sustainability

MDPI

Article

Adapting to the Agricultural Labor Market Shaped by Robotization

Vasso Marinoudi [1,2], Lefteris Benos [3], Carolina Camacho Villa [1], Maria Lampridi [2,3], Dimitrios Kateris [3,*], Remigio Berruto [4], Simon Pearson [1], Claus Grøn Sørensen [5] and Dionysis Bochtis [2,3]

1 Lincoln Institute for Agri-Food Technology (LIAT), University of Lincoln, Lincoln LN6 7TS, UK; v.marinoudi@farm-b.com (V.M.); ccamachovilla@lincoln.ac.uk (C.C.V.); spearson@lincoln.ac.uk (S.P.)
2 farmB Digital Agriculture S.A., Dekatis Evdomis (17th) Noemvriou 79, 55534 Thessaloniki, Greece; m.lampridi@certh.gr (M.L.); d.bochtis@certh.gr (D.B.)
3 Institute for Bio-Economy and Agri-Technology (IBO), Centre of Research and Technology-Hellas (CERTH), 57001 Thessaloniki, Greece; e.benos@certh.gr
4 Interuniversity Department of Regional and Urban Studies and Planning, Viale Matttioli 39, 10125 Torino, Italy; remigio.berruto@unito.it
5 Department of Electrical and Computer Engineering, Aarhus University, DK-8000 Aarhus, Denmark; claus.soerensen@ece.au.dk
* Correspondence: d.kateris@certh.gr

Abstract: Agriculture is being transformed through automation and robotics to improve efficiency and reduce production costs. However, this transformation poses risks of job loss, particularly for low-skilled workers, as automation decreases the need for human labor. To adapt, the workforce must acquire new qualifications to collaborate with automated systems or shift to roles that leverage their unique human abilities. In this study, 15 agricultural occupations were methodically mapped in a cognitive/manual versus routine/non-routine two-dimensional space. Subsequently, each occupation's susceptibility to robotization was assessed based on the readiness level of existing technologies that can automate specific tasks and the relative importance of these tasks in the occupation's execution. The qualifications required for occupations less impacted by robotization were summarized, detailing the specific knowledge, skills, and work styles required to effectively integrate the emerging technologies. It was deduced that occupations involving primary manual routine tasks exhibited the highest susceptibility rate, whereas occupations with non-routine tasks showed lower susceptibility. To thrive in this evolving landscape, a strategic combination of STEM (science, technology, engineering, and mathematics) skills with essential management, soft skills, and interdisciplinary competences is imperative. Finally, this research stresses the importance of strategic preparation by policymakers and educational systems to cultivate key competencies, including digital literacy, that foster resilience, inclusivity, and sustainability in the sector.

Keywords: Occupational Information Network (O*NET) system; process automation; technological substitution/complementarity; agricultural workforce capacity-building

Citation: Marinoudi, V.; Benos, L.; Camacho Villa, C.; Lampridi, M.; Kateris, D.; Berruto, R.; Pearson, S.; Sørensen, C.G.; Bochtis, D. Adapting to the Agricultural Labor Market Shaped by Robotization. *Sustainability* **2024**, *16*, 7061. https://doi.org/10.3390/su16167061

Academic Editors: Nan Sun and Kun Cheng

Received: 9 July 2024
Revised: 8 August 2024
Accepted: 15 August 2024
Published: 17 August 2024

1. Introduction

Currently, the labor landscape is changing due to technological advancements and digitalization, including innovations like the internet of things (IoT), artificial intelligence (AI), big data analytics, and robotics. The recent COVID-19 pandemic accelerated digitalization, remarkably impacting the agricultural workforce [1,2]. Research efforts have intensified to analyze the key trends influencing labor markets and the necessary skills for professionals to navigate this transition effectively [3–5]. Key trends include automation's impact on job destruction and task modification within occupations [6,7]. Specifically, automation is shifting tasks from physical and repetitive to social and intellectual, and creating new roles, such as data management and robotics maintenance. This shift generates a series of emerging phenomena in the labor landscape like job polarization, where both high- and low-skill jobs are growing, while middle-skill positions decline. This is accompanied by wage and working condition polarization, and reduced job stability [8]. Additionally, knowledge work in services is becoming more standardized, while new employment practices including teleworking and digital platforms are emerging, favoring high-skilled workers and offering global talent access [9]. These changes often lead to unstable, on-demand jobs with income insecurity [10].

To address these disruptions, a mindset of lifelong learning is essential. Individuals need to engage in up-skilling (improving existing skills), re-skilling (learning new skills), multi-skilling (developing skills in interrelated domains), and cross-skilling (combining skills applied in different domains for the purpose of having a broader perspective) to remain relevant [11,12]. In the context of a dynamic labor market, individuals should manage by themselves their careers through continuously acquiring new knowledge and mastering skills that are in demand at a high speed. In brief, knowledge is related to theory, while skills are associated with practice and developed trait through experience, with the link between them being competencies [13]. Skills needed span from technical to socioemotional [14], with high-order cognitive and socioemotional skills, known as "new economy skills", offering better job prospects and conditions [15]. Considering the policy at an international level for greening economies, "green" skills are also increasingly important for sustainable practices.

In this evolving labor market, the agricultural sector is increasingly integrating advanced robotics and computerization, which are not only handling repetitive and physically demanding tasks but also performing non-routine tasks requiring cognitive abilities [16]. As a consequence, a gradual transition from humans to robots is apparent, while simultaneously, new strategies are emerging to foster complementarity between humans and robots [17,18]. In particular, the landscape of the agricultural labor market is undergoing a profound transformation. This shift towards automation not only boosts productivity and efficiency, but also necessitates a reassessment of the key skills required in this volatile labor market. The necessity for continued education has been recognized in the relevant literature on the transition towards more sustainable and digitized agricultural systems [19–24]. The results of the related literature converge in five broad categories of qualifications [13]: (a) lifelong learning: continuous learning is essential, extending beyond formal education to everyday engagement with new technologies and labor market changes; (b) systems perspective: understanding the complexities of diverse agricultural systems [24], expanding beyond basic competencies to include the broader scope of Agriculture 4.0 [25]; (c) knowledge integration: combining interdisciplinary knowledge from both scientific and practical farmer experience to bridge theoretical and empirical gaps; (d) subject-specific technical knowledge: updated technical expertise is required to meet the demand for efficiency, safety, and sustainability in agriculture [26,27]; (e) building and maintaining networks: engaging in learning communities and networks to share knowledge, foster new ideas, and include diverse perspectives, including those from outside the agricultural sector [28].

The common denominator of the practices applied in the above studies for investigating the most valuable skills was group discussions and interviews. Moreover, secondary data from previous surveys have been integrated to summarize the content of the skill set that different worker groups should develop. Nevertheless, in order to identify the key qualifications required for individuals to adapt in the evolving landscape of the agricultural labor market considering the advancements in automation, a systematic methodological approach is needed. To this end, this study initially selects the occupations purely associated with crop and livestock production. Subsequently, each agricultural occupation is decomposed into the various tasks it involves. The scope is the mapping of the selected occupations in a routine/non-routine versus cognitive/manual two-dimensional (2D) space and an evaluation of their susceptibility to robotization. As a final point, focusing on the less susceptible to robotization occupations, the most important sets of knowledge, skills, and work styles are summarized.

To address the objectives of the present study, the methodology used by Marinoudi et al. [29] was adopted, where 17 agricultural occupations were mapped with respect to their routine/non-routine and cognitive/manual nature, while their susceptibility to robotization was also assessed. In comparison with [29], the updated version of the O*NET Online tool [30] was used in the present study, where some occupations were either integrated into other occupations or the number and the content of the tasks they encompass were modified. Furthermore, two new agricultural occupations were added for the sake of completeness. Finally, the present analysis utilized the expansive database of O*NET, also encompassing a diverse array of qualifications necessary for executing tasks within the selected occupations. Leveraging this tool enabled us to assess both the importance and proficiency level associated with each qualification, thereby facilitating a systematic quantification of our findings. This study's outcomes highlight the urgent need for targeted skill development and policy interventions, making it a valuable contribution to managing the impacts of technological change in the agricultural sector, a challenging sector due to its reliance on traditional practices and manual labor. To the best of our knowledge, this is the first instance in the pertinent literature where such quantification has been achieved.

2. Materials and Methods

2.1. Reviewed Occupations

As mentioned above, the O*NET-SOC system was implemented for this work, a database that contains 1016 occupational titles categorized in broadly defined occupations. This classification system defines occupations in the context of their content, tasks, technology skills, and work activities, in conjunction with the required worker qualifications, and integrates them into a functional system. The required information is gathered statistically directly from a random sample of workers at business establishments via standardized questionnaires and is continually updated. The open-source online tool of O*NET is used by a broad range of audiences for career development, public policy, and research.

As far as the present analysis is concerned, 15 agricultural occupations were selected. Their O*NET-SOC title, code, comparison with [29], as well as the number of tasks, knowledge, skills, and work styles are summarized in Table 1.

Overall, compared to [29], two new occupations have been added, namely, "Precision Agriculture Technicians" (19-4012.01) and "Farm and Home Management Educators" (25-9021.00). The remaining 13 occupations resulted from either merging previous occupations into a broader category, augmenting the existing tasks, or maintaining the same code and tasks. For the sake of clarity, Figure 1 provides a schematic comparison of changes in the examined occupations between the current study (green) and the previous study [29] (orange).

Table 1. Summary of the 15 reviewed occupations accompanied by the O*NET 8-digit code, comparisons with [29], as well as number of tasks, knowledge, skills, and work styles, according to [30].

O*NET-SOC 2019 Title	O*NET Code	Comparison with [29]	Tasks	Knowledge	Skills	Work Styles
Farmers, Ranchers, and Other Agricultural Managers	11-9013.00	New code (resulting from the merger of "Nursery and Greenhouse Managers" (11-9013.01) and "Farm and Ranch Managers" (11-9013.02))	30	13	20	16
Farm Labor Contractors	13-1074.00	Same code; same tasks	8	7	8	15
Agricultural Engineers	17-2021.00	Same code; 1 task added	14	16	23	15
Animal Scientists	19-1011.00	Same code; same tasks	9	10	22	15
Soil and Plant Scientists	19-1013.00	Same code; 7 tasks added	27	12	19	15
Agricultural Technicians	19-4012.00	New code (resulting from "Agricultural Technicians" (19-4011.01)); 1 task added	26	11	14	16

Table 1. *Cont.*

O*NET-SOC 2019 Title	O*NET Code	Comparison with [29]	Tasks	Knowledge	Skills	Work Styles
Precision Agriculture Technicians	19-4012.01	New occupation and code	22	13	15	15
Farm and Home Management Educators	25-9021.00	New occupation and code	15	9	20	16
First-Line Supervisors of Farming, Fishing, and Forestry Workers	45-1011.00	New code (resulting from the merger of "First-Line Supervisors of Agricultural Crop and Horticultural Workers" (45-1011.07) and "First-Line Supervisors of Animal Husbandry and Animal Care Workers" (45-1011.08))	30	9	22	16
Agricultural Inspectors	45-2011.00	Same code; Same tasks	22	7	15	16
Graders and Sorters, Agricultural Products	45-2041.00	Same code; 1 task added	6	3	0 *	8
Agricultural Equipment Operators	45-2091.00	Same code; same tasks	17	1	7	16
Farmworkers and Laborers, Crop, Nursery, and Greenhouse	45-2092.00	New code (resulting from the merger of "Agricultural Equipment Operators" (45-2092.01) and "Farmworkers and Laborers, Crop" (45-2092.02))	30	0 *	2	16
Farmworkers, Farm, Ranch, and Aquacultural Animals	45-2093.00	Same code; same tasks	22	7	11	15
Farm Equipment Mechanics and Service Technicians	49-3041.00	Same code; 1 task added	14	8	15	16

* Did not meet the minimum required O*NET threshold.

Figure 1. Schematical presentation of O*NET changes in occupations definitions and number of tasks; previous O*NET version (orange, used in [29]) versus updated version (green, this study). Circles denote the number of tasks related to each occupation, with added tasks indicated above the corresponding arrows.

As can be seen in Figure 2, out of the fifteen reviewed occupations listed in Table 1, six of them come from "Farming, Fishing, and Forestry", and four from "Life, Physical, and Social Science" major groups of occupations. Furthermore, there is a single representation from each of the following categories: "Management", "Business and Financial Operations", "Architecture and Engineering", "Educational Instruction and Library", and "Installation, Maintenance, and Repair". This distribution clearly demonstrates the heterogeneity of the contemporary agricultural domain, which is built on diverse actors' experiences and knowledge towards adapting to the current market needs and challenges.

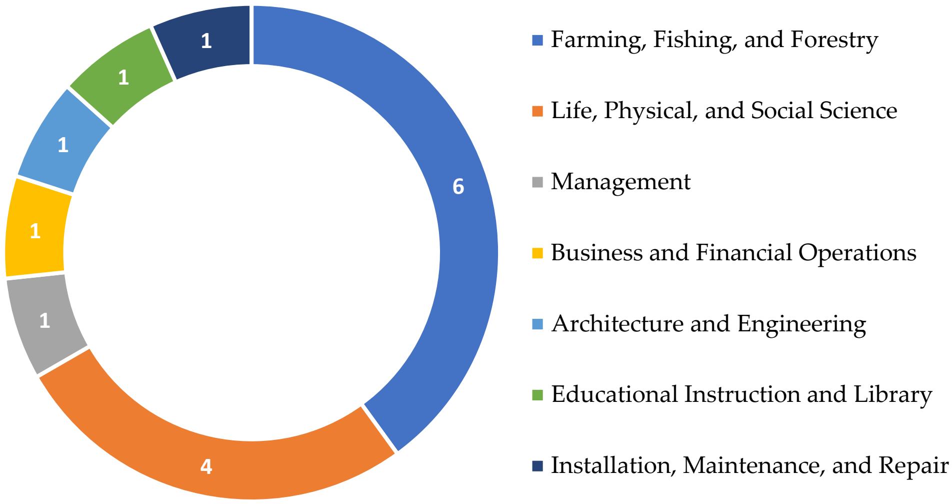


Figure 2. Distribution of the 15 reviewed occupations based on the major group classification of [31].

2.2. Occupation Mapping and Susceptibility to Robotization Rating

This part of the present work follows the methodology developed in [29] and refers, as a first step, to the mapping of the occupations in a 2D graph on the basis of their nature of work, and, as a second step, to the assessment of the level of susceptibility to robotization for each occupation. The methodology is summarized below.

The tasks of an occupation can be classified as (a) manual routine; (b) manual non-routine; (c) cognitive routine; and (d) cognitive non-routine. The distinction between "cognitive" and "manual" refers to the type of mental or physical effort required for a task, respectively, while "routine" and "non-routine" refer to the involving standardized or non-standardized activities, respectively. Having all the related occupations integrated in a common 2D graph—the vertical axis representing the cognitive versus manual nature of the occupation, and the horizontal axis the non-routine versus routine nature—is particularly important in light of examining possible human–machine substitution or complementarity [29,32].

In the initial step, the importance of each individual task within an occupation is assessed by assigning an "importance weight". This weight is derived from the average results of a series of participatory interviews conducted with professionals in agricultural occupations. Each interviewed professional rates the importance of the task within the occupation using the following scale: (a) not important: Score 1; (b) slightly important: Score 2; (c) important: Score 3; (d) very important: Score 4; (e) strongly important: Score 5.

After rating the "importance" of each individual task within the occupation, the process of indexing the nature of each task is conducted. Assessors assign values from the set [0, 0.25, 0.5, 0.75, 1] to each task to quantify the contribution of cognitive routine, cognitive non-routine, manual routine, and manual non-routine attributes to the execution of the task. These values must sum to 1 for each task. The cognitive/manual balance for a task is calculated by summing the values of the cognitive routine and cognitive non-routine indexes and subtracting the values of the manual routine and manual non-routine indexes. The cognitive/manual balance for an occupation (corresponding to the

y-coordinate of the occupation in the 2D graph, I^{C-M}) is then determined by summing the cognitive/manual balances of each task, each weighted by the importance of the task. Analogously, the routine/non-routine balance for a task is calculated by summing the values of the cognitive non-routine and manual non-routine indexes and subtracting the values of the cognitive routine and manual routine indexes. The routine/non-routine balance for an occupation (corresponding to the x-coordinate of the occupation in the 2D graph, I^{R-nR}) is then determined by summing the routine/non-routine balances of each task, each weighted by the importance of the task.

Next, an overall normalized susceptibility rate to robotization, $\hat{s}_i$, is calculated. The rating refers to three scores, namely: (a) Score 0: there is no technology at technology readiness level (TRL) 3 or higher demonstrated, or there is no reasonable indication that the task can be computerized or robotized in the short- or mid-term future; (b) Score 0.5: a significant part (or parts) of the task can be computerized or robotized; and (c) Score 1: there is an existing technology or a technology under development at least at TRL 3 that can be implemented for the execution of the task. Tasks with a score of 0.5 are typically subject to transformation, often evolving into roles that require human–machine collaboration, where human oversight complements automated processes. In contrast, tasks with a score of 1 are predominantly automated or replaced entirely by machines, resulting in a more significant shift towards full automation [33].

Towards providing a clearer understanding of the technologies being addressed, several robotics and automation technologies relevant to the agricultural sector are considered indicatively, including (a) self-driving vehicles, like tractors, which can perform tasks like plowing and seeding with high precision [34]; (b) robotic harvesters, such as strawberry-picking robots and grape harvesters, which are equipped with advanced sensors to minimize manual involvement [35]; (c) automated irrigation systems that use IoT sensors and AI to optimize water usage by monitoring soil moisture and weather conditions [36]; (d) unmanned aerial (UAV) and ground vehicles (UGV), which include drones for aerial crop monitoring, weed detection, and field mapping, as well as ground robotic systems for soil sampling, autonomous equipment transport, and various maintenance tasks such as harvesting and applying fertilizers or pesticides [37]; (e) computerized systems, which manage logistics, inventory, and distribution of agricultural products, thus reducing the need for manual coordination and tracking [38]; and (f) machine learning models, which analyze data from soil sensors, weather forecasts, and UAV and satellite imagery to detect diseases early, predict crop yields, and optimize farming practices [39]. These technologies collectively drive the transformation in agriculture, enhancing efficiency while reducing the demand for manual labor.

The overall susceptibility rating of an occupation results as the weighted—in terms of the task importance—average value of the tasks it contains. These values classify the occupations into three zones:

- The "green zone", which denotes a very low potential to robotization, $\hat{s}_i \in [0,\ 0.33)$;
- The "yellow zone", which represents a low to medium potential to robotization, $\hat{s}_i \in\ [0.33\,,\ 0.66)$;
- The "red zone", which signifies a very high potential to robotization, $\hat{s}_i \in\ [0.66\,, 1]$.

The values of the aforementioned coefficients, regarding the level of importance, the nature of each task, and the level of susceptibility to robotization, were independently provided by the assessors. A consensus tele-meeting of the authors was held for the sake of resolving any disagreement of opinion and evaluating the final scores. The assessors possessed proven knowledge in a wide range of scientific areas, such as agricultural robotics, human–robot interaction, precision agriculture, operations management, logistic operations, sustainability assessment, informatics, and AI, to mention but a few. The score scales used in this analysis could be considered arbitrary, as any other scales could be applied. This may introduce biases inherent to that dataset. However, by incorporating the critical opinion of a group of assessors and professionals, coming from multidisciplinary research fields and labor categories, this study aimed to mitigate potential biases and provide a more comprehensive understanding of the subject matter by shedding light on the labor market trends in the agricultural sector.

2.3. Investigation of the Most Required Qualifications to Cope with Robotization

The second aspect of this work deals with the filtering of a wide range of qualifications related to the occupations engaged in agricultural sector. For this scope, for each occupation, the required set of knowledge, skills, and work styles was considered as listed and described in the O*NET database. Specifically, these categories concern the following:

- Knowledge: related to knowledge of principles and methods of different disciplines, such as mathematics, chemistry, and management;
- Skills: contains a variety of skills, including, indicatively, critical thinking, identifying the reasons behind operational errors, and system analysis;
- Work styles: This set includes several personal characteristics, such as stress tolerance, leadership, and concern for others.

For the purpose of quantifying our analysis, the "importance" and "level" ratings for each qualification were also considered, as they have been identified in O*NET by occupational analysts according to established protocols for reviewing the occupational information. The importance rating spans from 0 (signifying insignificance or irrelevance to the occupation in question) to 100 (indicating utmost importance). Likewise, the level rating ranges from 0 to 100, representing the degree of proficiency, with higher scores indicating greater expertise or mastery. The final category of work styles, commonly referred to as "soft skills", could not be assessed for proficiency level due to the unavailability of data. Therefore, only their importance was considered.

In order to determine the essential qualifications needed to adapt to robotization, our analysis focused on the occupations belonging to the "green zone", which corresponds to the low susceptibility to robotization, as was elaborated in Section 2.2. In particular, overall normalized values were calculated based on the following:

$$\text{Overall normalized importance}: \ \hat{I}_i = \sum_{i=1}^{n} \frac{I_i}{100 \cdot \text{n}} \longrightarrow [0,1], \tag{1}$$

$$\text{Overall normalized level}: \ \hat{L}_i = \sum_{i=1}^{n} \frac{L_i}{100 \cdot \text{n}} \longrightarrow [0,1], \tag{2}$$

where n stands for the total number of occupations with a very low susceptibility rate, while I_i and L_i represent the importance and level rating of the ith occupation, respectively. Finally, upon consolidating all the necessary qualifications, our analysis results in the most significant ones, specifically those with an overall normalized importance rating of 0.5 or higher, in accordance with the importance rating guidelines outlined by O*NET.

3. Results

Subsequently, in Section 3.1, the mapping of the 15 reviewed occupations in the cognitive/manual versus routine/non-routine 2D space is described in conjunction with their susceptibility rate to robotization. In Section 3.2, each category of qualifications (i.e., knowledge, skills, and work styles) is separately scrutinized to delve into the specific intricacies associated with each category.

3.1. Occupation Mapping in Terms of Their Cognitive/Manual and Routine/Non-Routine Nature and Susceptibility Rate to Robotization

The coefficients l_i^{R-nR} and l_i^{C-M} are firstly calculated that correspond to the horizontal and vertical coordinates, respectively, of a 2D graph representing the virtual cognitive/manual versus routine/non-routine space according to the methodology described in Section 2.2. The occupations belonging to the first quadrant of the graph depicted in Figure 3 are those of a cognitive non-routine nature, which correspond to positive values of both l_i^{C-M} and l_i^{R-nR}. In contrast, the occupations situated within the third quadrant are those of a manual routine nature, which correlates to negative values of both l_i^{C-M} and l_i^{R-nR}. Combination of positive l_i^{C-M} values and negative l_i^{R-nR} values represents occupations of the second quadrant, being of cognitive routine nature. Finally, the combination of negative l_i^{C-M} values and positive l_i^{R-nR} values represents occupations of the fourth quadrant, being of manual non-routine nature. To enhance the information content within the graph in Figure 3, the susceptibility rate to robotization for each occupation is also included. In brief, the "green zone" denotes a very low rate of susceptibility to robotization, the "yellow zone" signifies a medium to high susceptibility rate, and the "red zone" represents a very high susceptibility rate. In addition, the sizes of the circles are proportional to the susceptibility rate to robotization.

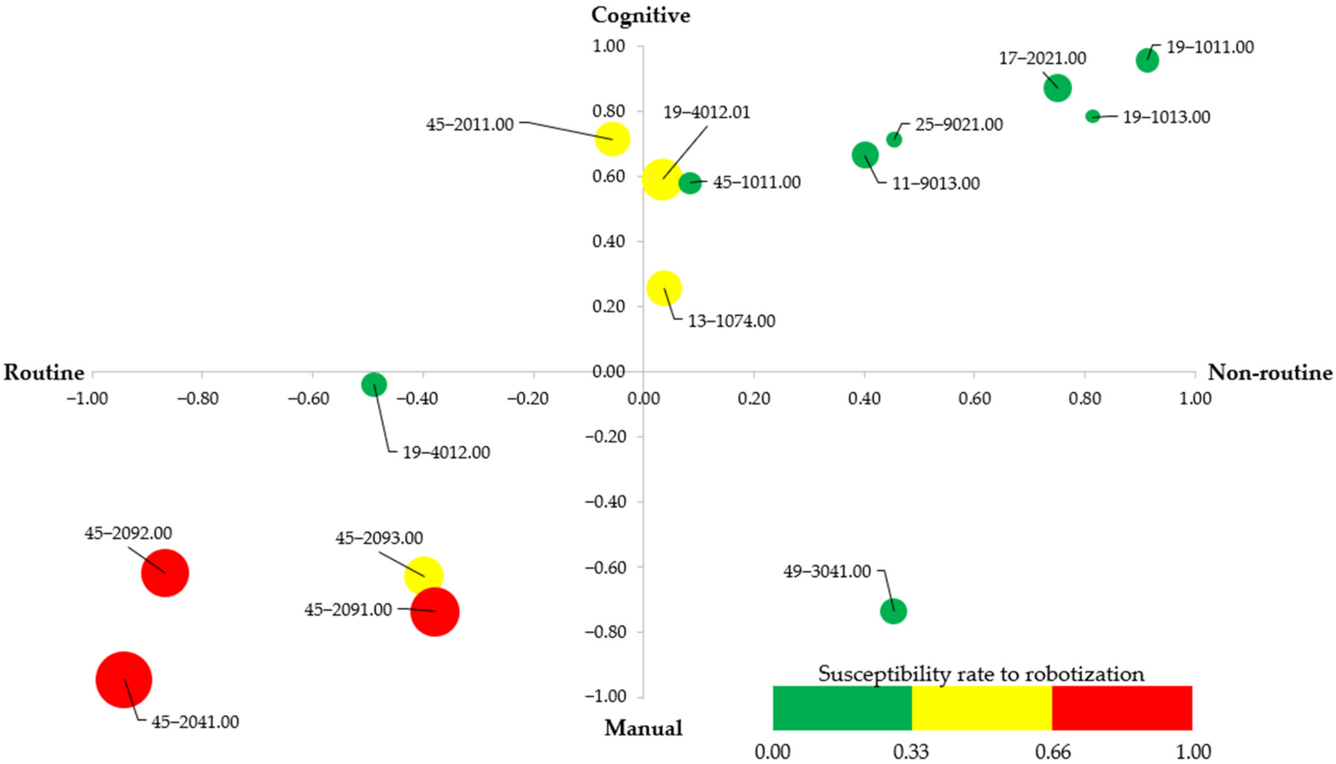


Figure 3. Mapping of the estimated cognitive/manual versus routine/non-routine levels along with the susceptibility rate to robotization of the reviewed occupations.

As a representative example of the methodology described, consider the occupation of Animal Scientists (19-1011.00), which involves nine distinct tasks. Among these, the task of studying nutritional requirements of animals and nutritive values of animal feed materials was rated as "strongly important" (Score 5) due to its significant and direct impact on animal health and productivity. This task was predominantly classified as cognitive non-routine, receiving a value of 1 for this component, while the values for cognitive routine, manual routine, and manual non-routine attributes were all zero. Additionally, this task was assigned an average score of 0 for its potential to be robotized, indicating minimal susceptibility to robotization. After evaluating all tasks within the Animal Scientist occupation, the overall susceptibility to robotization was calculated as 0.17. The cognitive/manual coordinate (l^{C-M}) was determined to be 0.96, and the routine/non-routine coordinate (l^{C-M}) was 0.91. Based on these metrics, the occupation was positioned in the first quadrant of the 2D graph and classified within the "green zone", indicating very low susceptibility for robotization.

Based on the present methodology, the occupation that appeared to be mostly susceptible to robotization was "Graders and Sorters, Agricultural Products" (45-2041.00; $\hat{s}_i = 0.92$), whose responsibilities indicatively involve grading, sorting, and classifying agricultural products by condition, color, size, and weight. Obviously, all the responsibilities include mainly manual and routine tasks and, therefore, the occupation was placed in the third quadrant. The other four occupations of this quadrant are "Agricultural Equipment Operators" (45-2091.00; $\hat{s}_i = 0.71$), "Farmworkers and Laborers, Crop, Nursery, and Greenhouse" (45-2092.00; $\hat{s}_i = 0.67$), "Farmworkers, Farm, Ranch, and Aquacultural Animals" (45-2093.00; $\hat{s}_i = 0.46$), and "Agricultural Technicians" (19-4012.00; $\hat{s}_i = 0.21$). Similarly, the first three occupations include primarily manual routine tasks usually carried out with the use of hand tools so as to cultivate, harvest, and prune crops or apply fertilizers and pesticides. These tasks have already been robotized to a great extent, at least in developed countries, although some of them, such as assessing the quality of a crop, identifying pests and weeds, as well as monitoring the work of seasonal workers, presupposes some cognitive skills. Furthermore, agricultural equipment operators, who have to control or drive equipment towards supporting agricultural operations, also carry out some cognitive tasks, which, however, now tend to be automated with the progress in AI. Interestingly, agricultural technicians (19-4012.00) were positioned near the boundary between cognitive and manual regions of the graph, primarily due to the distinct nature of their tasks compared to the occupations analyzed above. This difference is also reflected in the lower value of $\hat{s}_i$.

Only one occupation was found in the second quadrant, namely, that of "Agricultural Inspectors" (45-2011.00; $\hat{s}_i$ =0.36), which, although requiring mostly cognitive routine tasks, also necessitates a considerable contribution of non-routine aspects. Indicatively, an agricultural inspector has to document findings in reports and advise farmers on necessary corrective actions. It should be noted that the horizontal coordinate (l_i^{R-nR}) of this occupation was calculated equal to -0.06, demonstrating that the tasks it encompasses have a propensity for being non-routine in nature. Likewise, only one occupation was placed in the fourth quadrant, mainly containing manual tasks, however of non-routine nature, namely, "Farm Equipment Mechanics and Service Technicians" (49-3041.00; $\hat{s}_i = 0.21$). This occupation involves tasks such as diagnosis, adjustment, and repair of farm machinery like tractors, dairy equipment, and irrigation systems.

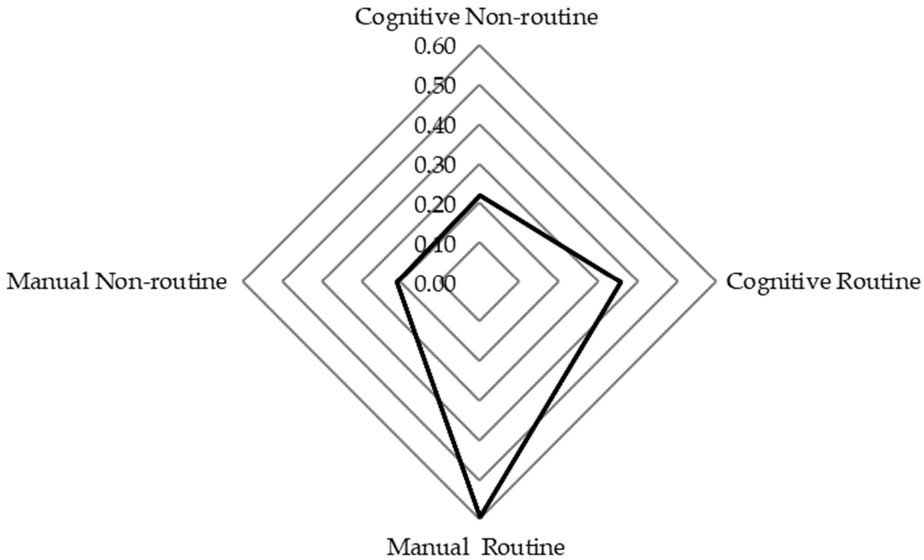
Remarkably, almost half of the reviewed occupations were placed in the first quadrant, encompassing occupations whose tasks are mainly of non-routine nature and require cognitive involvement. Nevertheless, some of them contain several routine processes. As a result, these occupations were placed in the left side of the first quadrant, because of its relatively low (positive) horizontal coordinate (l_i^{R-nR}). These two occupations are "Farm Labor Contractors" (13-1074.00; $\hat{s}_i = 0.37$) and "Precision Agriculture Technicians" (19-4012.01; $\hat{s}_i = 0.51$). Indicatively, the former occupation deals with recruiting and hiring seasonal workers as well as transporting and providing meals for them. The latter occupation involves applying geospatial technologies for management operations, like site-specific pesticide application and variable-rate irrigation. Very close to the vertical axis that separates routine from non-routine tasks is also "First-Line Supervisors of Farming, Fishing, and Forestry Workers" (45-1011.00; $\hat{s}_i = 0.15$), which encompasses supervising and coordinating the operations of agricultural workers.

In the upper right of the first quadrant, there are two occupations, namely, "Animal Scientists" (19-1011.00; $\hat{s}_i = 0.17$) and "Soil and Plant Scientists" (19-1013.00; $\hat{s}_i = 0.06$). As indicated by their name, these occupations may involve animal nutrition consultants and beef cattle specialists (Animal Scientists), as well as crop nutrition scientists, agronomists, and plant research geneticists (Soil and Plant Scientists). The very low susceptibility rate to robotization observed in these occupations is strongly related to the high order of cognitive non-routine skills required to perform their tasks, as will be discussed next. The list of occupations with strong non-routine nature also includes "Agricultural Engineers" (17-2021.00; $\hat{s}_i = 0.22$), which entails planning or coordinating policies, programs, and services, and identifying potential customers.

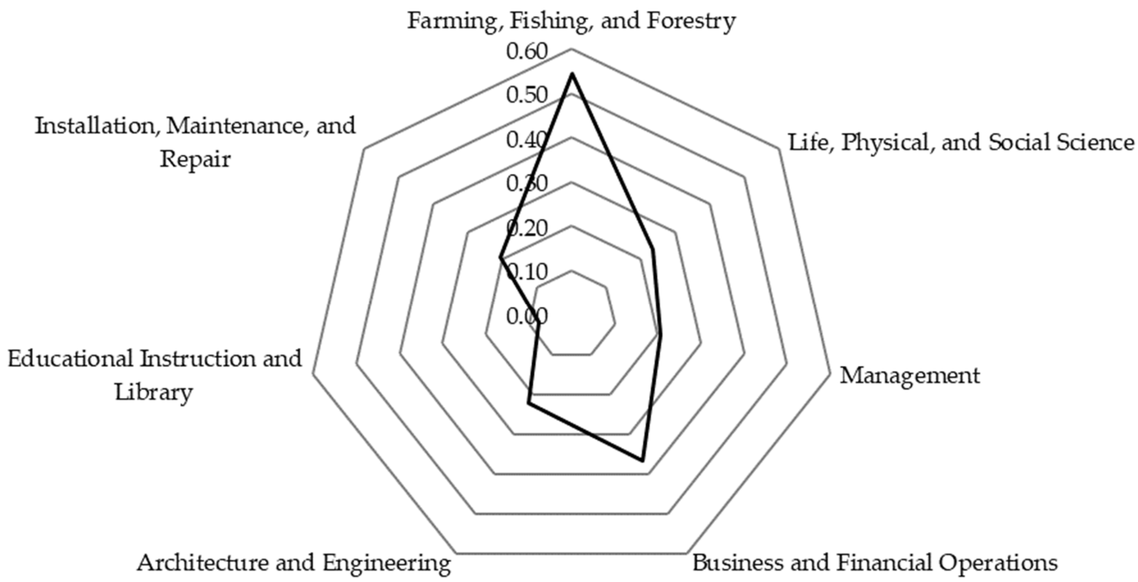
Finally, there are two occupations with l_i^{R-nR} between 0.4 and 0.5, namely, "Farmers, Ranchers, and Other Agricultural Managers" (11-9013.00; $\hat{s}_i = 0.21$) and "Farm and Home

Management Educators" (25-9021.00; $\hat{s}_i = 0.08$). These occupations are associated with management, involved in overseeing agricultural operations or providing education in farm management, respectively.

In conclusion, as expected, the occupations mainly involving tasks of routine nature exhibited a high susceptibility to robotization, as they follow well-defined sets of repetitive procedures. In particular, as can be seen in Figure 4a, the average susceptibility rate of manual routine occupations was found equal to 0.59, while the corresponding rate of cognitive routine occupations was 0.36. In contrast, non-routine occupations exhibit a lower average susceptibility rate, with cognitive non-routine occupations having 0.22 and manual non-routine ones having 0.21.



(**a**)



(**b**)

Figure 4. Spider charts showing the susceptibility rate to robotization in relation to (**a**) the task nature of an occupation and (**b**) major groups of occupations.

A similar analysis was conducted for the major occupational groups, as illustrated in Figure 4b. The analysis revealed that the six occupations within "Farming, Fishing, and Forestry" had the highest average susceptibility, equal to 0.55. This high susceptibility to robotization is primarily due to the routine nature of the activities involved in these occupations. Following, in descending order of average susceptibility, are "Business and Financial Operations" at 0.36, "Life, Physical, and Social Science" at 0.24, "Architecture and Engineering" at 0.22, and "Management" and "Installation, Maintenance, and Repair" both at 0.21. Notably, "Educational Instruction and Library" had the lowest average susceptibility, at 0.08. This low value can be attributed to the predominantly interactive nature of tasks in this field, which require critical thinking and personalized instruction, making them less susceptible to robotization.

3.2. Comparison of the Present Results with Those of Marinoudi et al. [29]

As compared with the findings of Marinoudi et al. [29], where the previous version of O*NET was used, the content of the tasks involved within five occupations remained the same (Figure 1). Hence, the position of these occupations in the updated cognitive/manual versus routine/non-routine graph of Figure 3, as well as the susceptibility rate to robotization, stayed unchanged. Two new occupations, namely, "Precision Agriculture Technicians" (19-4012.01) and "Farm and Home Management Educators" (45-1011.00), were added in the updated graph. These new entries were both placed in the first quadrant. Remarkably, the merger of the previous two management-related occupations into "Farmers, Ranchers, and Other Agricultural Managers" (11-9013.00) shifted the occupations from the second to the first quadrant. In addition, as can be seen in Table 2, they had an average $\hat{s}_i$ equal to 0.38 that decreased to 0.21 in the current analysis, owing to the new defined tasks. In this fashion, it should be stressed that the position of the previous management-related occupations was very close to the vertical axis dividing routine work from work non-routine in nature in [29].

Similarly, the merger of the previous two first-line supervisor-related occupations into "First-Line Supervisors of Farming, Fishing, and Forestry Workers" (45-1011.00) created an occupation located in the left side of first quadrant, having a slight decrease from an average $\hat{s}_i$ of 0.17 to 0.15 (Table 2). In the previous graph presented in [29], these occupations had been placed in the first and second quadrant. In contrast, the merger of the previous two occupations associated with manual routine labor resulted in placing the new integrated occupation of "Farmworkers and Laborers, Crop, Nursery, and Greenhouse" (45-2092.00) in an almost similar position in the third quadrant. Additionally, the new $\hat{s}_i$ was slightly reduced from an average 0.71 to 0.67.

In all other instances, as shown in Table 2, the inclusion of additional tasks within existing occupations led, most of the time, to a decrease in $\hat{s}_i$, varying according to the number of added tasks. This increase in responsibilities for the examined occupations caused a shift in their position on the graph mainly upwards and to the right. Consequently, more cognitive and non-routine tasks were incorporated as compared to [29]. Figure 5 offers a qualitative depiction of how agricultural occupations are evolving. Figure 5a,c correspond to the present study while Figure 5b,d to [29]. Focusing on the nearly identical contour plots of Figure 5a,b, which use equal intervals and three classes for $\hat{s}_i$, it is clear that occupations with low susceptibility to robotization (indicated by dark green) cover almost the entire first, second, and third quadrants. The prominence of dark green in the first quadrant emphasizes the difficulty of cognitive and non-routine tasks to be automated. The fourth quadrant displays a similar pattern due to the prevalence of non-routine tasks. However, this similarity breaks mainly in the second quadrant, where the merger of previous management-related occupations (both with medium susceptibility rates) shifted the new occupation (with a relatively low susceptibility rate) to the first quadrant, as mentioned above. The redistribution also impacted the third quadrant, which previously included two medium susceptibility occupations in [29]. The presence of dark green in this manual routine quadrant is justified by the inclusion of an occupation with a relatively low susceptibility rate at the boundaries of the second and third quadrants in both analyses.

Table 2. Summary of the susceptibility rate to robotization of the reviewed occupations in comparison with the findings of [29].

O*NET-SOC 2019 Title	O*NET Code	$\hat{s}_i$	Average $\hat{s}_i$ in [29]	Percentage Change
Farmers, Ranchers, and Other Agricultural Managers	11-9013.00	0.21	0.38	−44.7%
Farm Labor Contractors	13-1074.00	0.37	0.37	0%
Agricultural Engineers	17-2021.00	0.22	0.23	−4.3%
Animal Scientists	19-1011.00	0.17	0.17	0%
Soil and Plant Scientists	19-1013.00	0.06	0.04	+50%
Agricultural Technicians	19-4012.00	0.21	0.19	+10.5%
Precision Agriculture Technicians	19-4012.01	0.51	-	-
Farm and Home Management Educators	25-9021.00	0.08	-	-
First-Line Supervisors of Farming, Fishing, and Forestry Workers	45-1011.00	0.15	0.17	−11.8%
Agricultural Inspectors	45-2011.00	0.36	0.36	0%
Graders and Sorters, Agricultural Products	45-2041.00	0.92	0.95	−3.2%
Agricultural Equipment Operators	45-2091.00	0.71	0.71	0%
Farmworkers and Laborers, Crop, Nursery, and Greenhouse	45-2092.00	0.67	0.71	−5.6%
Farmworkers, Farm, Ranch, and Aquacultural Animals	45-2093.00	0.46	0.46	0%
Farm Equipment Mechanics and Service Technicians	49-3041.00	0.21	0.23	−8.7%

The hyphen (-) denotes that the occupation was not included in [29], while a percentage reduction equal to 0% indicates that the content of the occupation remained unchanged.

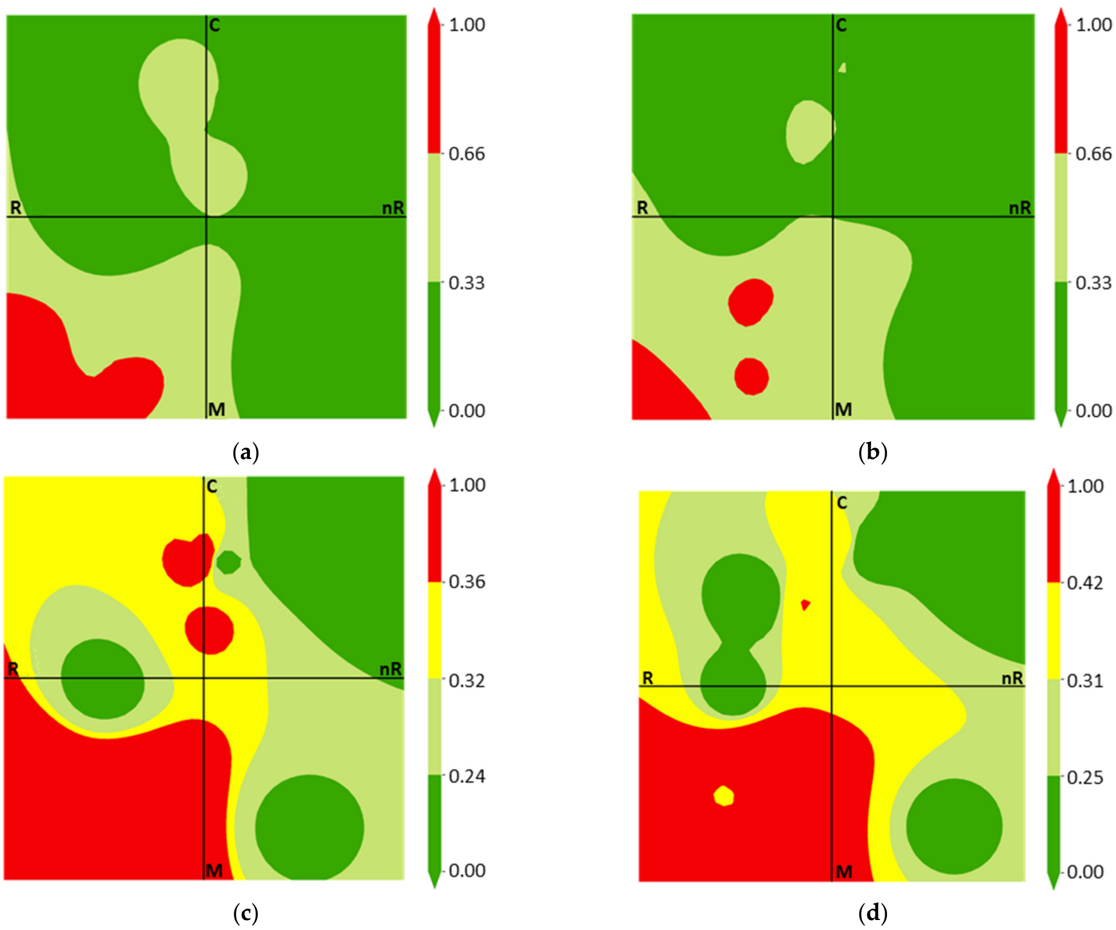


Figure 5. Contour plots of the susceptibility rate to robotization of the reviewed occupations in the cognitive (C)/manual (M) versus routine (R)/non-routine (nR) space by means of equal intervals and three classes (**a**,**b**) and quantiles with four classes (**c**,**d**); left plots correspond to the present study while the right plots to [29].

When using four quantile classes (Figure 5c,d), more information about the underlying distribution is revealed, as each class contains the same proportion of data. Both these plots demonstrate that manual routine tasks, located in the third quadrant, exhibit the highest susceptibility to robotization, indicated by the red areas. In contrast, cognitive non-routine tasks show the lowest susceptibility, as highlighted by dark green areas in the top-right region of the first quadrant. The dark green circle in the fourth quadrant of both Figure 5c,d corresponds to the "Farm Equipment Mechanics and Service Technicians" occupation, common in both studies. The existence of an extra dark green circle in the second quadrant of Figure 5d is due to an occupation relatively resilient to robotization in [29], such that the present study shifted it to the first quadrant. Additionally, transition zones of yellow and light green represent tasks with moderate to high susceptibility to robotization.

3.3. Investigation of Key Qualifications towards Adapting to the Ongoing Labor Market Changes in Agriculture

This section delves into the exploration of key qualifications for adapting to the dynamic shifts occurring in agricultural practices and employment patterns. Towards this direction, the analysis focuses on the corresponding information of [30], which is provided for those occupations belonging to the "green zone" in Figure 3, namely, occupations with a very low rate of susceptibility to robotization, i.e., $\hat{s}_i \in [0, 0.33)$. Most specifically, we concentrate on the common knowledge, skills, and work styles that are required for the following eight non-routine occupations: (1) "Farmers, Ranchers, and Other Agricultural Managers" (11-9013.00); (2) "Agricultural Engineers" (17-2021.00); (3) "Animal Scientists" (19-1011.00); (4) "Agricultural Technicians" (19-4012.00); (5) "Soil and Plant Scientists" (19-1013.00); (6) "Farm and Home Management Educators" (25-9021.00); (7) "First-Line Supervisors of Farming, Fishing, and Forestry Workers" (45-1011.00); and (8) "Farm Equipment Mechanics and Service Technicians" (49-3041.00). After summarizing all the requisite qualifications using the methodology outlined in Section 2.3, the analysis identifies the most critical ones. Specifically, these are qualifications (knowledge, skills, and work styles) with an overall normalized importance rating, $\hat{I}_i$, equal to or exceeding 0.5 similarly to [30].

3.3.1. Knowledge

Figure 6 illustrates a broad spectrum of knowledge aspects exhibiting a low susceptibility rate to robotization, in descending order of importance, $\hat{I}_i$, which is represented by blue bars. Focusing on those with $\hat{I}_i \geq 0.5$, biology provides essential understanding of ecosystems and crop management, while mathematics aids in data analysis and decision-making processes. Administration and management are vital for coordinating agricultural operations, and education and training facilitate knowledge dissemination and skill development within the agricultural community. Proficiency in food production ensures the implementation of sustainable methods, thereby safeguarding food security, while competency in computers and electronics enables the integration of innovative technologies. Additionally, customer and personal service abilities enhance communication and stakeholder relationships and expertise in chemistry contributes to food safety and quality control measures. Finally, proficiency in production and processing, engineering, and technology, and mechanical expertise, optimizes machinery utilization and automation implementation in agricultural processes.

The proficiency level of each analyzed aspect is also visually represented in Figure 6 by orange bars, accompanied by the corresponding bar signifying its importance. Indicatively, in [30], three level examples are provided for biology: (a) $\hat{L}_i = 1$: isolate and detect a new virus; (b) $\hat{L}_i = 0.71$: examine the impacts of pollution on both plant and animals; and (c) $\hat{L}_i = 0.14$: feed domestic animals.

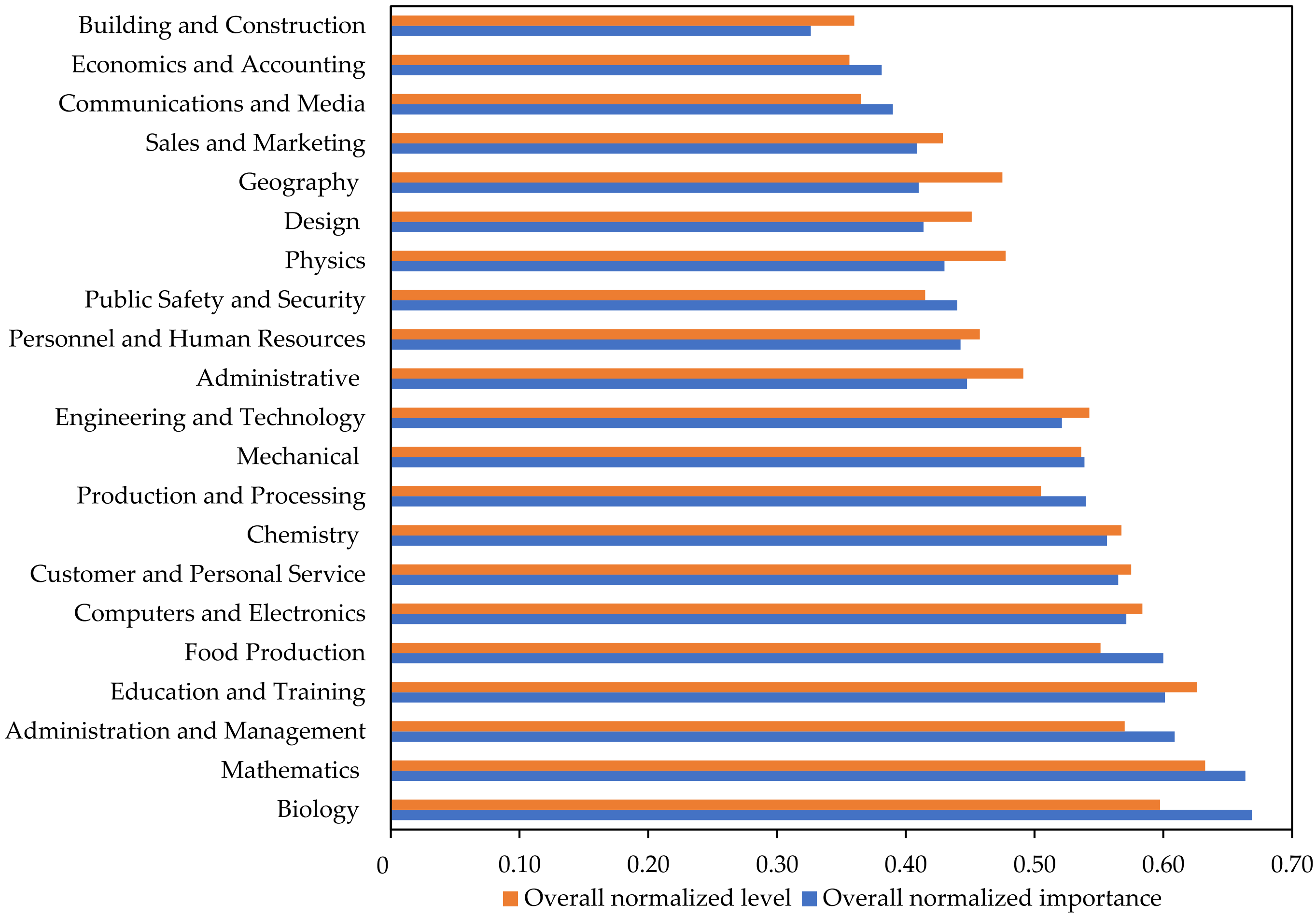


Figure 6. The critical knowledge domains associated with low susceptibility to robotization, alongside the corresponding importance and proficiency level for each analyzed aspect.

3.3.2. Skills

As depicted in the bar chart of Figure 7, a diverse array of skills demonstrates a low susceptibility to robotization. In line with the previous analysis, we focus on skills with $\hat{I}_i \geq 0.5$ depicted together with proficiency level for each examined skill. The key skills include critical thinking, which involves analyzing and evaluating issues to make sound decisions, and active learning and listening, essential for understanding instructions and collaborating effectively. Complex problem-solving, judgment- and decision-making, and time management are also crucial for choosing the best course of action under varying circumstances. Writing, speaking, and reading efficiency is also important for clear documentation and communication of agricultural practices. Monitoring and systems evaluation and analysis help in assessing performance and ensuring optimal functioning of operations. Social perceptiveness and coordination enhance interpersonal interactions and teamwork, while instructing is an essential skill for breaking down complex concepts or processes into manageable steps. Learning strategies facilitate continuous improvement and adaptation to new technologies. Lastly, a solid grounding in science is critical for applying scientific principles to improve, inter alia, crop yields, pest management, and overall productivity. Mastery of these skills is vital for adapting to the demands of modern agriculture driven by technological advancements. Remarkably, no purely technical skills were found from this analysis that meet the criterion of $\hat{I}_i \geq 0.5$, such as equipment maintenance, selection, and repairing, obviously because the occupations that are associated with these skills involve mainly tasks of routine nature. These kinds of skills are also presented in Figure 7, displaying, however, lower overall importance.

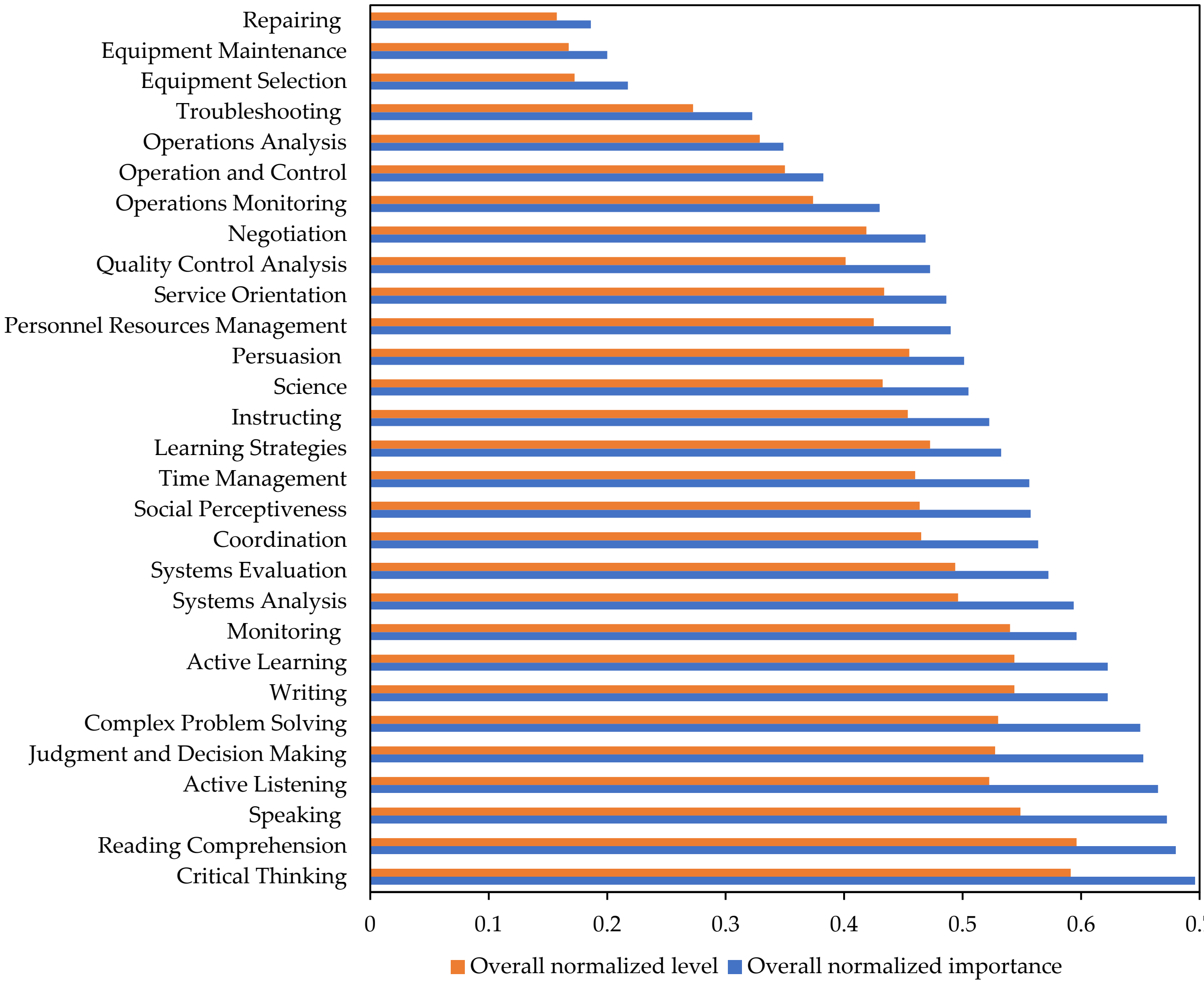


Figure 7. The key skills associated with low susceptibility to robotization, alongside the corresponding importance and proficiency level for each investigated skill.

In the same vein as above, the proficiency level of each analyzed skill is also represented in Figure 7. For instance, concerning critical thinking, three level examples are outlined in [30]: (a) $\hat{L}_i = 0.85$: compose a legal document contesting a federal law; (b) $\hat{L}_i = 0.57$: evaluate customer complaints and determine proper actions; and (c) $\hat{L}_i = 0.28$: Assess whether a subordinate has a valid justification for tardiness.

3.3.3. Work Styles

Regarding the personal characteristics, they are also crucial, as they provide the ability to adapt to unpredictable situations, which are prevalent in agricultural settings [40]. In addition, they enhance confidence and increase opportunities for career advancement. Figure 8 summarizes a wide range of work styles that contribute towards building resistance to robotization. It is noteworthy that all of them surpassed the threshold of $\hat{I}_i \geq 0.5$. In summary, dependability and integrity ensure reliability and trustworthiness in performing various tasks, while attention to detail and analytical thinking enable effective problem-solving. Initiative drives proactive and creative approaches to work, while cooperation and leadership promote effective collaboration, and team management. Persistence and stress tolerance enable individuals to persevere in the face of challenges, and adaptability/flexibility and self-control empower them to navigate changing circumstances with composure and agility. Lastly, achievement/effort, independence, concern for others, and social orientation stress the significance of personal motivation, empathy, and social skills in fostering positive work environments and achievements.

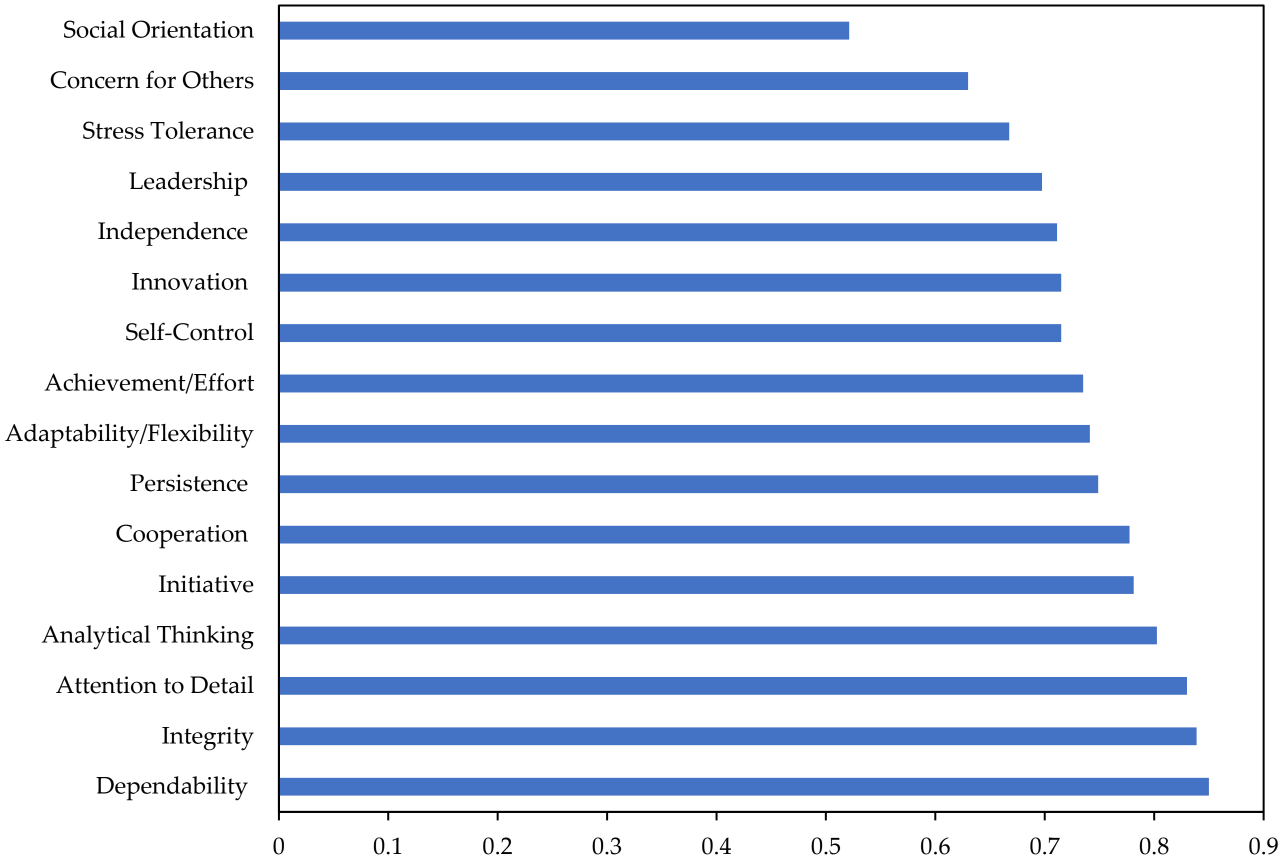


Figure 8. The principal work styles associated with low susceptibility to robotization, alongside the corresponding importance for each studied aspect.

4. Discussion and Conclusions

As agriculture experiences unprecedented changes at its core due to the advancement of technology, the existing skill set seems to become obsolete faster compared to previous technology revolutions. For the purpose of identifying the critical qualifications for adapting to the ongoing labor market changes, a bottom-up approach was followed. To that end, the analysis started from the task level of each related occupation via assessing the effect of automation on them through the prism of the nature of each task. In total, 15 occupations were investigated, based on [30]. Similarly to the methodology developed in [29], the reviewed occupations were placed in a virtual cognitive/manual versus routine/non-routine 2D space. The majority of occupations, namely, eight of them, were placed in the first, cognitive non-routine, quadrant. As compared to the previous mapping in [29], the updated analysis shifted some of the commonly investigated occupations to the right and upwards, since the content of their tasks was updated primarily with responsibilities of non-routine and cognitive nature, respectively.

Focusing on the automation potential, occupations primarily involving routine tasks face high susceptibility to robotization, due to their adherence to repetitive procedures. In particular, manual routine occupations proved to be particularly vulnerable (mean $\hat{s}_i = 0.59$), with cognitive routine roles also displaying significant, but lower susceptibility (mean $\hat{s}_i = 0.36$). Conversely, non-routine occupations demonstrate lower vulnerability, with both cognitive and manual non-routine roles showing reduced susceptibility to robotization (mean $\hat{s}_i = 0.22$ and 0.21, respectively). The present results align with recent studies indicating that automation is not only automating repetitive tasks, but also reshaping job roles to include non-routine and cognitive tasks [41,42]. This is particularly evident in agriculture, where advancements, such as agri-robotics, are transforming both the tasks performed and the skills required [13,16,29,32]. As stressed in [43], automation widens the wage gap between unskilled and skilled workers compared to medium-skilled workers, aligning with the observed trend of wage polarization. This results in greater economic inequality and fewer opportunities for those with moderate skill levels, especially in industrialized developed countries [44].

Subsequently, the key knowledge, skills, and work styles required for occupations with very low susceptibility to robotization were examined. As robotization replaces mainly routine tasks, there is a greater emphasis on qualifications for operating and supervising automated systems and using data analysis tools. This shift necessitates a workforce skilled in leveraging automation to boost productivity and efficiency in agriculture. At the same time, there is a rising demand for workers proficient in non-routine tasks that require critical thinking, problem-solving, and adaptability. Consequently, soft skills like analytical thinking, attention to detail, cooperation, and dependability are becoming increasingly more important, reflecting trends in other sectors [45]. The growing emphasis on intellectual and social activities is driving demand for higher-order cognitive skills, while physical task demands are decreasing. Cognitive skills are crucial for adapting to new environments and addressing challenges, with soft skills complementing them [14]. Our analysis stresses the need to integrate STEM skills with management, interdisciplinary, and socioemotional competencies to thrive in the evolving agricultural labor market.

However, as robotization continues to transform the agricultural sector, skill adaptation should extend beyond traditional STEM fields to include a range of competencies. Specifically, skills in sustainability practices are increasingly essential for implementing eco-friendly farming and optimizing resource use [46]. Moreover, digital literacy is crucial in agriculture, as it empowers farmers to utilize advanced technologies for precision farming, efficient data management, and market access, ultimately contributing to a more inclusive and informed agricultural sector [47]. To cultivate resilience in the agricultural workforce amidst robotization, policymakers should implement training programs that integrate STEM education with interdisciplinary skills, such as sustainability practices and digital literacy mentioned above. Lifelong learning and upskilling initiatives, supported by funding and incentives, are also important to ensure the workforce remains competitive and adaptable. Inclusive policies must address the needs of low-skilled workers by providing targeted support programs to promote social equality. Evaluation of potential pathways and support mechanisms for employees who face challenges in acquiring new skills will help to better understand the necessary interventions to facilitate their adaptation and integration into new roles or responsibilities.

Future directions for research could also explore the long-term implications of automation on the agricultural labor market, considering factors such as job displacement/complement alongside cost analysis and the emergence of new job opportunities. Future research aligns with the need of workers to adapt and acquire new skills to effectively collaborate with the emerging AI systems or to transition into roles that exploit their unique human capabilities to remain relevant in the labor market. Additionally, conducting socioeconomic cost–benefit analyses is imperative to assess the profitability and also the broader societal implications of replacing humans with machines, especially given the prevailing climate of uncertainty surrounding technology adoption in agriculture. Finally, considering the interdisciplinary nature of the topic in question, further investigation could involve experts from various disciplines, including agriculture, as a means of examining the broader implications of automation in employment dynamics.

As a final note, optimal development and usage of human capital are required with the intention of adapting to change, as human capital is needed to create value. Human capital involves all the investigated aspects of the qualifications and attributes of labor that affect its productive capacity as well as earning potential [48]. Investing in people turns out to be increasingly critical, since optimizing human capital constitutes a determinant factor for innovation and adoption in the digital transformation of agriculture. Policymakers and educational systems must strategically prepare future workers with various kinds of interdisciplinary knowledge, skills, and competences that have the potential to complement new digital technologies as a means of making the agricultural sector more prosperous, reliant, sustainable, and inclusive.

Author Contributions: Conceptualization, V.M., L.B., C.C.V. and D.B.; methodology, V.M., D.B., S.P., C.C.V., R.B. and C.G.S.; validation, M.L. and D.K.; formal analysis, L.B., D.B. and C.G.S.; investigation, V.M., D.K., M.L., C.C.V. and L.B.; resources, C.G.S., R.B. and D.B.; data curation, M.L., R.B. and D.K.; writing—original draft preparation, V.M. and L.B.; writing—review and editing, R.B., C.C.V., S.P., C.G.S. and D.B.; visualization, M.L. and D.K.; supervision, D.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: Authors Vasso Marinoudi, Maria Lampridi, and Dionysis Bochtis were employed by the company farmB Digital Agriculture S.A. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Amankwah-Amoah, J.; Khan, Z.; Wood, G.; Knight, G. COVID-19 and digitalization. *J. Bus. Res.* **2021**, *136*, 602–611. [CrossRef] [PubMed]
2. Bochtis, D.; Benos, L.; Lampridi, M.; Marinoudi, V.; Pearson, S.; Sørensen, C.G. Agricultural workforce crisis in light of the COVID-19 pandemic. *Sustainability* **2020**, *12*, 8212. [CrossRef]
3. Santos, G.; Sá, J.C.; Félix, M.J.; Barreto, L.; Carvalho, F.; Doiro, M.; Zgodavová, K.; Stefanović, M. New Needed Quality Management Skills for Quality Managers 4.0. *Sustainability* **2021**, *13*, 6149. [CrossRef]
4. Ciarli, T.; Kenney, M.; Massini, S.; Piscitello, L. Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Res. Policy* **2021**, *50*, 104289. [CrossRef]
5. Almeida, F.; Duarte Santos, J.; Augusto Monteiro, J. The Challenges and Opportunities in the Digitalization of Companies in a Post-COVID-19 World. *IEEE Eng. Manag. Rev.* **2020**, *48*, 97–103. [CrossRef]
6. Frey, C.B.; Osborne, M.A. The future of employment: How susceptible are jobs to computerisation? *Technol. Forecast. Soc. Chang.* **2017**, *114*, 254–280. [CrossRef]
7. Arntz, M.; Gregory, T.; Zierahn, U. *The Risk of Automation for Jobs in OECD Countries*; OECD: Paris, France, 2016. [CrossRef]
8. Heyman, F. Job polarization, job tasks and the role of firms. *Econ. Lett.* **2016**, *145*, 246–251. [CrossRef]
9. Döhring, B.; Hristov, A.; Maier, C.; Roeger, W.; Thum-Thysen, A. COVID-19 acceleration in digitalisation, aggregate productivity growth and the functional income distribution. *Int. Econ. Econ. Policy* **2021**, *18*, 571–604. [CrossRef]
10. Watson, G.P.; Kistler, L.D.; Graham, B.A.; Sinclair, R.R. Looking at the Gig Picture: Defining Gig Work and Explaining Profile Differences in Gig Workers' Job Demands and Resources. *Group Organ. Manag.* **2021**, *46*, 327–361. [CrossRef]
11. Lagorio, A.; Cimini, C.; Romero, D. A Reflective Framework for Understanding Workforce Evolutionary Pathways in Industry 5.0. In *Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures, Proceedings of the IFIP WG 5.7 International Conference, APMS 2023, Trondheim, Norway, 17–21 September 2023*; FIP Advances in Information and Communication Technology; Springer: Cham, Switzerland, 2023; Volume 689, pp. 501–512.
12. Li, L. Reskilling and Upskilling the Future-ready Workforce for Industry 4.0 and Beyond. *Inf. Syst. Front.* 2022, *online ahead of print*. [CrossRef]
13. Sørensen, L.B.; Germundsson, L.B.; Hansen, S.R.; Rojas, C.; Kristensen, N.H. What Skills Do Agricultural Professionals Need in the Transition towards a Sustainable Agriculture? A Qualitative Literature Review. *Sustainability* **2021**, *13*, 13556. [CrossRef]
14. Danner, D.; Clemens, L.; Spengler, M. Editorial: Do We Need Socio-Emotional Skills? *Front. Psychol.* **2021**, *12*, 723470. [CrossRef] [PubMed]
15. World Bank World Development Report 2016: Digital Dividends. Available online: https://www.worldbank.org/en/publication/wdr2016 (accessed on 7 July 2022).
16. Benos, L.; Sørensen, C.G.; Bochtis, D. Field Deployment of Robotic Systems for Agriculture in Light of Key Safety, Labor, Ethics and Legislation Issues. *Curr. Robot. Rep.* **2022**, *3*, 49–56. [CrossRef]
17. Benos, L.; Moysiadis, V.; Kateris, D.; Tagarakis, A.C.; Busato, P.; Pearson, S.; Bochtis, D. Human-Robot Interaction in Agriculture: A Systematic Review. *Sensors* **2023**, *23*, 6776. [CrossRef]

18. Benos, L.; Bechar, A.; Bochtis, D. Safety and ergonomics in human-robot interactive agricultural operations. *Biosyst. Eng.* **2020**, *200*, 55–72. [CrossRef]
19. Charatsari, C.; Lioutas, E.D. Is current agronomy ready to promote sustainable agriculture? Identifying key skills and competencies needed. *Int. J. Sustain. Dev. World Ecol.* **2019**, *26*, 232–241. [CrossRef]
20. Migliorini, P.; Lieblein, G. Facilitating Transformation and Competence Development in Sustainable Agriculture University Education: An Experiential and Action Oriented Approach. *Sustainability* **2016**, *8*, 1243. [CrossRef]
21. Šūmane, S.; Kunda, I.; Knickel, K.; Strauss, A.; Tisenkopfs, T.; Rios, I.d.I.; Rivera, M.; Chebach, T.; Ashkenazy, A. Local and farmers' knowledge matters! How integrating informal and formal knowledge enhances sustainable and resilient agriculture. *J. Rural Stud.* **2018**, *59*, 232–241. [CrossRef]
22. Maïga, W.H.E.; Porgo, M.; Zahonogo, P.; Amegnaglo, C.J.; Coulibaly, D.A.; Flynn, J.; Seogo, W.; Traoré, S.; Kelly, J.A.; Chimwaza, G. A systematic review of employment outcomes from youth skills training programmes in agriculture in low- and middle-income countries. *Nat. Food* **2020**, *1*, 605–619. [CrossRef] [PubMed]
23. Blickenstaff, S.M.; Wolf, K.J.; Falk, J.M.; Foltz, J.C. College of Agriculture Faculty Perceptions of Student Skills, Faculty Competence in Teaching Areas and Barriers to Improving Teaching. *NACTA J.* **2015**, *59*, 219–226.
24. Cerutti, A.; Padovan, D.; Bruun, S.; Donno, D.; Beccaro, G. On the Use of Life Cycle Assessment to Improve Agronomists' Knowledge and Skills toward Sustainable Agricultural Systems. *Vis. Sustain.* **2017**, *7*, 38–53. [CrossRef]
25. Tagarakis, A.C.; Benos, L.; Kyriakarakos, G.; Pearson, S.; Sørensen, C.G.; Bochtis, D. Digital Twins in Agriculture and Forestry: A Review. *Sensors* **2024**, *24*, 3117. [CrossRef] [PubMed]
26. Francis, C.A.; Jensen, E.S.; Lieblein, G.; Breland, T.A. Agroecologist Education for Sustainable Development of Farming and Food Systems. *Agron. J.* **2017**, *109*, 23–32. [CrossRef]
27. Cecchini, M.; Bedini, R.; Mosetti, D.; Marino, S.; Stasi, S. Safety Knowledge and Changing Behavior in Agricultural Workers: An Assessment Model Applied in Central Italy. *Saf. Health Work* **2018**, *9*, 164–171. [CrossRef]
28. Laforge, J.M.L.; McLachlan, S.M. Learning communities and new farmer knowledge in Canada. *Geoforum* **2018**, *96*, 256–267. [CrossRef]
29. Marinoudi, V.; Lampridi, M.; Kateris, D.; Pearson, S.; Sørensen, C.G.; Bochtis, D. The Future of Agricultural Jobs in View of Robotization. *Sustainability* **2021**, *13*, 12109. [CrossRef]
30. O*NET OnLine. Available online: https://www.onetonline.org/ (accessed on 13 March 2024).
31. O*NET O*NET-SOC Resource Center. Available online: https://www.onetcenter.org/ (accessed on 13 March 2024).
32. Marinoudi, V.; Sørensen, C.G.; Pearson, S.; Bochtis, D. Robotics and labour in agriculture. A context consideration. *Biosyst. Eng.* **2019**, *184*, 111–121. [CrossRef]
33. Moencks, M.; Roth, E.; Bohné, T.; Romero, D.; Stahre, J. Augmented Workforce Canvas: A management tool for guiding human-centric, value-driven human-technology integration in industry. *Comput. Ind. Eng.* **2022**, *163*, 107803. [CrossRef]
34. Hamza, A.; Riaz, F.; Abid, S.; Raza, U.; Holderbaum, W.; Chowdhry, B.S. A Comprehensive Study of the Role of Self-Driving Vehicles in Agriculture: A Review. In Proceedings of the 2023 7th International Multi-Topic ICT Conference (IMTIC), Jamshoro, Pakistan, 10–12 May 2023; pp. 1–7.
35. Kootstra, G.; Wang, X.; Blok, P.M.; Hemming, J.; van Henten, E. Selective Harvesting Robotics: Current Research, Trends, and Future Directions. *Curr. Robot. Rep.* **2021**, *2*, 95–104. [CrossRef]
36. Vallejo-Gómez, D.; Osorio, M.; Hincapié, C.A. Smart Irrigation Systems in Agriculture: A Systematic Review. *Agronomy* **2023**, *13*, 342. [CrossRef]
37. Ju, C.; Kim, J.; Seol, J.; Son, H. Il A review on multirobot systems in agriculture. *Comput. Electron. Agric.* **2022**, *202*, 107336. [CrossRef]
38. Bigliardi, B.; Bottani, E.; Casella, G.; Filippelli, S.; Petroni, A.; Pini, B.; Gianatti, E. Industry 4.0 in the agrifood supply chain: A review. *Procedia Comput. Sci.* **2023**, *217*, 1755–1764. [CrossRef]
39. Cravero, A.; Pardo, S.; Sepúlveda, S.; Muñoz, L. Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review. *Agronomy* **2022**, *12*, 748. [CrossRef]
40. Bechar, A.; Vigneault, C. Agricultural robots for field operations: Concepts and components. *Biosyst. Eng.* **2016**, *149*, 94–111. [CrossRef]
41. Eloundou, T.; Manning, S.; Mishkin, P.; Rock, D. GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models 2023. *arXiv* **2023**, arXiv:2303.10130.
42. Filippi, E.; Bannò, M.; Trento, S. Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technol. Forecast. Soc. Chang.* **2023**, *191*, 122448. [CrossRef]
43. Afonso, Ó.; Forte, R. Routine and non-routine sectors, tasks automation and wage polarization. *Appl. Econ.* **2023**, 1–24. [CrossRef]
44. Villanthenkodath, M.A.; Pal, S.; Mahalik, M.K. Income Inequality in Globalization Context: Evidence from Global Data. *J. Knowl. Econ.* **2024**, *15*, 3872–3902. [CrossRef]
45. Thornhill-Miller, B.; Camarda, A.; Mercier, M.; Burkhardt, J.-M.; Morisseau, T.; Bourgeois-Bougrine, S.; Vinchon, F.; El Hayek, S.; Augereau-Landais, M.; Mourey, F.; et al. Creativity, Critical Thinking, Communication, and Collaboration: Assessment, Certification, and Promotion of 21st Century Skills for the Future of Work and Education. *J. Intell.* **2023**, *11*, 54. [CrossRef]

46. Carlisle, L.; de Wit, M.; DeLonge, M.S.; Iles, A.; Calo, A.; Getz, C.; Ory, J.; Munden-Dixon, K.; Galt, R.; Melone, B.; et al. Transitioning to sustainable agriculture requires growing and sustaining an ecologically skilled workforce. *Front. Sustain. Food Syst.* **2019**, *3*, 96. [CrossRef]
47. Hackfort, S. Patterns of Inequalities in Digital Agriculture: A Systematic Literature Review. *Sustainability* **2021**, *13*, 12345. [CrossRef]
48. Bardak, U. Global trends shaping labour markets and the demand for labour in the world: An overview. In *Changing Skills for a Changing World; Understanding Skills Demand in EU Neighbouring Countries*; European Training Foundation: Torino, Italy, 2021; ISBN 978-92-9157-729-3.