		IMU (high price)	0.42	1,616
		Total	**3.32**	**6,116**
	Ted	GPS (double antenna, high price)	3.5	12,500
		RGB camera (color, high price)	2.4	1,200
		LiDAR (2D, high price)	8.4	4,770
		Total	14.3	**14,670**

cost should diminish over time as new technologies and low-cost high-quality sensors hit the market. In the next section we analyze another factor that plays an important role on the adoption of CARs: business models.

4. Business models for robotics companies: the case of CARs

CARs business models can be broadly categorized in two cases: direct sales and recurring revenue in the form of leasing or subscription. Usually, viable business models for innovative technological markets need a continuous expenditure on R&D innovation. However, the main characteristics of the two business models used in CARs are not related with a sustainable R&D innovation. This section describes how the companies obtain benefits with such business models.

4.1. Direct sales model

The direct sales model, in which the companies sell a CAR directly to the end-user (without intermediaries), is a challenge for new and less-known companies. Because CARs must meet demanding requirements to operate under hard conditions (e.g., deep changes in temperature, moisture conditions), the CARs' hardware becomes costly. This leads to an elevated CAR final price, undesirable for farmers.

An example of a robot company applying direct sales is iRobot, with its product Roomba for autonomous vacuum cleaner. For CARs, the Oz weeding robot of Naïo Technologies applies direct model as well. The selling success of these robots relies on satisfying the need of conventional farmers to reduce the use of herbicides and of organic farmers to reduce the use of costly, manual weeding.

4.2. Recurring revenue model

This model engages customers to pay a certain amount for a specific time period, usually monthly, seasonally, or yearly. In this category, leasing and subscription are the most common modes of operation adopted by agricultural robotics companies. The reason for this is that the farmer must get used to working with a robot. Initially, the farmers tend to use it in a simplistic way and without taking advantage of its maximum potential. Also, the planting layout of the field may need to be adapted to the requirements of the robot, for example, creating spaces to perform turning maneuvers. These learning periods require several seasons (i.e., about two years).

The leasing model, which consists of renting a product during a short period of time with the possibility of purchasing it, is broadly applied by companies with well-established products and specialized to precise tasks. This model relies on the convenience, for the customer, of testing the equipment for a certain time period. A typical example of leasing can be seen in the rental of machinery for the construction industry (e.g., cranes or excavators). These companies attract customers by adding extra value to machine usage, such as improving fuel efficiency (reducing operating costs), integrating safety systems to monitor blind spots, and providing safer workplace conditions.

The company Universal Robots offer a leasing program for collaborative robots that can be customized for the client's needs, including the number of robots for the contract term, upgrades, seasonally increase of robots, and the possibility of buying the fleet once the contract has come to an end [50]. An example of this business model in CARs is the Ara robot, which targets a niche market whose land fields could benefit from its autonomous and solar-powered selective weed spraying. This convenience represents cost savings in terms of herbicide without adding external labor or additional costs. And each farmer decides the rental time in function of the field type and size.

The subscription model is goal-oriented, focused on learning about its customers' needs and on preserving a long-term relationship with them. If the goal fails, the customer is free to unsubscribe. An example of this is the Community-Supported Agriculture model. We can mention the successful cases of Teikei [51] in Japan and AMAP [52] in France, for which the client purchases the harvest from a group of local organic farms, leading to a weekly or bi-weekly box of farm goods. This allows the participants to share the risks of farming between producer and consumer while ensuring a sustainable way to minimize the ecological footprint due to food transportation and enable the spreading of organic farming.

An example of a subscription model from the analyzed robots in Section 2 is the Vitirover. This company provides the service of grass floors maintenance using an herbicide-free approach, ensuring a certain threshold of grass height through the deployment of a swarm of mini lawnmower robots.

5. Similarities in successful business models of robotics companies

The high-tech industry has an important innovation component, which plays a significant role in distinguishing each product from alternative solutions. Robotic companies are not the exception; however, the commercial continuity of a robotic solution does not rely merely on innovation, instead in a viable manner to carry out R&D to produce innovation. This involves the context of the solution in the market and the company's strategy.

An iconic case of a robotic company that went bankrupt is Rethink Robotics, the first to provide low-cost collaborative robots. After ten years of operations worldwide and with a current co-robotic market in expansion, their single focus on innovation was not enough to secure new sales. In 2018 it was purchased by HAHN Group to complement its extensive offer of industrial automation products [53]. Thus, the business models are critical for the success of robotic companies.

Here we shortly analyze four successful robotic companies belonging to two different business sectors: surgical and agriculture robotics. We included surgical robots because the USA stock market (Fig. 1) shows that this technology is an example of a robot market that has been profitable for more than 15 years. From these figures we can observe that the ratio Revenue/Earnings spanned from 2.56 to 5.29 with an average of 3.92 times, so this business reference might be reproduced to CARs.

Table 5 presents the name and size of the analyzed companies, their principal innovations, and the added value for the clients, which is the way for the company to secure revenues. The business models and strategies to secure a share of the market of these companies are briefly presented in the next two subsections.

5.1. Surgical robotic cases

Securing the exploitation of the innovation by patents up to 20 years was the key asset to become the world leader in the surgical robotics industry. The patenting of a disruptive innovation, the concept of remote center of motion [54–56], enabled Intuitive Surgical, Inc. to develop and deploy its robotic surgical platform almost without direct competition for about 15 years. During this time, the company target was high selling prices (direct sales) while keeping investing in improving the robot. Even with a selling price of around $2 million per robot, the company arrived to deploy the Da Vinci® robot globally (more than 5000 systems in 66 countries) before competitors could start selling similar alternatives.

Nowadays, the company's income comes from the recurring revenue produced by the disposable surgical tools and the maintenance of its large fleet of robots sold. To compete with new companies, they did not choose to decrease the selling price of the robot; instead, they started to lease the robot backed on the reputation gained in the large medical community. This change in their business model shows the company's intention of securing its market share while pushing further the capabilities of their solution bringing new services for the hospitals. This is consistent with the deployment of a "black box" (i.e., robot data logger called dVLogger), which stores all surgical procedures sending the anonymized data to the company, which returns to the hospital statistics about the performance of the surgeon [57,58] for further medical outcome improvements. In this case, the company created a new service, similar to surgical proctoring, that did not exist before and at the same time collect data that will lead to globally improve the robot usage.

In this context, new competitors such as Asensus Surgical with its Senhance® robot are targeting complementary or niche markets to quickly gain market share. The fundamental strategy here is to replace the instruments of established medical procedures (recurring revenue model) for a robotically assisted system that could achieve better medical outcomes. In this manner, laparoscopic surgeons and their surgical team can use the system without extensive specialized training in robot teleoperation (i.e., lack of learning curve) [59]. This system was designed to allow a quicker conversion from a robotized assisted surgery to a traditional laparoscopic one in case of emergency, ensuring safety for surgeon adopters.

Examples of niche markets are the hysterectomy [60] and pediatric surgeries, in which the usage of very small surgical instruments is a real advantage and its bigger competitor does not provide. Complementary markets are hospitals with modest resources, which cannot ensure enough surgeries per year to amortize and finance the maintenance of Da Vinci® robots. This is the case of hospitals from developing countries, which have almost abandoned their attempts of using the Da Vinci® robots due to the increasing cost per surgery and the associated maintenance costs [61,62].

Possibly for this reason, most medical research publications using Senhance® robot [63] come from developing countries and small hospitals [59–64], which are the natural adopters of this surgical technology due to the high occurrence of laparoscopic surgery. In the case of Japan (second world's largest surgical robotics market), the government in-

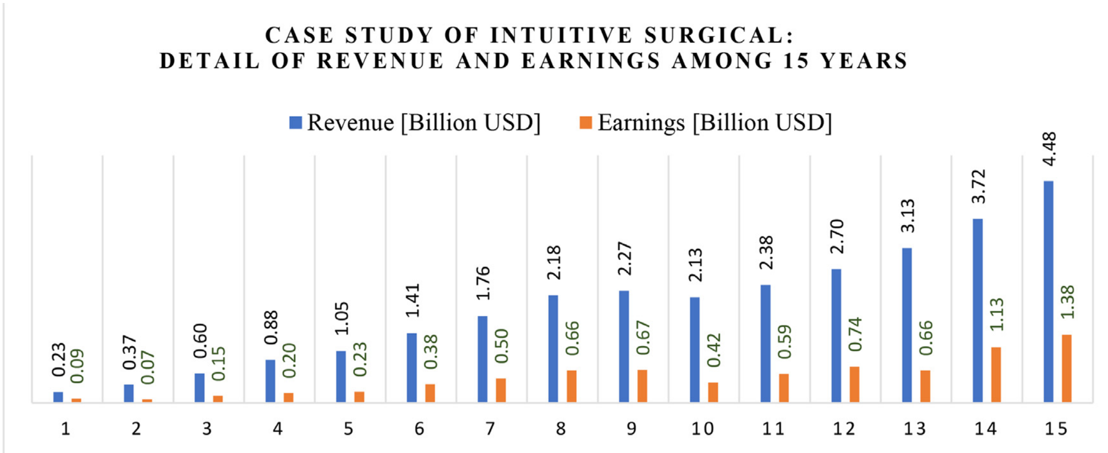


Fig. 1. Case study: revenues and earnings of Intuitive surgical (2005–2019), a robotic-assisted surgery company.

Table 5
Main features of the successful robotics companies (examples of two different domains).

Business	Company (size)	Innovation	Added value
Surgical robotics	Intuitive surgical (Big)	* Remote center of motion — trocar insertion * 7 DoF surgical tools (disposable ones) * 3D endoscopic visualization * Great improvement of surgeon ergonomics	* Disposable surgical instrument * In some cases, better clinical outcomes w.r.t. manual laparoscopic surgery * Enable surgical data analytics
	Asensus Surgical (Small)	* Haptic force feedback (user's tactile sense) * Simple conversion from robotic assisted surgery to manual laparoscopic surgery * Good improvement of surgeon ergonomics	* Smaller surgical instrument (up to 3 mm) * Low-cost per surgery w.r.t. other robotic assisted minimally invasive systems * Enable surgical data analytics
Agricultural robotics	Naïo Technologies (Small)	* Collaborative robotics brought to the farm to assist in organic agriculture tasks	* Chemical-free wedding * Taking over part of the physical labor * Some robots can collect field data
	Vitirover (Small)	* Swarm robotics approach for grass mowing * Totally autonomous system	* Autonomous control of grass height * Includes the robot maintenance service

cluded the Senhance® solution in its social security reimbursement system for comparable operative costs with traditional laparoscopic surgeries.

From these two successful robotic companies we can identify a set of distinctive features that defined the adopted business models, which may be used by CARs companies. The main reasons to obtain a healthy Revenue/Earnings ratio were: 1) securing innovation through patents in order to avoid direct competition while supporting extensive R&D activities; 2) addressing niche markets to gain market share and build up reputation; 3) creating a robotic platform that allows the future introduction of new services for the clients; and 4) target governmental goals and subsidies that help clients to adopt the technology.

5.2. Agricultural robotic cases

The first robot of Naïo Technologies was a lightweight robot called Oz. It is a weeding solution that complements manual labor in organic farms. The low complexity of navigation requirements to accomplish the farming tasks allowed a competitive sale price, around $70,000 per unit, suitable for a direct sales strategy. Numerous French subsidies backed the company due to the innovative aspect of the product, which contributed to their business development during the company's initial years. This enabled the building of a reputation in the agricultural machinery market and a diversification of their products.

Due to the novel collaborative robotic aspect of the Oz robot, the company also turned to a leasing model to facilitate its adoption in clients' fields (i.e., smoothing the learning curve for the usage of the robot). Based on the experience gained with their initial customers, Naïo could offer a more attractive deal to new clients adopting CARs in traditional farming tasks.

Naïo Technologies is currently well established and started to commercialize more complex robotic solutions across the continents. The cornerstone of this company are the different autonomous navigation technologies developed, that combine reliability with cost-effective solutions for diverse farm field operations.

Regarding the more expensive heavyweight robots, Naïo recently successfully implemented a service business model. Instead of selling the Dino robots to landowners or agricultural cooperatives, they offered mechanical weeding labors as a service to solve the labor shortage in the USA. This case study consists of 395 hectares in California from March to October 2020, in which 3 Dino robots operated at the same time; +3 hectares/day (978 working hours); and 13 different crops settings (e.g., romaine salad, cilantro, iceberg salad, broccoli cauliflower, spinach fennel, parsley, leeks beet, and celery). In this case, the sophistication of the CARs of Naïo allowed them to offer services of high-throughput mechanical weeding for diverse types of cultures.

The case of Vitirover is very different, because it is a service-oriented company. The company ensures a goal (i.e., grass cutting) without selling or renting a robot to the final client. As such, there is no learning curve for the clients. The company developed a swarm robotic approach to control grass height by grass mowing. Their autonomous solution is based on key functional principles protected by patents, so other companies cannot replicate their strategy for the moment. This allows building up a reputation in the agricultural market and establishing a network to deploy the robots for each mission.

Vitirover employs its lightweight robot in a large variety of fields. To achieve this, they first identify the features of each client field to estimate how many robots must be deployed to reach the agreed goal, which consists of cutting the grass of a specific surface in a certain amount of time. Note that, as the company owns the robots used in the client field, it can test their solution regularly in a practical setting, enabling the systematic improvement of their offered solution. An efficient work of the robotic swarm solution (fewer robots deployed at each client field) using this business model can lead to working on more clients simultaneously and achieving better margins for the company.

From these two profitable CARs companies, we can identify 3 out of the 4 distinctive features that defined the business models adopted on the 2 successful surgical robotics companies previously presented. The one lacking is the one that relates to the targeting of governmental goals and subsidies, which can help clients to adopt the technologies. Although Naïo could secure public funding for the initial development of his robots, they are not targeting such governmental goals and subsidies. This element was essential for the small company Asensus Surgical to start its operations in Japan, the second world's largest surgical robotics market.

6. Discussion

A reliable autonomous navigation system is a must in any CAR. The strategy of a CAR that specializes in a simple task, moves over smooth lands, and with excellent GNSS coverage is relatively simple. This type of robot uses a small number of sensors, displaces at low speed (< 1 km/h), and consumes low power. In contrast, a CAR used for multiple tasks or operated on uneven lands requires more sophistication. ROS is widely adopted in robots capable of handling more complex navigation tasks or environments, with relaxed constraints of real-time. It is currently common to find advanced versions of ROS2, such as ROS-Industrial, applied in manufacturing plants, and agricultural robots should follow.

Reliable navigation and obstacle avoidance in unstructured environments require a combination of different types of sensors, and because GNSS suffers from inaccuracy and signal losses, the CARs' navigation strategies cannot rely only on satellite information. Moreover, when unexpected or moving obstacles appear on the way, the robot cannot be redirected by GNSS measurements. In these conditions, and particularly for heavier and bigger robots, CARs need to integrate perception sensors (proximal sensing), which leads to costlier machines. On the other hand, the appearance of new technologies and the development of low-cost sensors that can be used for navigation purposes will contribute to a cost reduction in terms of navigation hardware.

From a commercial point of view, new CARs companies face challenges in selling their products directly to farmers. Because these companies lack reputation, larger competitors can be more attractive. In addition, to keep innovation important expenditure must be carried out in R&D in a sustainable manner, which is not compatible with low selling price robots. Thus, pricing and inadequate understanding of the robot maintenance for agricultural workers impose a barrier to adopt CARs. If farmers consider that the CAR prices are too high, these companies could not compete without a solid scheme of subsidies offered by the nations or regions.

In addition, CARs must be rugged machines that include high-priced hardware components (as shown in Section 3). Therefore, the price could be too high for farmers if a direct sales business model is adopted. Finally, a better understanding of the customers and offering tailored solutions and business proposals could help small companies compete with already established and resourceful companies.

In the following, we shortly discuss four of the main topics that motivate the establishment of CARs.

6.1. Sustainable food production and food valorization

The mono-crop agricultural approach turned farmlands into high yields food sources but at the expense of mortgaging the environment. For example, the decrease in soil and crop biodiversity in the EU is a cause of alarm. The big data that CARs can generate (digital farming [65]) could empower farmers and consumers worldwide with updated and objective information about the ecological footprint of the food produced in specific regions. All this information can support a quick dietary change in the global population. Research shows that a shift towards a higher proportion of plant-based diet will result in a significant environmental improvement [66,67]. Therefore, a future in which CARs and technologies such as artificial intelligence (AI) [68,69] and satellite observation systems [70–73] are widely used will enable a systematical data collection and analysis of dense data of site-specific crop and soil conditions. And based on the analysis results, these technologies will also enable autonomous or human based decisions and actions to be performed in the field.

Precedents of this scenario are connected vineyards, which farmers see as an effective solution to manage water stress scenarios. In this manner, field monitoring of individual plants and soil regions together with AI driven data analysis can contribute to a better understanding of the problems at hand. Thus, supporting sustainable agricultural practices and maintaining high crop yields.

Unlike satellite-based measurement, CARs can collect complex and accurate geo-located data under the plants' canopy (e.g., nitrogen and moisture concentration in leaves, concentration of different types of pests and weeds, temperature and multispectral crop data, statistical information about the development of each plant) by proximal sensors at a higher spatial resolution. The complementary nature of data, big local data (CARs), and extensive monitoring (satellite) may provide quick insights into crop field status at different levels of accuracy. The historical of big local data produced by CARs will quantify the crop and soil health status over the seasons. This information may become a sustainability metric, and then, an asset of the associated land that may help the farmer to commercialize its produce as high quality goods.

6.2. Autonomy regulations in agricultural robotics

In addition to data collection, CARs will play a decisive role in the near future, collaborating with humans in physically demanding tasks (e.g., selective pruning, harvesting, weeding operations). It is also important to mention that there are other challenges that CARs need to overcome before they become fully established. One of them is the lack of regulation for autonomous agricultural vehicles. Although still far from solved, the matter has been widely discussed in the context of driverless cars [74–76].

However, the situation is very different for autonomous off-road vehicles. Although these are usually deployed in private land fields, there should exist a legal framework to regulate the interaction of these autonomous machines with humans and with their environment. This framework requires setting rules to determine the civil or criminal liabilities in case of accidents or damages to property, animals, the environment, among others.

Finally, there are still several legal gray areas concerning autonomous decision-making, self-learning, and autonomy. For example, there is no definition of autonomous robots under EU law [77]. Still, it is also important to mention the publication in 2018 of a new standard for highly automated agricultural vehicles: ISO 18497 [78]. Also, collaborative robotics in the field will require a framework for risk assessment, including the tooling or implementation for specific farming tasks.

6.3. Business models for commercial agricultural robots

As stated in Section 4, the business models used by the agricultural robotics companies are mainly two: the direct sales model (that may adopt a leasing scheme) and the recurring revenue model. The direct sales model contributes to lowering the final price of the CAR by avoiding resellers' costs, but due to the low company reputation, the revenues are less predictable. Conversely, the recurring revenue model offers affordable services, but the agricultural robotic company needs to face significant investments to have a fleet of CARs ready to use in these cases. In both cases, government support – in the form of tax reduction or subsidy schemes – could prove a key enabler for small innovative companies. Naïo Robotics is an example of a now successful and established company that was initially supported by French agricultural policies.

For a robotic company, there are two important advantages regarding the ownership of the robotic fleet deployed in the fields: (1) shorter product time to market by improving their robots progressively; and (2) understanding customers' needs, which are linked to their field state and its yield potential. These two advantages are essential in this context because farm characteristics are site-specific.

For companies whose strategy is to provide agricultural services, goals subscribed by farmers can be ensured by increasing the CAR fleet size working on the same field. This temporarily increases the operational costs of the robotic company, but the company can capitalize on the circumstance to make their CARs more efficient. In this manner, the robotic company will be better prepared to deliver and to improve their farming services in each subsequent work field.

In terms of product development time, the performance increment of a single CAR may require several seasons of trials to be noticed. Instead, the overall performance of a swarm of robots is simpler to predict. Thus, it is possible to attain specific objectives in a predefined time. Robotic companies that accomplish the goals agreed with farmers will reinforce partnerships and promote a long-term relationship with farmers.

6.4. Economic feasibility of CARs in different cases

From a series of recent case studies [79,80,81], we identify two important factors for the feasibility of using CARs in small and medium size farms. These factors are: (1) the farm size within the crop type; and (2) the CAR weight, which indirectly relates to the available capacity of the robot in terms of labor throughput during the time (labor and power budget).

The systematic review [79] found a variety of crop production scenarios in which automation and robotic technologies were profitable. Additionally, the review identified a need for in-depth study on the economic implications of the technologies. In a 3-year field experiment [80], the working performance and the mowing cost (annual ownership, maintenance, energy, lubrication, and labor) of a robotic lawnmower was studied. The economic analysis compared the performance of the CAR in small, medium, and large orchards against the estimated performances of other 3 conventional methods (riding mower, brush cutter, and a walking mower). The study revealed that the CAR was more profitable than other conventional mower methods only in the small orchard. We conclude with a case study [81] that analyzed the economic implications of autonomous crop equipment for arable agriculture using a grain-oilseed farm. The study revealed that the robotic solution achieved minimum production costs in medium-size farms.

7. Conclusions

In the present article, we seek to understand the drivers and enablers for a wide adoption for CARs, and for this we analyze various factors (technology, reliability, cost, marketing models, etc.) of agricultural robots used in the industry and academia. Then, we provide a concise understanding of the current challenges for the commercial viability of CARs, which spans from technical factors in relation to the degree of autonomous operation of the agricultural robots to the tough financial scenario that emerging CARs companies face during development and commercialization of their products and services. In fact, reaching a Revenue/Earnings ratio that sustains the operation of robotic companies during the initial years of the activity is the main barrier.

We expect this paper to be of interest to robotic companies, investors, farmers, agricultural insurers, and policymakers interested in sustainable farming, as well as for researchers working in field robotics. Regarding policymakers, we bring some elements to support governmental subsidy schemes, which can certainly contribute to reach sustainable food production through a digital agriculture approach.

We believe that, in the future, CARs can be the drivers of new sources of knowledge about the ecological footprint of the local food production system (agroecological footprint). A quantitative field (plant-by-plant and soil) status monitoring enabled by the digitalization of the agriculture, will facilitate the empowerment of society far beyond the detailed expertise that each farmer can get about their field. For example, the analysis of data collected by CARs will most likely enable new high qualified job opportunities in agroecological conservation and food production close to the farms.

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Author contributions

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Declaration of Competing Interest

The authors declare no conflict of interest.

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Appendix A

The cost of several robot parts used for navigation tasks is presented in Table A1.

Table A1
Typical navigation sensors for agricultural robots, including their power consumption and selling price.

Type	Price Category	Model	Power [W]	Price [USD]	Average Power / Price (1)
Proximity sensors					
2D LiDAR	Low	SICK TiM5xx	4	2,826	3,44 W / 2,047 USD
		Pepperl-Fuchs OMD8000-R2100	2.88	1,268	
	High	Hokuyo UTM-30LX	8.4	4,770	—
3D LiDAR	Low	SICK Visionary-T	< 22	3,250	— W / 3,625 USD
		Velodyne Puck VLP16	8	4,000	
	High	Hitachi FX-10	< 6	6,000	
Infrared	Low	Generic IR sensor	<0.01	15	—
GNSS					
Single Antenna	Low	Novatel SMART6-L on L1 and WAAS	< 3.5	1,300	—
	High	Novatel SMART6-L on TerraStar	2.9	4,500	3.95 W / 4,647 USD
		SXBlue L1/L2 GNSS	5	7,495	
Double Antenna	Low	Novatel FlexPak6-D on RTK	1.8	8,700	—
	High	SGR6-D	3.5	12,500	—
IMU / AHRS					
IMU	Low	ST LSM6DS3 (electronic chip)	0.00125	3	0.043 W / 16,3 USD
IMU		BNO055 (electronic chip)	< 0.035	10	
IMU		9DoF Razor IMU	<0.092	35.96	
IMU	High	Xsens MTi-10	0.4 to 0.5	850	0.42 W / 1,616 USD
AHRS		Xsens MTi-30	0.5	1,500	
IMU		AD IS16497	0.3	2,500	
Camera / Stereo camera / Lens / Ultrasound					
Monochrome	Low	FL3-U3-13S2M-CS	<3	525	—
	High	IDS UI-5240CP-C-HQ	1.8 to 2.4	1,200	—
Color (RGB)	Low	FL3-U3-13E4C-C	<3	695	—
	High	IDS UI-5240CP-C-HQ	1.8 to 2.4	1,200	—
Stereo camera	High	SceneScan	20	2,900	12W / 3200 USD
		BBX3-13S2C-38	4	3,500	
	Low	Stereolabs ZED stereo vision camera	1.75	449	
Lens	–	KOWA LM5NCL	—	150	—
Ultrasound	–	TrashSonar-WR ultrasonic sensors	0.059	100	—

(i) In the column Average, the cell marked as '—' indicates that the average was not calculated because either there is only one model in the table or they present very different specifications (e.g., 3D LiDARs with different FoV).

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