Applications of Robotics and Extended Reality in Agriculture: A review

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Abstract

Agriculture is facing a labour shortage problem that affects global food safety and security. Robotic and extended reality (XR) technologies can prove as potential solutions to this problem. The aim of this study was to map and assess the way robotics and XR can mitigate labour shortage problem. PRISMA methodology was followed to identify relevant articles from the last five years, while frequency and correspondence analyses were used for identifying the corresponding trends. In total 210 relevant research studies were identified. These were analysed under the scope of crops, operations, robotics, XR and Human Robot Interaction (HRI). Vegetable crops (36%) followed by orchard crops (34%) were the most studied crop types. Additionally, the results presented that operation-specific robots (27%) were the most used robot type, while 68% referred to wheeled robots. Also, the robots did not present any collaboration level with human in most relevant studies (43%). Collision avoidance was the most frequently implemented safety feature (36%) in the studies that included this type of information. Moreover, operations with high demand in accuracy, frequency or labour were connected with robots that were developed for a single operation. Thus, end-effectors that were specialized in one operation were more preferable than generic end-effectors. However, not all studies referred to all these topics, indicating a need for further investigation. Finally, future studies should further explore the use of Mixed Reality, safety, connectivity and data governance.

Keywords: XR, robotics, Agriculture 5.0, labour shortage, smart farming, human robot interaction

1. Introduction

Nowadays, agriculture is facing problems on labour shortage due to urbanization [1], seasonal work, low wages and poor working conditions [2], stigmatization of agricultural work [3], and aging [4]. This phenomenon was accelerated after the COVID-19 pandemic [5]. Moreover, environmental concerns regarding agriculture keep rising due to the impact to climate change [6] and air [7], water [8] and soil pollution [9]. Due to the aforementioned, there are also concerning issues on food safety and security and their impact on the society [10,11]. Thus, there is a need to transitioning to more resilient systems in agricultural production.

A potential solution to the labour shortage problem can be the use of smart farming technologies such as robots and extended reality (XR) in the context of Agriculture 5.0 [12]. Agricultural robots can be defined as mechatronic devices that consist of sensors, actuators and software for data collection, analysis and task execution which can be performed without human intervention [13]. There are ground and aerial robots that have been developed for research and commercial purposes which cover a broad range of applications in the agricultural sector. Specifically, there are ground robots of different locomotion types based on legs wheels and tracks. These robots have different sensors and actuators that are used for crop scouting, seeding, transplanting, weeding (mechanical, chemical and thermal), fertilizing, harvesting and pruning [14–18]. Similarly, aerial robots or unmanned aerial systems (UAS) or drones as they are commonly referred, are of different types such as fixed wing, helicopter or multi-rotor systems [19]. They are used mainly for crop scouting and mapping, crop protection, seeding, fertilization and pollination [16,20–23]. Both ground and aerial robots can be used in heterogeneous and homogeneous swarms depending on the task for increased efficiency [24,25].

Indeed, agricultural robots can significantly increase productivity. Robots can increase strawberry harvest efficiency by 10% while reducing the mean non-productive time by 60% [26]. A precision spraying robot can reduce pesticides by 40% and decrease worker exposure in pesticides by 45% [27]. An automatic intra-row, weeding co-robot system can reduce hand labour by up to 58% [28]. UAS can save up to 4 seasonal labour days in high disease pressure conditions in grapevines [29]. A co-robot can increase grapevine harvesting efficiency by up to 50% while lowering labour costs by 22.5% [30].

Accordingly, XR can provide significant solutions in mitigating labour shortage and environmental concerns in agriculture. XR is an umbrella term for virtual reality (VR), mixed reality (MR) and augmented reality (AR) applications. It can be used for education, training, decision and action purposes in the context of agriculture by utilizing different viewing (e.g., head mount displays, portable devices) and controlling devices (e.g., voice, handheld controller, wearable devices) [31]. Specifically, VR environments constructed by UAS data can be used for teleoperation of ground robots [32]. Also, VR can be used for training personnel for greenhouses [33]. The use of VR exhibited strong preference from viticulture stakeholders to enhance their understanding in precision farming [34]. Coupled use of VR with AI in a simulated agricultural environment can for instance offer a practical application of theoretical knowledge to university students and enhance their decision-making processes [35]. Moreover, VR can enable the use of robot for tomato harvesting through teleoperation [36]. In the same manner, AR can be used for crop disease identification, crop information overlay, internet of things (IoT) data visualization and autonomous machines monitoring [37]. AR can assist users for precision soil sampling [38]. Additionally, MR although being at a very early stage, can be used for interacting with physical controls like for controlling robots [39] or irrigation equipment [40].

However, the successful use of robots and XR in agriculture is highly affected by the way farmers and agricultural workers interact and collaborate. So, Human – Robot Interaction (HRI) has emerged as a research topic to address this need [41]. Efficient HRI must consider different aspects like safety, ergonomics, awareness and productivity [42]. HRI can present significant benefits compared to traditional methods of conducting agricultural operations. For example, HRI can be used for significantly optimizing the avocado [43] and grape harvesting processes [44] through human robot collaboration and leading to higher harvest productivity. Also, HRI can be used for teleoperation of robots resulting to less health risks for agricultural workers [45].

From the abovementioned, it is clear that the use of HRI through the coupling of XR technologies with robots is an emerging topic. Thus, the main aim of this review article is to map applications of robotics and XR in agriculture as well as to assess them in terms of types and use along with their HRI aspects.

2. Materials and Methods

2.1 Prisma Methodology

Relevant information on agricultural robotics and XR was identified through research articles that were retrieved through the Web of Science and Scopus databases. The main aim was the identification of the robotic and XR configurations. For this purpose, queries were inserted to the search engines to identify relevant research articles (Table 2) in December 16, 2024.

Table 1. Query used in the Scopus and Web of Science databases to identify relevant publications.

Database	Query
Scopus	TITLE ("Agribot*" OR "*ROBOT*" OR "COBOT*" OR "Extended Reality" OR "Virtual Reality" OR "Augmented Reality" OR "Mixed Reality") AND TITLE ("Agricultur*" OR "Crop*" OR "Orchard" OR "Vineyard*" OR "Greenhouse*") AND PUBYEAR > 2020 AND PUBYEAR < 2025 AND (LIMIT-TO (OA , "all")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))
Web of Science	TI=("Agribot*" OR "*ROBOT*" OR "COBOT*" OR "Extended Reality" OR "Virtual Reality" OR "Augmented Reality" OR "Mixed Reality") AND TI=("Agricultur*" OR "Crop*" OR "Orchard" OR "Vineyard*" OR "Greenhouse*")

2.2 Results Filtering

To focus on contemporary research publications, the selected research articles were published from 2020 until 2024. The literature review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to map the relevant research articles and to ensure a systematic and transparent approach. PRISMA is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses. PRISMA primarily focuses on the reporting of reviews evaluating the effects of interventions but can also be used as a basis for reporting systematic reviews with objectives other than evaluating interventions (e.g. evaluating aetiology, prevalence, diagnosis or prognosis) [46].

The aforementioned queries yielded 726 research articles. As a result, the first outcomes were filtered to exclude articles that, based on the title and abstract were unrelated to the study's goal. Thus, 438 of these items met the aforementioned criteria and hence were omitted. With the remaining 288 scientific articles available, the manual selection of articles was expanded in one more round to exclude research articles for which there was no access to the full text and those that were outside this study's scope based on the entire text. Thus, the final number of suitable articles that were evaluated in depth for this study were 210 (Figure 1).

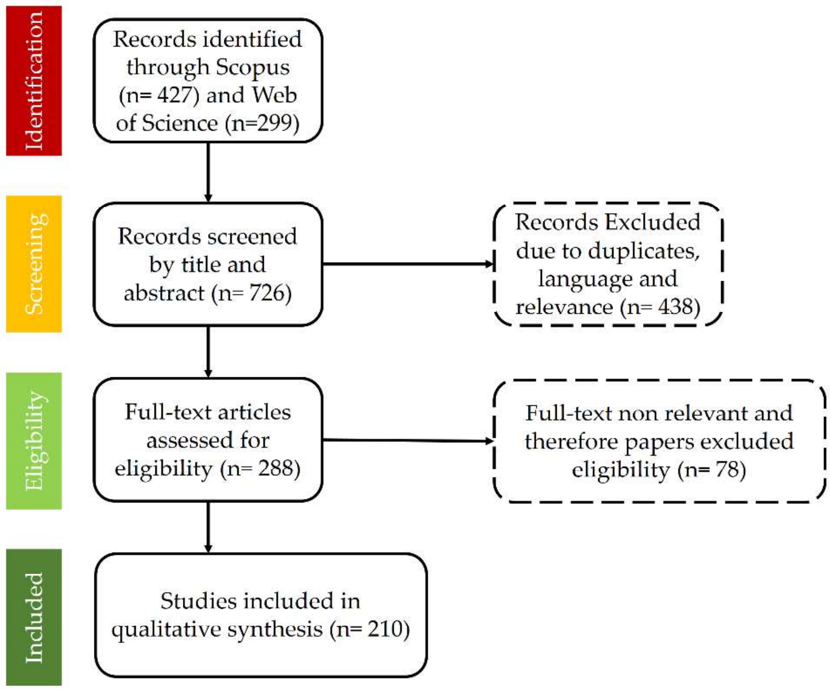


Figure 1. The PRISMA workflow diagram of the research articles search.

2.3 Classification

The selected articles were categorized into three generic categories consisting of subcategories based on relevant research to robotics [14,47–49], XR [31,50,51] and HRI [41,42,52]. Additionally, the selected articles were categorized based on crop types, namely arable crops, orchards, vegetables and vineyards [16] while a subcategory for greenhouses was also included due to the specific characteristics which robotic solutions exhibit [53,54]. Similarly, the agricultural operations were identified for assessing the different solutions based on the scientific literature [14,47–49]. The final selection of studies was subjected to qualitative and statistical analysis to extract key insights into existing agricultural robotics and XR applications.

Table 2. Technical Aspect keywords used in Literature Review.

Category	Subcategory
Crop Type	Arable Crops
	Orchards
	Vegetables
	Vineyards
	Greenhouses
Operations	Navigation
	Planting and Sowing

Category	Subcategory
	Harvesting and Picking
	Mechanical weeding
	Spraying
	Fertilization
	Crop scouting
	Pruning
	Irrigation
	Pollination
	Soil preparation
Robotics	Type
	Locomotion Type
	Active monitoring for guiding the end-effector
	End-effector types
XR	Type
	Interaction devices
	Display devices
	XR application types
HRI	Collaboration levels
	Safety

2.4 Analysis

The statistical analysis included the number of research studies published annually and per type. In addition, frequency analysis was performed for the robotic aspects (focus, locomotion, active monitoring, and end-effector types), XR (type, display device, interaction device, and application) and HRI (type, collaboration level and safety feature). Finally, simple tabulated correspondence analysis with biplot graphs was performed among the different areas by using the statistical software Statgraphics 19 (StatPoint Technologies Inc., Warrenton, VA, USA). The main aim for the correspondence analysis was to identify the relations between the different categories as well as the variance that can be explained by the two-dimensional visualization of the selected data.

3. Results and Discussion

3.1 Cumulative number of research studies

According to the results (see Appendix 1), the number of articles relevant to the topic of this study were increasing from 2020 until 2024 with a small decrease in 2023 (Figure 2). This indicated the importance of developing relevant integrated systems to address agricultural challenges like labour shortage and suggests that this trend will further increase the following years. These results are in accordance with other surveys on robotics and XR which presented similar trends [31,47].

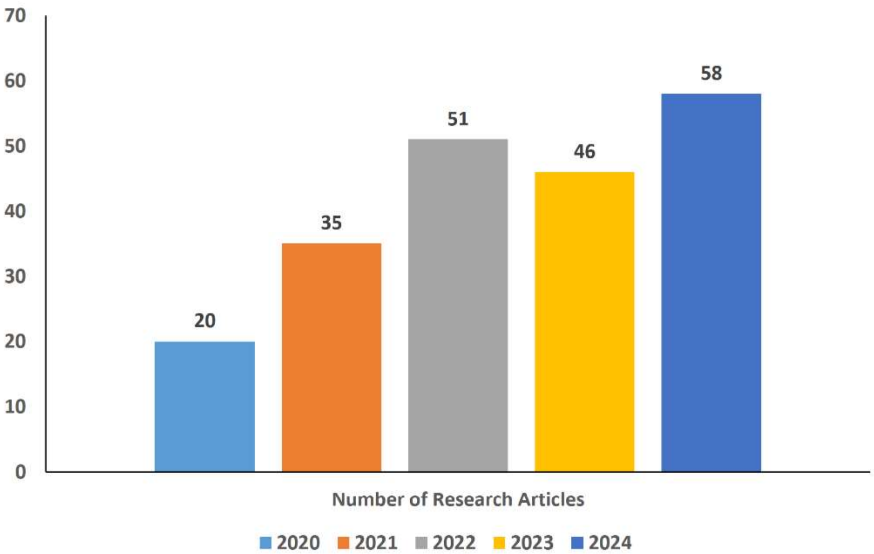
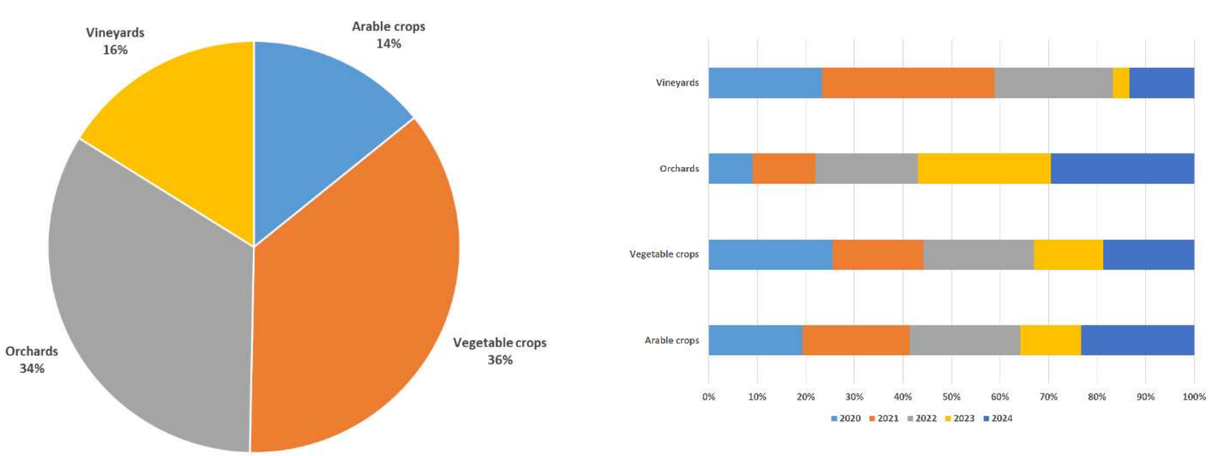


Figure 2. Number of research articles relevant to agricultural robotics and XR from 2020 until 2024.

3.2 Frequency Analysis

3.2.1 Crop Types

As presented in Figure 3, most robotic applications were integrated in vegetable crops (36%), followed closely by orchards at 34%, then vineyards at 16%, and finally arable crops at 14%. These proportions have evolved annually, indicating a gradual decrease in the share of arable crops and vineyards over time, with a corresponding rise in orchard crops. This suggests a notable shift of robotic applications toward higher-value or more profitable crop types. This can be justified by the increased production cost and value compared to arable crops and vineyards along with the fact that they have more labour demanding operations compared to arable crops [48,55–57]. Also, high-value crop growers are more prone to adopt more expensive smart farming solutions [58–60].

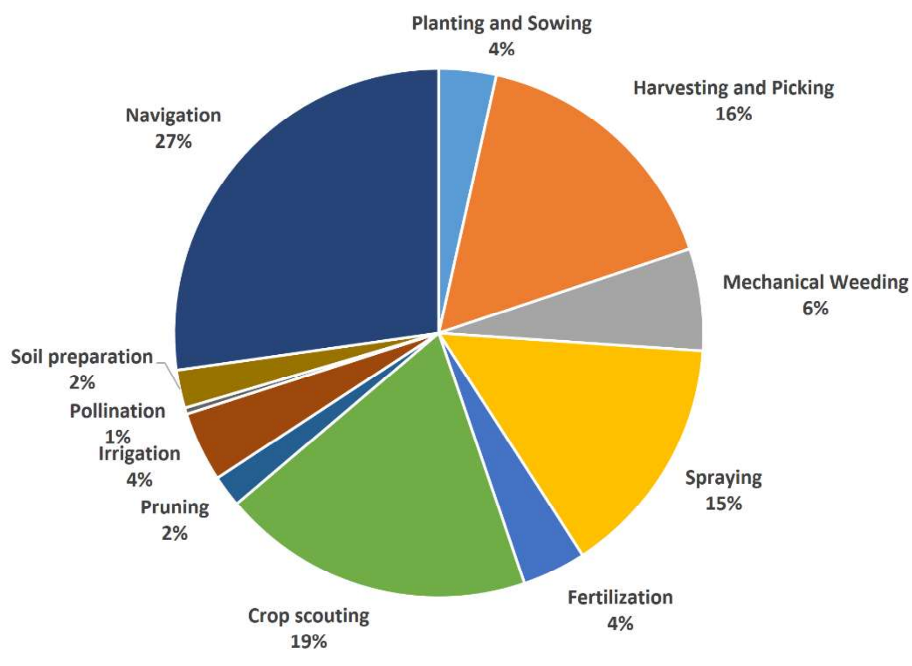


(a) (b)

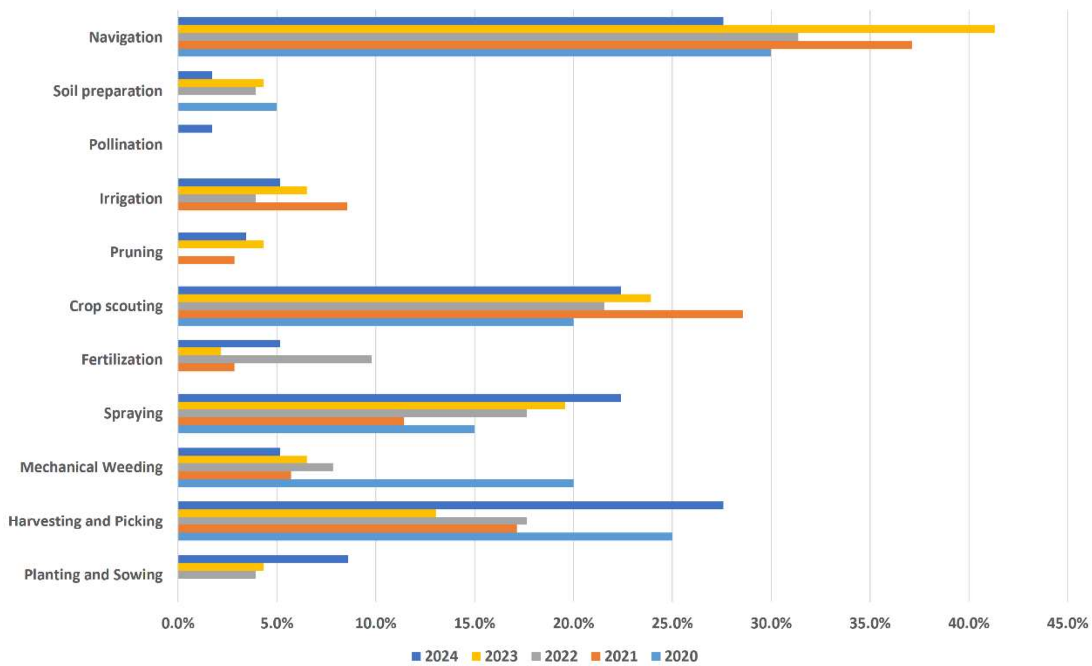
161 Figure 3. (a) Frequency of research articles per crop type and (b) frequency of research articles applications per crop type and year.

3.2.2 Operations

Regarding the operations for which robots are used in field environments, navigation emerged as the most frequently referenced robotic task at 27%, followed by crop scouting at 19%, harvesting and picking at 16% and spraying at 15%. Mechanical weeding (6%), irrigation (4%), planting and sowing (4%) and fertilization (4%) occupy mid-level shares, while pruning (2%), soil preparation (2%), and pollination (1%) each hold smaller proportions. The bar chart shows that navigation, harvesting and picking, spraying and crop scouting are dominant robotic tasks over time from 2020 to 2024 (Figure 4). From the above results, navigation is the most frequently referred operation due to the fact that robots must be able to operate autonomously in the field to conduct the different treatments [61]. Similarly, crop scouting is considered as a core operation because it enables other agricultural operations such as harvest, pest control, irrigation and fertilization [62,63]. From the rest of the operations, harvesting and picking is considered a laborious task and the importance of automating this process is significant due to the challenges that agriculture is currently facing like ageing, urbanization and labour shortage [49,56]. Accordingly, spraying operation is mainly utilized for crop protection in conjunction with pesticide application. Inappropriate application can result to health problems to farm workers among others and thus automation through robotics can mitigate these risks [16,20].



(a)



(b)

Figure 4. (a) Frequency of agricultural operations and (b) frequency of agricultural operations for safety and year.

3.2.3 Robotics

Operation-specific robots dominated in the research articles at 27% of the total, followed by monitoring robots (19%) and multi-purpose robots (18%), while greenhouse robots (14%), robotic implements (11%) and autonomous tractors (10%) and UAS (1%) had smaller shares (Figure 5a). As presented in Figure 5b for the locomotion of robots, wheeled robots made up the largest portion at 68%, followed by tracked robots (13%) and on-rails robots at about 7%. Pulled/carried robots (6%), aerial (3%), and legged (3%) robots account for smaller shares. Regarding the sensors used for actuation of the robots, as presented in Figure 5c, imaging sensors represented the largest segment at 52%, followed by at 29%, proximity sensors at 11%, and tracking sensors at 8%. As presented in Figure 5d, sensors and cameras constitute the largest share at 29%, followed by spraying systems at 25% and grippers at 24%. Cutting tools exhibited a smaller share at 12%, while cultivators (4%), fertilization (2%), drilling and planting (2%), vacuum or suction end effectors (1%), and laser tools (1%) occupy smaller portions.

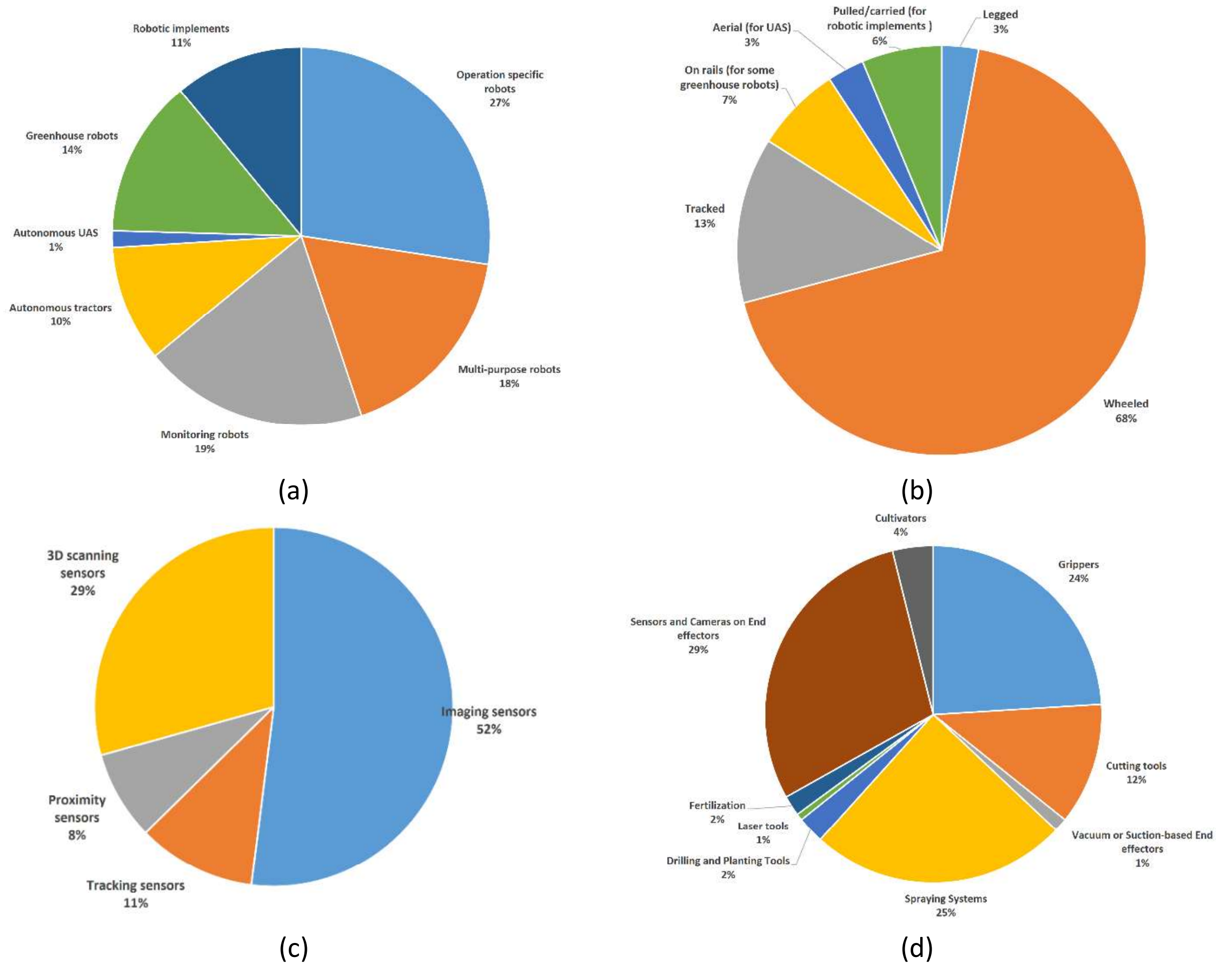


Figure 5. (a) Frequency of robots per type; (b) Frequency of robots per locomotion type; (c) Frequency of active monitoring sensor type for robots; (d) Frequency of end-effectors per type.

Operation specific robots were focused on conducting one operation only, like fertilization (e.g., [46]), chemical weeding (e.g., [47], harvesting (e.g., [48]), blossom thinning (e.g., [49]). This type of robots is less complicated than the multi-purpose robots regarding their design and software needs. However, they are more expensive than multi-purpose robots [47]. Monitoring robots utilize various sensors such as multi- or hyperspectral, RGB or RGB-D cameras, LiDAR, which are important for detecting weeds (e.g., [68]), diseases and insects (e.g., [69]), and crop growth parameters (e.g., [70]). The data collected by these sensors enables data-driven crop management decisions. Accordingly, the multi-purpose robots are versatile and have been developed for conducting different operations. These robots integrate different systems (e.g., for sowing, pruning and harvesting [71]). They are appropriate for farmers because most field operations have a short time window and cost less than purchasing robots for each operation [47]. Regarding greenhouse robots, this type is adapted for conducting operations (e.g., monitoring [72], harvest [73]) in greenhouse environments which are characterized by high complexity due to plant distances and environmental conditions (e.g., illumination) [54]. This can explain the low rate of research articles compared to the other types. Autonomous tractors correspond to conventional tractors that have been upgraded with retrofitted systems and devices that allow autonomous operation. Autonomous tractors have the advantage of using already available conventional implements [74] although they may have high cost for implementation [75]. UAS are mainly used for crop monitoring due to the fact that they can quickly cover large areas. Although, they can be used for various other agricultural operations (e.g., spraying, fertilization, sowing) besides crop monitoring their use is limited due to legislation and payload restrictions [76–78]. Examples of the robots identified in this review can be seen in Figure 6.

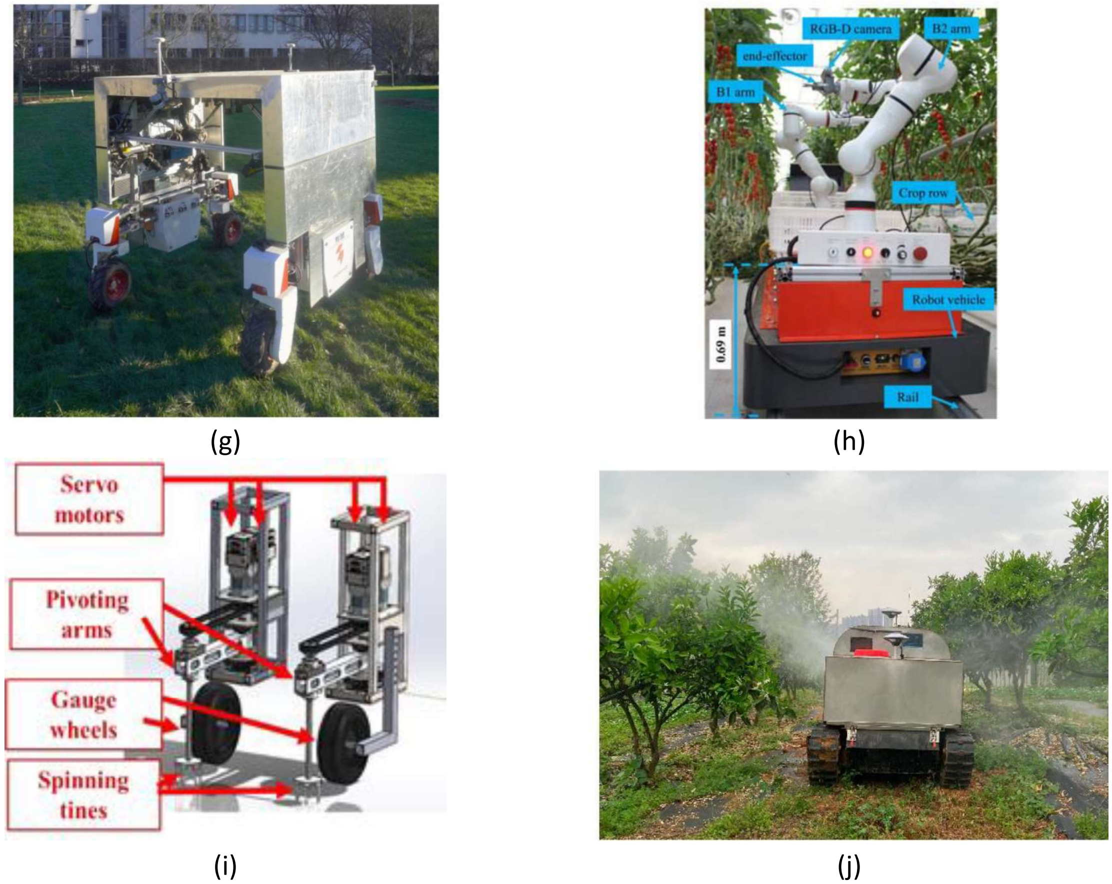


Figure 6. Examples of robots found in the assessed research articles. (a) wheeled fertilization robot [64]; (b) wheeled chemical weeding robot [65]; (c) robotic implement for harvesting [66]; (d) blossom thinning robotic implement [67]; (e) wheeled multi-purpose robot [71] ; (f) wheeled robot for pests and disease detection [69]; (g) wheeled robot for crop growth monitoring [70]; (h) greenhouse robotic harvester on rails with cutting end effectors[73]; (i) robotic implement for mechanical weeding [79]; track type spraying robot [80].

Regarding locomotion of robots, wheeled type robots are considered to provide many advantages such as simplicity, stability, energy efficiency and ease of use. This explains the high percentage of wheeled robots. Additionally, tracked robots present greater manoeuvrability, higher traction and lower ground pressure making them ideal for high-slope fields although they are more complicated than wheeled robots regarding locomotion [81]. Rail robots imply additional costs for infrastructure and are mainly used in greenhouses [53]. Moreover, legged robots present higher agility in rough terrain and high slopes but they can achieve higher compaction compared with wheeled and tracked robots [82,83].

Imaging sensors are ideal for collecting data rich information and enable actuation based on spectral, geometrical and morphological data [16]. Imaging sensors in robotic integrations can be used for crop monitoring (e.g., [84,85]), pest detection (e.g., [86]), weeding (e.g., [87,88]), harvesting (e.g., [89]), spraying (e.g., [90]) and pruning (e.g., [91]) among other operations. Also, they can be used along with other sensors (e.g., LiDAR) for more accurate actuation (e.g., [92]). This justifies the high rate of this segment. Regarding the 3D scanning sensors, which ranked second, they are not affected by light conditions and consequently are not facing illumination-derived problems that can lead to inaccurate operations (e.g., harvesting [93]) therefore they are integrated in many robotic applications, although they present complicated data processing pipelines [94]. The rest of the sensor types, namely tracking and proximity sensors presented limited use due to the limited information they can offer. Therefore, these sensors are mainly being used for actuation. More specifically, tracking sensors can be used for tracking crop rows to adjust robot navigation and operation in the field (e.g., [95]), while proximity sensors can adjust the distance from the target (e.g., for spraying application [96]).

Regarding the end effector types, sensors and cameras are important for providing accurate positioning for the operation of robotic arms. These can be coupled with other end-effector types (e.g., grippers [97], spraying [98]) or used solely for crop scouting purposes (e.g., [69]). As mentioned above, different end effectors have been developed according to the needs of each agricultural operation. Thus, spraying based end-effectors have been developed for precision spraying (e.g., [86]), grippers (e.g., [99]) and vacuum suction end-effectors for harvesting (e.g., [100]), cutting tools for pruning (e.g., [101]), and sowing implements (e.g., [71]). It is worth highlighting that the different end-effectors may result in different results in operation efficiency (e.g., harvesting) depending not only on the type but on the crop and operation time as well [102].

3.2.4 XR

It is worth noticing that from the total of 210 articles only 19 (9%) exhibited use of XR. Specifically, mixed reality (MR) was the most common XR type at 74%, followed by augmented reality (AR) at 21%, and virtual reality (VR) at 5% (Figure 7a). Regarding the interaction devices, which can be used to non-XR application included in the analysis, they were referenced in only 58 articles (28%). As presented in Figure 6b, eight different devices were used with monitor devices that occupy the largest share at 51%, followed by handheld controllers at 20%. Eye-tracking devices had a share of 10%, while hand-tracking devices accounted for 8% and the rest of the devices having lower rates (hand tracking systems, gesture-based, wearables, and spatial tracking systems) (Figure 7b). Additionally, handheld devices accounted for the vast majority at 89%, with monitors making up the remaining 11% regarding the display devices from 53 articles (25%) that were included for this analysis.

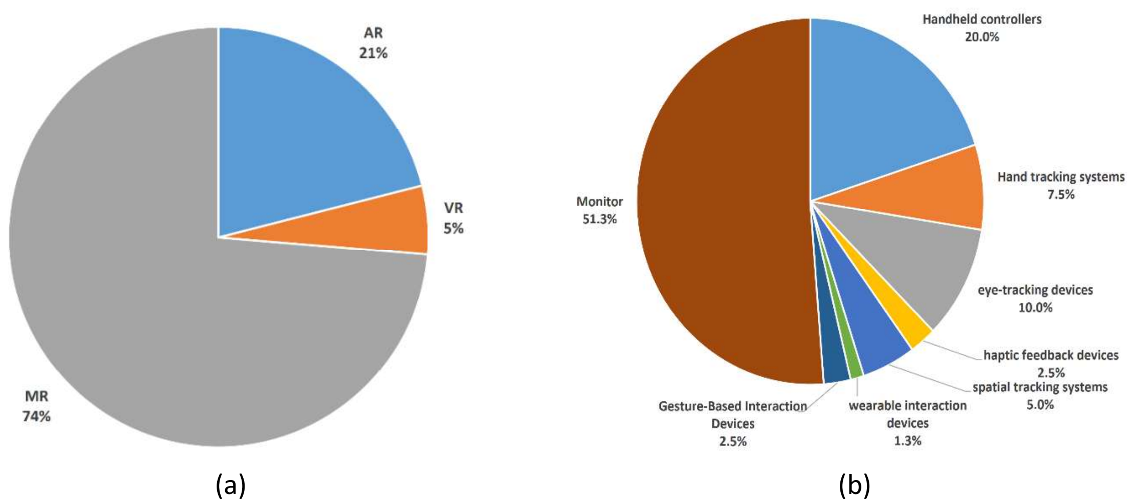


Figure 7. (a) Frequency of XR use type and (b) Frequency of interaction devices per type.

MR overlays digital information on physical objects and enables the interaction of digital systems with the physical world. This technology can be used for teleoperation of robots (e.g., for plant-lowering [103], harvesting [104] and fertilization [20]). Thus, MR offers an enhanced interaction compared to AR which only is used for overlaying information on physical objects and thus can be used for monitoring (see e.g., [20,88]). Finally, VR is used as a simulation tool where all actions are taking place in a digital environment. For example, this can be used for simulating human grasping to develop robotic grippers [105].

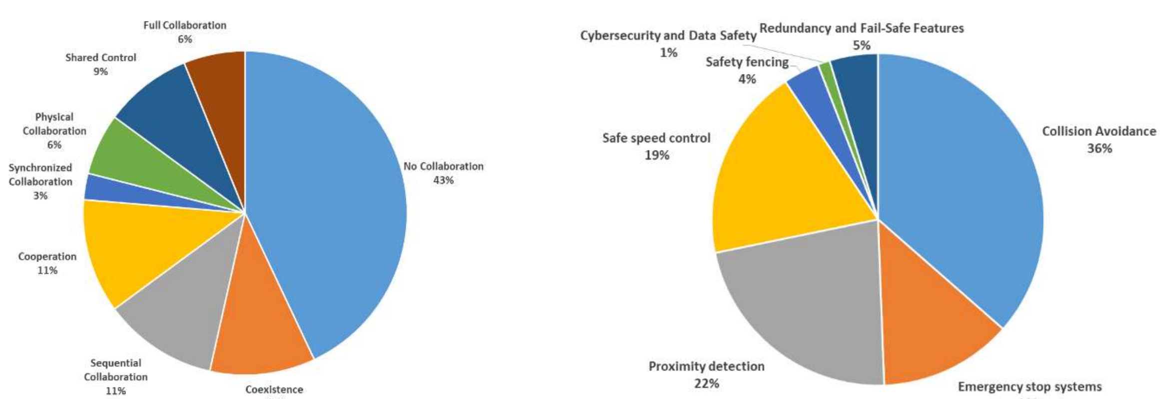
The results on the interaction devices indicate that there can be many devices for interacting with the robots at the different XR environments. Monitors with integrated controllers can play a significant role because they not only visualize all information to the operators of the robots but they can simultaneously be used for control. Also, separate handheld controllers can be used for that purpose. This technology is mature and is already being used for many years. Also, recent technological advances allowed the development of other types of controllers that can be used for human-robot interaction like hand tracking (e.g., [67]), gesture (e.g., [101]), eye-tracking (e.g., [103]), wearables (e.g., [106]), haptic feedback (e.g., [105]) and spatial tracking (e.g., [107]) controllers. These technologies can identify movements of the human body and transform them into actions. However, they are limited by the fact that human operators cannot memorize a lot of different body movements for control as well as to the technological complexity of developing these solutions [31,108].

Regarding the display devices, the results indicated that monitors are the main device for display of information. This can be explained by the fact that they offer less attention and posture shifts while being richer in information although handheld devices offer better mobility [109].

3.2.5 HRI

Regarding the HRI component of the reviewed articles that are related to the collaboration levels of the robots with the human workers, the most frequent level was “No Collaboration” at 43%, followed by “Cooperation”, “Sequential Collaboration” and “Coexistence” each of them having a share at 11%. Smaller shares exhibited for “Shared Control” (9%), “Physical Collaboration” (6%), “Full Collaboration” (6%), and “Synchronized Collaboration” (3%). The “No Collaboration” segment presented the most frequent type across all years (Figure 8a).

Regarding the safety features of robots, it was referred in 51 articles (24%). According to the analysis collision avoidance emerged as the most prevalent safety feature at 36% and proximity detection following at 22%. Meanwhile, safe speed control (19%) and emergency stop systems (13%) exhibited moderate rates. Redundancy and fail-safe features (5%), safety fencing (4%), and cyber security and data safety (1%) had the smallest rates (Figure 8b). It is worth noting that in 21 of these articles there was reference to more than one safety features.



(a) (b)

Figure 8. (a) Frequency of collaboration level type; (b) Frequency of safety feature type.

Most of the articles presented robots with no level of collaboration with human workers because the aim was to showcase applications in agricultural environments to replace human workers to mitigate labour shortage in agriculture (e.g., [84,92,97,110–114]. However, some studies presented levels of limited collaboration, namely “Cooperation” (e.g., [107,115]), “Sequential Collaboration” (e.g., [116]) and “Coexistence” (e.g., [117]). This can be explained by the fact that these types of collaboration aim to lighten the mental and physical workload and provide safety to human workers [118]. The limited shares that “Shared Control” (e.g., [88,115,119]), “Physical Collaboration” (e.g., [68,120,121]), “Full Collaboration” (e.g., [122]) , and “Synchronized Collaboration” (e.g., [123]) levels exhibited can be explained by the fact that these levels demand higher-level automation processes, like anticipation of human behaviour [124].

Although there was limited presentation of the safety systems in the research articles that were analysed, it can be concluded that agricultural robots may include more than one safety system (e.g., [20,84,92,95,125–127]. These systems can refer to collision avoidance, proximity detection, emergency stop, safe speed control, safety fencing, and fail-safe. These were developed for protecting human workers from accidents as well as for preventing operation failures and therefore incidents that can cause bigger problems to crop production [128,129]. Also, the features of cyber security and data safety are gaining momentum for being incorporated into the safety systems of robots due to the potential problems that cyber-attacks can cause [130,131]. The limited reference to this type of system can be explained by the fact that focus was on the development and not on commercialization. Commercial robots must integrate safety features according to the corresponding standards (e.g., ISO 10218, ISO 18497) [132,133].

3.3 Correspondence Analysis

3.3.1 Robot types and Operations

As presented in Figure 9, operation-specific robots were strongly connected with spraying, monitoring robots with crop scouting, and greenhouse robots with harvesting and picking and spraying. This can be explained by the fact that these operations are highly demanding in accuracy and labour under the specific environments, and therefore it is recommended to develop a robot that conducts one operation [53,134,135]. Multipurpose robots presented significant correspondence with mechanical weeding and limited correspondence with pruning and fertilization. These can be justified by the fact that these operations do not present high repetitiveness during a crop season, and there is a need for more versatile robots [55]. It is worth mentioning that the two dimensions of the analysis explain more than 76 % of the variance between the selected categories, indicating that a small portion of the insights are missing from the two-dimensional plot.

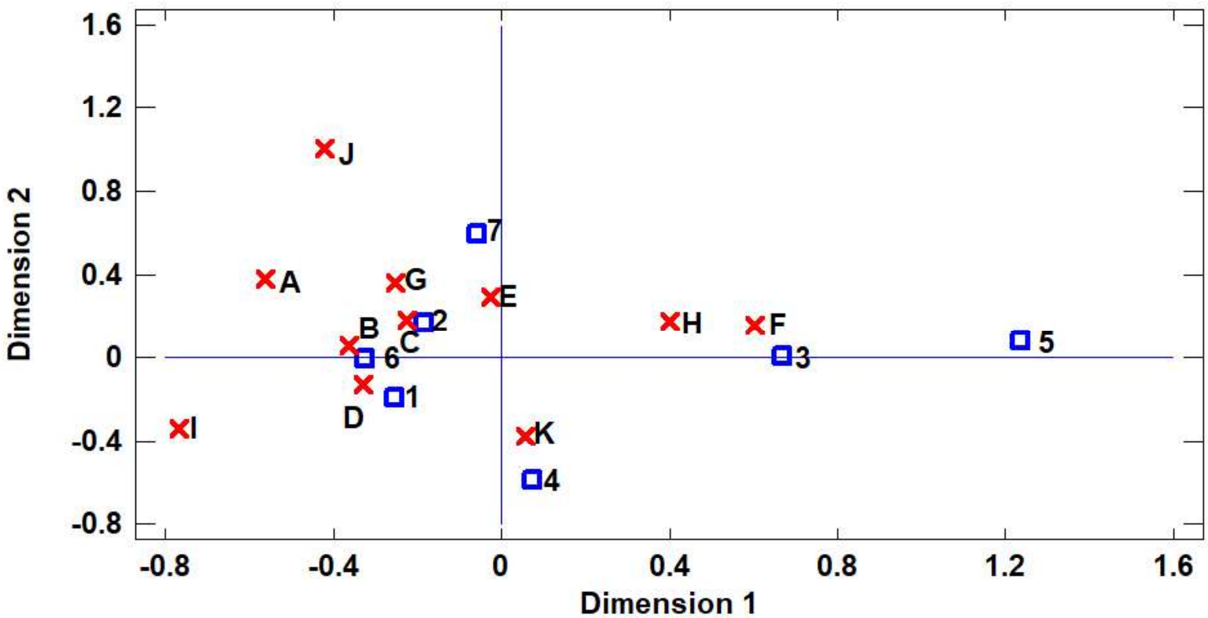


Figure 9. Correspondence plot between robot type and operations. (where 1: Operation specific robots; 2: Multi-purpose robots; 3: Monitoring robots; 4: Autonomous tractors; 5: Autonomous UAS; 6: Greenhouse robots; 7: Robotic implements; A: Planting and Sowing; B: Harvesting and Picking; C: Mechanical Weeding; D: Spraying; E: Fertilization; F: Crop-scouting; G: Pruning; H: Irrigation; I: Pollination; J: Soil preparation; K: Navigation)

3.3.2 Robot locomotion and Operations

Regarding the correspondence between locomotion of agricultural robots and operations (Figure 10), it is evident that wheeled, pulled/carried, and legged-type robots presented strong correspondence with most of the operations except pollination and pruning. This can be explained by the fact that these systems can offer increased mobility [81]. Moreover, tracked robots presented strong correspondence with navigation, soil preparation, spraying, and mechanical weeding. Tracked systems can offer lower compaction and better traction on flat fields as well as on fields with high slopes, which are needed for these operations [81]. On rails robots presented strong correspondence with pruning. This can be justified by the fact that the studies included in the analysis were relevant to pruning of greenhouse crops (e.g., [91,136]). Finally, aerial systems did not present any strong correspondence with any operation. The reason for this is that aerial robots had limited occurrence in the analysis (e.g., [77,137–139]). This can be explained by the fact that many don’t consider UAS as robots and therefore were underrepresented in the reviewing searching process [140]. Moreover, the two dimensions of the analysis explain more than 74 % of the variance between the selected categories, indicating that a small portion of the insights are missing from the two-dimensional plot like in the previous case.

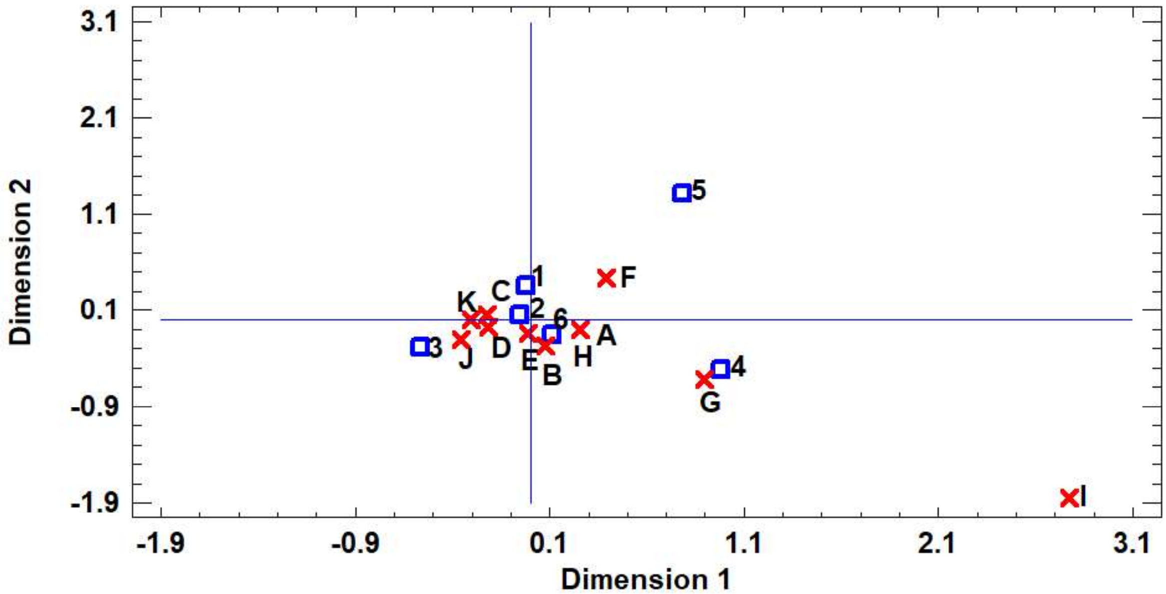


Figure 10. Correspondence plot between track type based robots and agricultural operations. (where 1: Legged; 2: Wheeled; 3: Tracked; 4: On rails; 5: Aerial; 6: Pulled/Carried; A: Planting and Sowing; B: Harvesting and Picking; C: Mechanical Weeding; D: Spraying; E: Fertilization; F: Crop-scouting; G: Pruning; H: Irrigation; I: Pollination; J: Soil preparation; K: Navigation)

3.3.3 End-effectors and Operations

As presented in Figure 11, there was strong correspondence between spraying end-effectors with spraying operations, sensors and cameras end-effectors with navigation and crop scouting, cultivation tools with soil preparation, and cutting tools with mechanical weeding. These results are logical considering the specialized use of these end-effectors for the corresponding operations. Additionally, correspondence was presented for gripper-type end-effectors with irrigation and harvesting and picking operations. The correspondence of gripper with irrigation can be justified by the limited number of studies that were included in the analysis [141–143] while many others presented the use of grippers for harvesting and picking operations (e.g., [66,71,89,92,93,95,107,144,145]. Based on the aforementioned, it is evident that there is specialization among the end-effector types and the operations. This can be justified by the fact that the different agricultural operations exhibit different requirements, and therefore a generic solution cannot be applied due to more complicated hardware and software designs [49]. Regarding the variance, the two dimensions of the analysis explain only 61 % of the variance between the selected categories, indicating that additional dimensions should also be considered to better identify insights between end-effectors and operations.

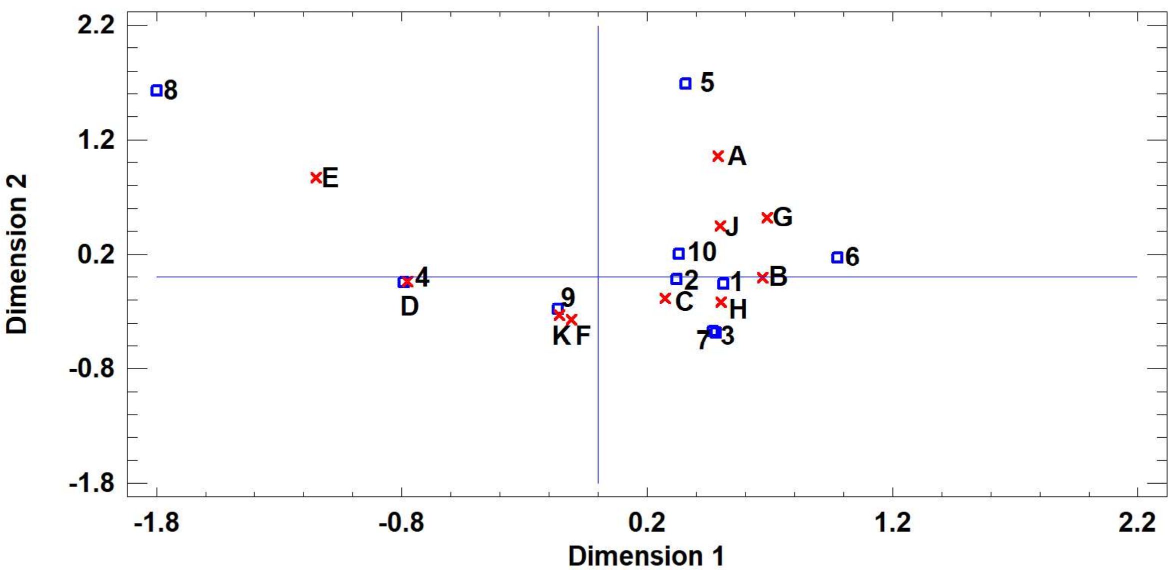


Figure 11. Correspondence plot between end-effector type and agricultural operations. (where 1: Grippers; 2: Cutting tools; 3: Vacuum or Suction-based End-effectors; 4: Spraying Systems; 5: Drilling and Planting Tools; 6: Harvesting Tools; 7: Laser Tools; 8: Fertilization; 9: Sensors and Cameras on End effectors; 10: Cultivators; A: Planting and Sowing; B: Harvesting and Picking; C: Mechanical Weeding; D: Spraying; E: Fertilization; F: Crop-scouting; G: Pruning; H: Irrigation; I: Pollination; J: Soil preparation; K: Navigation)

3.3.2 HRI and Operations

Regarding the correspondence analysis between HRI and operations, the results presented strong correspondence between full collaboration with pruning, no collaboration and coexistence with navigation, and physical collaboration with harvesting and picking (Figure 12). Pruning can be considered a very complicated process, the automation of which began recently. Therefore, a lot of processes like working under different environments, accuracy, and trajectory planning must be improved to realize full automation [146]. The results regarding the navigation indicate that fully autonomous robots are preferable while there is no need for interaction with humans during this task. As stated by other authors, autonomous navigation is considered very mature and a key operation for the automation of all agricultural operations [147,148]. Regarding harvesting and picking and the corresponding HRI level, this can be justified by the fact that although this task has been significantly automated, this technology can be considered relatively immature while there is big uncertainty and variation in agriculture. Therefore, physical collaboration of robots with humans can be considered as an intermediate step until full automation of this process is realized [149]. Finally, the two dimensions of the analysis explain more than 68 % of the variance between the selected categories, indicating that additional dimensions should also be considered to better identify insights between HRI and operations.

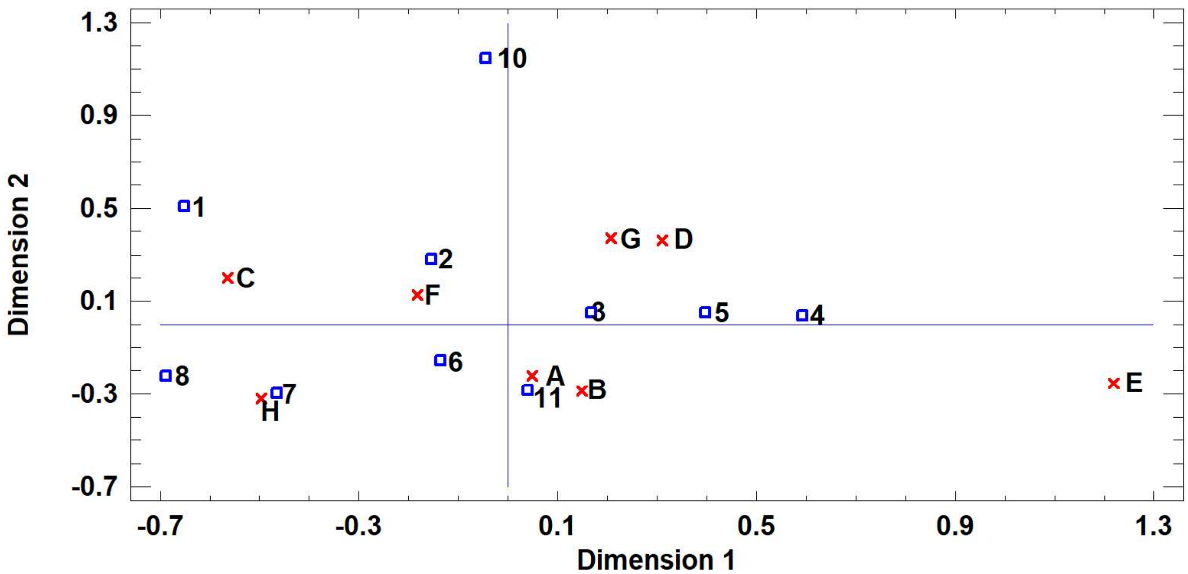


Figure 12. Correspondence plot between collaboration level and agricultural operations. (where 1: Planting and Sowing; 2: Harvesting and Picking; 3: Mechanical Weeding; 4: Spraying; 5: Fertilization; 6: Crop-scouting; 7: Pruning; 8: Irrigation; 9: Pollination; 10: Soil preparation; 11: Navigation; A: No Collaboration; B: Coexistence; C: Sequential Collaboration; D: Cooperation; E: Synchronized Collaboration; F: Physical Collaboration; G: Shared Control; H:Full Collaboration)

3.4 Study Limitations

The main limitations of this study include the five-year period that was selected for analysis and the application of the research queries only to titles. These restriction were selected to limit the results to contemporary and highly focused research on the topics of robotics and XR in agriculture due to the fact that these topics are gaining high attention and new research is presented in high frequency [31,47,51,82,108,109,150,151]. Also, many studies did not take into account all the topics addressed in this study. This had as a result that not all studies could be used in the correspondence analysis, leading to potential inaccuracy of the results with the current trends.

4. Conclusions

Robotics and XR in agriculture are gaining increasing attention in recent years. The coupled use of these technologies can significantly contribute to the mitigation of existing problems in agriculture like labour shortage and ageing. In this manuscript, 210 research articles were analysed under the scope of robotics and XR as well as HRI. According to the results, operation-specific and wheeled robots presented the highest frequency. Moreover, camera types were the mainly used devices both for active monitoring as well as end-effectors. Also, MR was the prevalent XR type used in the studies, with monitors being the main devices for interaction and display with the robots. The prevalent HRI level was no collaboration, and collision avoidance was the main safety feature that was included in the limited number of studies that referred to these components.

Regarding the correspondence analysis, operations with high demand in accuracy or frequency or labour (e.g., harvesting and picking, spraying and crop scouting) were connected with robots that were developed for a single operation or a specific environment, whereas multipurpose robots were connected with operations that have lower complexity and repetitiveness during a crop season. Also, most operations demand high mobility, and therefore wheeled, legged or pulled-carried robots are preferable, while tracked robots were connected with operations with high frequency (e.g., spraying) or need for better traction (e.g., soil preparation, navigation, mechanical weeding). It is worth noticing that UAS were underrepresented in the study due to the query limitations. Moreover, end-effectors were specialized for each operation (e.g., spraying end-effectors with spraying operations, sensors and cameras end-effectors with navigation and crop scouting, cultivation tools with soil preparation) indicating that generic end-effector technologies are not preferred for agriculture. Additionally, full automation is more prevalent in operations of low complexity (e.g., navigation) while more complicated operations like pruning, and harvesting and picking still demand collaboration between humans and robots to be performed.

Future studies should focus on the development of agricultural robots that exhibit a higher level of automation and can be applied to various operations to limit cost as well as in homogeneous and heterogeneous robotic fleets. Also, the use of MR should be further investigated along with the use of other interaction devices for control (e.g., voice control). Finally, safety features like cyber security, connectivity and data governance types should also be studied to further improve automation of agricultural robots as well as HRI.

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CRediT authorship contribution statement

Evangelos Anastasiou: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Supervision; **Georgios Ntakos:** Writing – original draft, Methodology, Investigation, Data curation; **Eirini Kanakari:** Writing – original draft, Visualization, Investigation, Data curation; **Stella Bitsika:** Investigation, Data curation; **Marilena Gemtou:** Writing – review & editing, Investigation, Data curation; **Manolis Katsaragakis:** Investigation, Data curation; **Dimitrios Soudris:** Investigation, Data curation; **Elvira-Maria Arvanitou**: Investigation, Data curation; **Maria-Theodora Folina:** Investigation, Data curation; **Thodoris Maikantis:** Investigation, Data curation; **Elisavet-Persefoni Kanidou:** Investigation, Data curation; **Maria Fountouli:** Investigation, Data curation; **Christina Volioti:** Investigation, Data curation; **Apostolos Ampatzoglou:** Investigation, Data curation; **Nikolaos Tsiogkas:** Investigation, Data curation; **Andrés Villa-Henriksen:** Investigation, Data curation; **Søren Marcus Pedersen:** Investigation, Data curation; **Tseganesh Wubale Tamirat:** Investigation, Data curation; **Annalisa Milella:** Investigation, Data curation; **Soussana Simopoulou:** Investigation, Data curation; Project Administration; **Gregory Mygdakos:** Investigation, Data curation; Project Administration; **Spyros Fountas:** Writing – review & editing, Conceptualization, Supervision

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used QuillBot in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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