Smart Agricultural Technology xxx (xxxx) 100677

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.elsevier.com

Journal Cover Image

Large language models impact on agricultural workforce dynamics: Opportunity or risk?

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ARTICLE INFO

Keywords:
O*NET
Abilities
Skills, Substitution
Complementary
Artificial intelligence
Human-machine Interaction

ABSTRACT

Motivated by the rapid advancement of large language models (LLMs), this study explores the potential impact of them on agricultural labor market. Starting from the task level of each of the 15 selected occupations, their exposure to LLMs was assessed by rating the extent to which the required abilities are aligned with those of LLMs, taking also into account the importance of the abilities in each occupation. Findings indicate that while LLMs can significantly enhance cognitive functions, they cannot fully replace the physical, psychomotor, and sensory abilities. As a consequence, while certain tasks are either partially or highly susceptible to LLM implementation, a considerable proportion, involving manual responsibilities, remains largely unaffected. It was seen that occupations heavily reliant on data are at greater risk of substitution. Conversely, some occupations will probably experience an augmenting effect, as LLMs will automate certain cognitive routine tasks, freeing up human workers to focus on more creative non-routine aspects. Furthermore, a negative correlation between exposure to LLMs and exposure to robotization was found highlighting the interconnected dynamics between these two variables within the analyzed context. In conclusion, although LLMs can offer substantial benefits, their integration necessitates careful consideration of their inherent limitations to maximize efficacy and mitigate risks in the agricultural sector.

1. Introduction

Large language models (LLMs), a subset of natural language process (NLP), have made noteworthy advancements over the past few years. These innovative artificial intelligence (AI) models are designed to learn and generate human-like language patterns, syntax, and context by being trained on vast web-based datasets, refining their accuracy with reinforcement learning from human feedback [1,2]. Leveraging deep learning methods, LLMs can discern intricate patterns and semantic relationships demonstrating their proficiency in a range of cognitive tasks, such as: a) generating coherent text; b) producing code snippets; c) translating languages; d) summarizing information; e) answering questions; and f) data analysis [3]. Recent LLMs include also capabilities for image processing and generation, as well as interpreting and responding to voice queries, allowing for seamless communication through spoken language [4]. The key capabilities of current LLMs are summarized in Fig. 1.

LLMs trace their origins back to the early developments in language modeling and neural network technology, with the development of the Recurrent Neural Networks (RNN) being an important innovation enabling the modeling of sequential data like language. However, the introduction of the transformer architecture was proved to be a crucial breakthrough in LLMs that enabled parallel processing and effective handling of long-term dependencies [5]. The LLMs architectures have formed the foundation for various models including the series of OpenAI Generative Pre-training Transformer (GPT) [6], Language Model for Dialogue Applications (LaMDA) developed by DeepMind [7], Turing NLG developed by Microsoft [8], as well as Bidirectional Encoder Representations from Transformers (BERT) [9], Text-to-Text Transfer Transformer (T5), PaLM 2 [10], and Gemini [11] developed by Google. Overall, LLMs have made substantial impacts on the AI landscape, find-

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https://doi.org/10.1016/j.atech.2024.100677
Received 8 November 2024; Received in revised form 28 November 2024; Accepted 29 November 2024
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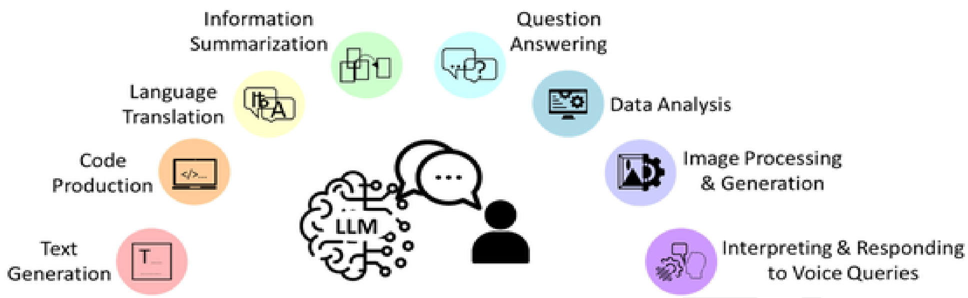


Fig. 1. Key capabilities of current large language models.

ing applications across various domains, such as education [12], e-commerce [13], communication networks [14], medicine [15], additive manufacturing [16], and hardware Trojan research [17], to mention but a few.

Taking into account the ever-increasing growth of LLMs in conjunction with the innovations shaping modern agriculture, including Internet of Things (IoT), agri-robotics, AI, and big data [18–20], the integration of LLMs in the agricultural sector appears inevitable, yet, at the same time as a strategic and transformative move. Indicatively, LLMs can enhance user interaction with agricultural systems, allowing access to tools that can analyze vast agricultural data related to resource management. By simplifying integration with IoT data, LLMs allow users to adjust practices based on real-time information [21]. LLMs could also support sustainable practices by connecting users to systems recommending resource-efficient strategies [22] and facilitate access to knowledge-sharing platforms, particularly in remote areas.

Motivated by the expected penetration of LLMs in agriculture, there can be a debate surrounding the potential changes to the agricultural labor market [23]. Based on previous experience of deploying cutting-edge technologies in agriculture, LLMs could create new roles and opportunities for skilled workers complementing their cognitive capabilities. On the other hand, automation via LLMs integration may lead to skills replacement and job substitution, while other labor roles, especially manual, may not affected at all [24–26]. Given the relative scarcity of literature on this topic, further research is needed to understand the full impact as a means of evaluating the long-term effects of LLMs on agricultural workforce dynamics.

To address this scope, in this work the 15 agricultural occupations selected in the recent study of Marinoudi et al. [27] were systematically examined on the basis of possible exposure to LLMs competencies. Similarly to [27,28], each occupation was decomposed into the tasks it involves according to O*NET Online tool [29], while a group of assessors with diverse expertise in agricultural sector analyzed these tasks to determine how well they can be performed by LLMs. Finally, an in-depth assessment was conducted on the prospective for substitution or complementarity, where substitution refers to replacing human tasks with LLMs, and complementarity involves using LLMs to assist human tasks [30,31].

2. Materials and methods

2.1. Occupations under examination

The O*NET-SOC system was used in this analysis, similarly to works such as [27,28,31–33]. This work focuses on 15 occupations related to agriculture [27], whose O*NET-SOC titles, codes, and number of tasks involved are presented in Table 1. Table 1 also classifies these occupations into four categories, based on the nature of the majority of tasks involved: a) "cognitive routine"; b) "cognitive non-routine"; c) "manual routine"; and d) "manual non-routine", as evaluated in [27]. This categorization is going to help in investigating the potential impact of LLMs on each category. In summary, Marinoudi et al. [27] integrated the agricultural occupations into a two dimensional graph depicting the cognitive/manual versus routine/non-routine nature by estimating the corresponding vertical and horizontal coordinates, respectively. To that end, a thorough examination of the importance of each individual task within an occupation was conducted (by assigning importance weights), along with a quantification of the contribution of each aspect, related to task nature, to its execution, averaged across the occupation under assessment.

Table 1
Summary of the reviewed occupations along with the 8-digit O*NET code, the categorization into four categories, based on the nature of the majority of tasks, and the corresponding number of tasks based on the O*NET data, [27,29].

a/n	Occupation	8-digit O*NET Code	Categorization	Tasks
1	Farmers, Ranchers, and Other Agricultural Managers	11-9013.00	CnR	30
2	Farm Labor Contractors	13-1074.00	CnR	8
3	Agricultural Engineers	17-2021.00	CnR	14
4	Animal Scientists	19-1011.00	CnR	9
5	Soil and Plant Scientists	19-1013.00	CnR	27
6	Agricultural Technicians	19-4012.00	MR	26
7	Precision Agriculture Technicians	19-4012.01	CnR	22
8	Farm and Home Management Educators	25-9021.00	CnR	15
9	First-Line Supervisors of Farming, Fishing, and Forestry Workers	45-1011.00	CnR	30
10	Agricultural Inspectors	45-2011.00	CR	22
11	Graders and Sorters, Agricultural Products	45-2041.00	MR	6
12	Agricultural Equipment Operators	45-2091.00	MR	17
13	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	45-2092.00	MR	30
14	Farmworkers, Farm, Ranch, and Aquacultural Animals	45-2093.00	MR	22
15	Farm Equipment Mechanics and Service Technicians	49-3041.00	MnR	14

CR: cognitive routine; CnR: cognitive non-routine; MR: manual routine; MnR: manual non-routine

2.2. Abilities under examination

2.2.1. Classification of the reviewed abilities

In the context of this study, "abilities" have been selected as the feature under questioning rather than "skills". Skills are specific learned competencies or expertise, typically task-oriented, that are acquired through practice and training; they can be developed or improved over time, reflecting their dynamic nature. In contrast, abilities refer to innate capacities that may or may not be transformed into skills. Thus, abilities serve as fundamental characteristics that determine the inherent constraints and limits in task execution. Given that this study aims to investigate the potential impact of LLMs on human substitution or complementarity, focusing on abilities allows for a more nuanced understanding of the long-term effects on workforce dynamics, rather than merely addressing the short-term skill changes that may arise from LLM implementation. Consequently, relying on the abilities, the analysis can evaluate how partial or full task exposure to LLMs might impact the agricultural workforce dynamics.

In total, 45 different abilities are involved in the reviewed occupations, a short description of which is provided in Table A1 of Appendix A. The corresponding ability abbreviation, description, and primary and secondary classification are listed in Table 2. Referring to [29], the abilities can be classified into:

Cognitive abilities, which impact the acquisition and use of knowledge for problem solving. They are further subdivided into abilities related to attentiveness, idea generation and reasoning, memory, perception, quantification, space, and verbality;

Physical abilities, which allow individuals to exert force, manipulate objects with precision, and sustain activity over time. They are further subdivided into abilities related to endurance, flexibility, balance and coordination, and physical strength; Physicomotor abilities, which determine how a person can handle and control objects. They are further subdivided into abilities related to control of movement, fine manipulation, and reaction time.

Sensory abilities, which influence the perception of visual, auditory, and verbal information. They are further subdivided into abilities related to auditory, oral, and visual sensory input.

Classifying abilities into cognitive, physical, psychomotor, and sensory categories, along with their secondary classifications, more accurate predictions can be accomplished on task exposure to LLM. In general, cognitive abilities, such as problem sensitivity and inductive reasoning, are essential for strategic planning, troubleshooting, and decision-making in agricultural operations, while physical and psychomotor abilities are critical for manual tasks, such as planting and harvesting. Finally, sensory abilities, such as near and far vision, are essential for detecting signs of pest infestations and monitoring environmental conditions.

The distribution of the 45 abilities investigated in this study, in the context of primary classification, is presented in the inner ring of Fig. 2, whereas the outer ring comprises the secondary classification.

In the present analysis, the majority of abilities are of cognitive nature, 20 in total, while physical abilities account for 8, psychomotor abilities for 9, and sensory abilities for 8. Focusing on cognitive abilities, most are related to idea generation and reasoning, like problem sensitivity, fluency of ideas, and originality, while also other cognitive aspects are presented, however with lower frequency. Concerning physical abilities, those involving exerting force, maintaining stability, and controlling body movements during tasks stand out. In the case of psychomotor abilities, those enabling individuals to perform precise and coordinated actions, manipulate small objects, and respond quickly to dynamic agricultural environments. Finally, visual and auditory abilities are equally represented in the respective sensory part, demonstrating their balanced significance in tasks requiring observation, monitoring, and communication within agricultural contexts.

2.2.2. Importance of the reviewed abilities

The importance of an ability reflects how critical that ability is for effectively performing a specific occupation. In [29], the degree of importance for an ability in a given occupation is rated on a scale from 0 (not important) to 100 (extremely important). Following the classification of the 15 agricultural occupations into four categories characterizing the nature of the majority of tasks involved, namely “cognitive non routine”, “cognitive routine”, “manual routine”, and “manual non-routine” [27], and examining the related importance, useful conclusions can be drawn. Fig. 3 provides a graphical representation of importance values for each occupation (based on importance ratings detailed in [29]), in the form of a heatmap, where the occupations are grouped by nature and the abilities by kind (primary classification). Overall, the dominance of light green and yellow-green in the upper left region of the heatmap is obvious, demonstrating a positive correlation of occupations of cognitive non-routine and routine nature with cognitive abilities. In contrast, as moving to the right and towards physical and psychomotor abilities, lower values of importance are observed, indicating the absence of cognitive tasks for these occupations. Concerning the

Table 2
Summary of the reviewed abilities along with their abbreviation, short description, and primary and secondary classification.

a/n	Ability	Abbreviation	Primary Classification	Secondary Classification
1	Oral Comprehension	OC	Cognitive	Verbal
2	Oral Expression	OE	Cognitive	Verbal
3	Written Expression	WE	Cognitive	Verbal
4	Written Comprehension	WC	Cognitive	Verbal
5	Problem Sensitivity	PS	Cognitive	Idea generation & reasoning
6	Deductive Reasoning	DR	Cognitive	Idea generation & reasoning
7	Inductive Reasoning	IR	Cognitive	Idea generation & reasoning
8	Information Ordering	IO	Cognitive	Idea generation & reasoning
9	Originality	OR	Cognitive	Idea generation & reasoning
10	Category Flexibility	CF	Cognitive	Idea generation & reasoning
11	Fluency of Ideas	FI	Cognitive	Idea generation & reasoning
12	Flexibility of Closure	FC	Cognitive	Perceptual
13	Speed of Closure	SCL	Cognitive	Perceptual
14	Perceptual Speed	PSP	Cognitive	Perceptual
15	Visualization	VS	Cognitive	Spatial
16	Mathematical Reasoning	MR	Cognitive	Quantitative
17	Number Facility	NF	Cognitive	Quantitative
18	Time Sharing	TS	Cognitive	Attentiveness
19	Selective Attention	SA	Cognitive	Attentiveness
20	Memorization	MZ	Cognitive	Memory
21	Stamina	ST	Physical	Endurance
22	Gross Body Equilibrium	GBE	Physical	Flexibility, balance & coordination
23	Gross Body Coordination	GBC	Physical	Flexibility, balance & coordination
24	Extent Flexibility	EF	Physical	Flexibility, balance & coordination
25	Static Strength	SS	Physical	Physical strength
26	Dynamic Strength	DS	Physical	Physical strength
27	Explosive Strength	ES	Physical	Physical strength
28	Trunk Strength	TST	Physical	Physical strength
29	Control Precision	CP	Psychomotor	Control movement
30	Multilimb Coordination	MC	Psychomotor	Control movement
31	Rate Control	RC	Psychomotor	Control movement
32	Response Orientation	RO	Psychomotor	Control movement
33	Arm-Hand Steadiness	AHS	Psychomotor	Fine manipulative
34	Finger Dexterity	FD	Psychomotor	Fine manipulative
35	Manual Dexterity	MD	Psychomotor	Fine manipulative
36	Wrist-Finger Speed	WFS	Psychomotor	Reaction time & speed
37	Reaction Time	RT	Psychomotor	Reaction time & speed
38	Far Vision	FV	Sensory	Visual
39	Near Vision	NV	Sensory	Visual
40	Visual Color Discrimination	VCD	Sensory	Visual
41	Depth Perception	DP	Sensory	Visual
42	Auditory Attention	AA	Sensory	Auditory & speech
43	Hearing Sensitivity	HS	Sensory	Auditory & speech
44	Speech Clarity	SC	Sensory	Auditory & speech
45	Speech Recognition	SR	Sensory	Auditory & speech

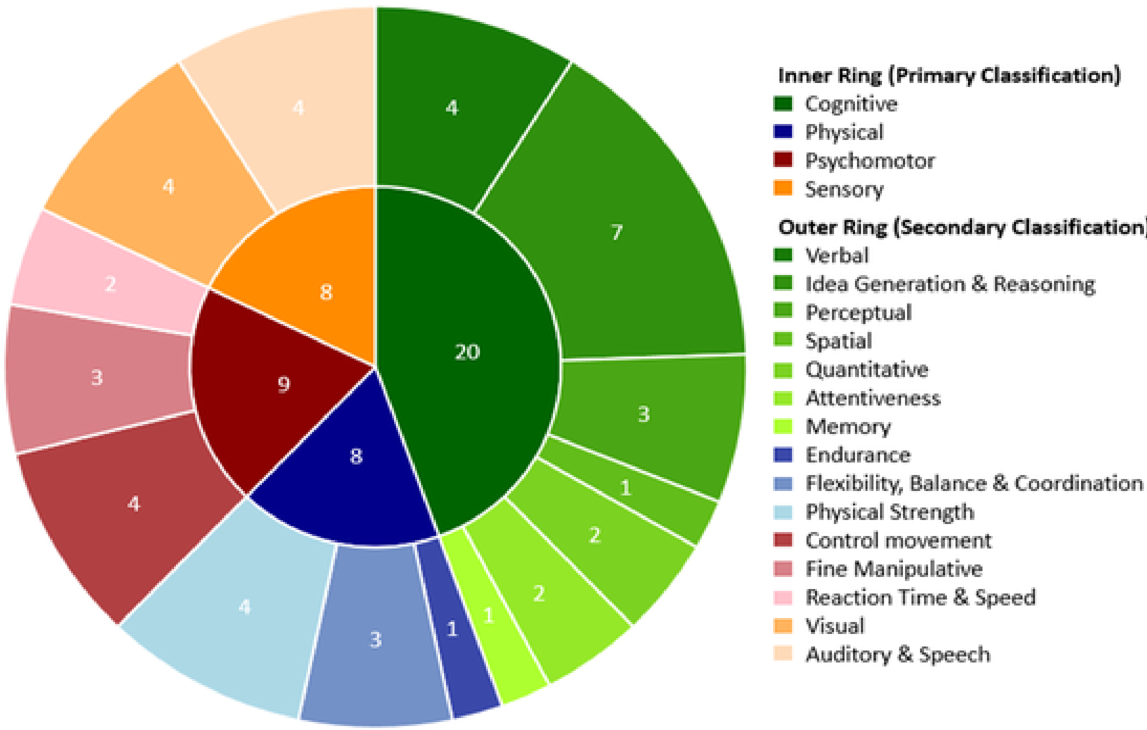


Fig. 2. The distribution of the reviewed abilities into the primary (inner ring) and secondary classification categories (outer ring).

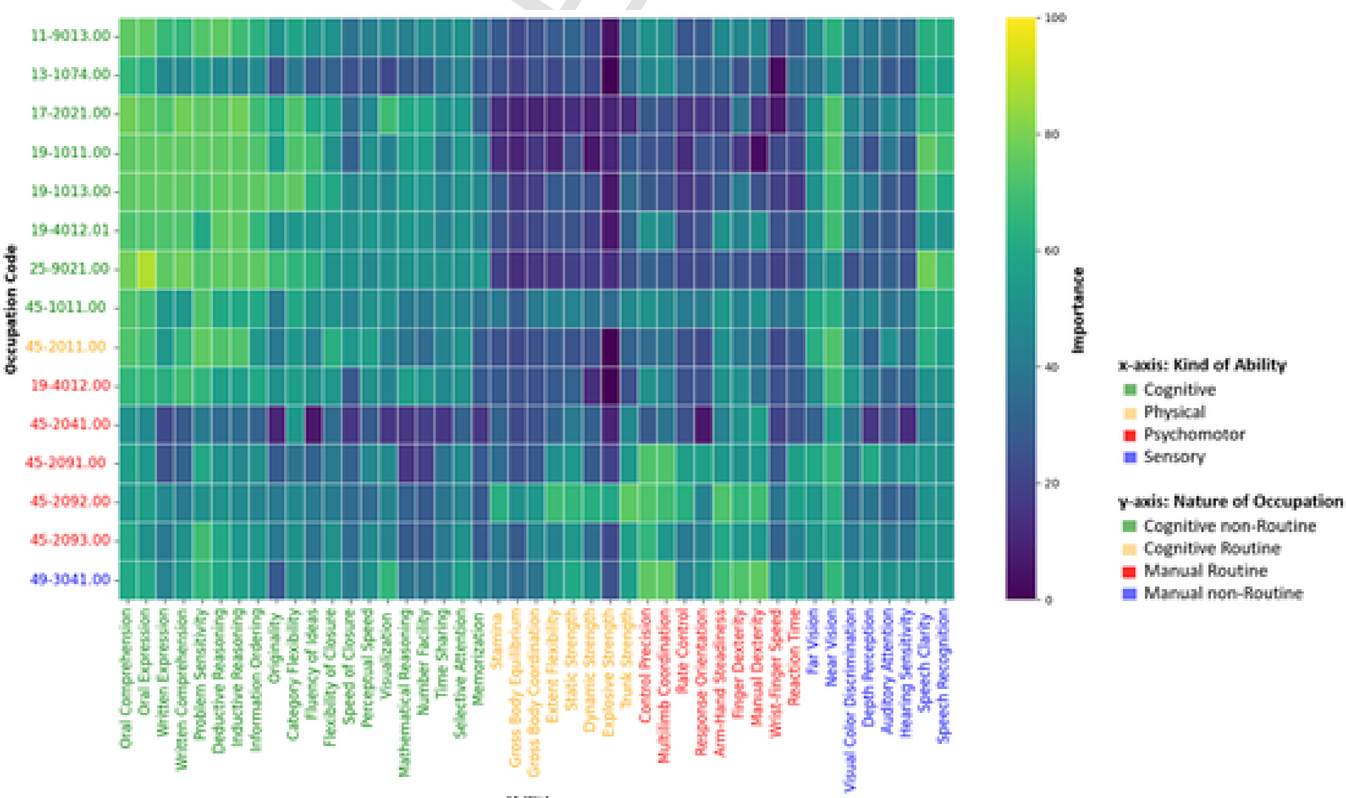


Fig. 3. Heatmap visualizing the importance of different kinds of abilities across various occupations of different nature.

sensory abilities, some of them, like speech recognition and clarity are important, whereas others like hearing sensitivity are less significant. As moving downwards, occupations of manual nature are noted reversing the above pattern, with physical, psychomotor, and sensory abilities being more important than cognitive ones.

2.3. Assessment of exposure to large language models

Let $O = \{1, 2, \ldots 15\}$ denote the set of indices of the occupations under examination (an occupation is symbolized as $o_j,\ j \in O$) in accordance with Table 1 and $T^j = \{1, 2, 3, \ldots\},\ j \epsilon O$ the set of indices of the tasks composing occupation o_j (a task is symbolized as $t_i^j,\ i \in\ T^j,\ j \in O$. Let $A = \{OC,\ OM, \ldots.\ \},\ |A| = 45$, denote the set of the defined abilities (an ability is symbolized as $a_k,\ k \in A$), based on the information in Table 2. Since not all abilities are connected to an occupation, we denote as $|A^j|,\ A^j \subseteq A,\ j \in O$, the number of the involved abilities in occupation o_j Finally, let $Imp_k^j,\ k \in A,\ j \in O$ denote that importance of ability k for occupation j, as provided in [29].

As a means of assessing the exposure to LLMs, a bottom-up approach was followed starting from the task level involved within the selected agricultural occupations. As a first step, focusing on a single occupation i, it was assessed whether each ability, $a_k,\ k \in A$, is required to perform the task$t_i^j,\ i \in\ T^j,\ j \in O$, at hand. If so, the assessors used the following three-tier scoring scale to approximate the different degrees of LLM capacity in covering the specific ability within the specific task under assessment:

$$C_{k,i}^j = \begin{cases} 1, & \textit{minimal or insignificant capacity} \\ 0.5, & \textit{intermidiate capacity} \\ 0, & \textit{full capacity} \end{cases},\ k \in A,\ i \in T^j, j \in O \tag{1}$$

It is important to note that the choice of this scoring scale was arbitrary, as any other scale could have been used. However, the aim of this study is to highlight trends in the transformation of agricultural occupations rather than offering precise measurements of the anticipated changes, which in any case is not possible. The rating was given independently by the assessors, namely the authors of this study, who also considered participatory interviews with agricultural professionals similarly to [27,28,34]. To resolve any disagreements and finalize scores, the authors held a consensus tele-meeting. The assessors possess expertise across diverse scientific fields including skills and workforce dynamics, agricultural robotics, AI, human-machine interaction, human factors, precision agriculture, and sustainability assessment, among others.

Next, considering also the effect of the importance Imp_k^i of k^{th}ability in the i^{th}occupation, the weighted exposure to LLM of a single ability was estimated by:

$$E_k^j = \frac{1}{|T^j|} \sum_{i=1}^{i=|T^j|} C_{k,i}^j \cdot Imp_k^j,\ k \in A, j \in O \tag{2}$$

In this stage, also the standard deviation of those weighted exposures of each ability is calculated as:

$$\sigma_k^j = \sqrt{\frac{1}{|T^j|} \cdot \sum_{i=1}^{i=|T^j|} \left(C_{k,i}^j \cdot Imp_k^j - \mathrm{E}_k^j \right)^2}, k \in A, j \in O \tag{3}$$

Finally, the average weighted exposure to LLMs and average standard deviation at occupation level are provided:

$$\hat{\mu}^j = \frac{1}{|A^j|} \cdot \sum_{k=1}^{|A^j|} \mathrm{E}_k^j, j \in O, k \in A \tag{4}$$

$$\hat{\sigma}^j = \frac{1}{|A^j|} \cdot \sum_{k=1}^{|A^j|} \sigma_k^j, j \in O, k \in A \tag{5}$$

2.4. Substitution versus augmentation potential assessment

In this section, we turn our interest into how LLMs could potentially affect the content of occupations, focusing on their substitution or complementarity potential [35]. On the one hand, substitution potential refers to the capability of technology to completely replace human workers in specific tasks or roles, aiming to increase efficiency and/or reduce direct human involvement [36,37]. On the other hand, complementarity potential, refers to also as augmentation potential, integrates technology to enhance human capabilities and decision-making without entirely replacing human workers. It gives emphasis to improving task performance through leveraging LLMs, thereby complement and empowering human workers rather than displacing them [25,38].

Seeing an occupation as an assembly of various tasks with different degrees of exposure to LLMs, it is of major importance to investigate, apart from the average weighted exposure ($\hat{\mu}$), also its average standard deviation ($\hat{\sigma}$) across the tasks on occupation level [30]. To determine whether the examined occupation has a substitution or complementarity potential through solely the use of LLM technology, combinations of $\hat{\mu}$ and $\hat{\sigma}$ can be examined. [2,8]. As can be seen in Fig. 4, when low values of both $\hat{\mu}$ and $\hat{\sigma}$ take place, these occupations are reasonably classified as "Not Affected" (green region), since LLMs have insignificant capacity to execute most of the involved tasks. Occupations with a moderate to high $\hat{\mu}$and low $\hat{\sigma}$ are classified as having "Substitution Potential" (red region), because most tasks within these jobs have remarkable exposure to automation via LLMs. The same classification is assigned for combinations of high $\hat{\mu}$ and moderate $\hat{\sigma}$. In contrast, occupations with "Complementarity Potential" (orange region) have a low $\hat{\mu}$and moderate to high $\hat{\sigma}$, indicating a mixture of tasks where some can be easily performed by LLMs while others cannot. Combinations of moderate $\hat{\mu}$ with high $\hat{\sigma}$ demonstrate also occupations with "Complementarity Potential".

The categorization of occupations into those having substitution potential, complementarity potential, or being not affected, left a group of occupations out of discussion. Towards filling this gap, occupations with high mean exposure to LLMs and significant variation in task-level scores can be characterized as "Unknown" (blue region). The same terminology applies to cases with moderate values of both $\hat{\mu}$ and $\hat{\sigma}$, where a balanced exposure to both complementarity and substitution is observed. For the sake of consistency and clarity, the same colors used in Fig. 4 are adopted for the graphs illustrating the above classification in the results section.

Finally, for the purpose of defining the thresholds for low, moderate, and high values of $\hat{\mu}$ and $\hat{\sigma}$, a method based on 33rd and 67th percentiles was utilized, allowing for clear interpretation and analysis of data based on their distribution in the dataset. In particular, values be-

	Low $\hat{\sigma}$	Moderate $\hat{\sigma}$	High $\hat{\sigma}$
Low $\hat{\mu}$	Not affected	Complementarity Potential	Complementarity Potential
Moderate $\hat{\mu}$	Substitution potential	Unknown	Complementarity Potential
High $\hat{\mu}$	Substitution potential	Substitution potential	Unknown

Fig. 4. The classification of the reviewed occupations based on their average weighted exposure to LLMs, $\hat{\mu}$, and average standard deviation, $\hat{\sigma}$.

low the 33rd percentile were classified as “low”, values between the 33rd percentile and 66th percentile were classified as “moderate”, and values above the 67th percentile were classified as “high”.

3. Results

3.1. Exposure to large language models

Following the methodology detailed in 2.3, the exposure to LLMs was evaluated by focusing on each occupation and the constituent tasks. In Appendix B, multinode graphs are provided for each agricultural occupation in Figures B1a-o. The main nodes, shown as light blue circles, represent the abilities being evaluated, while the target nodes, depicted as grey circles, indicate the specific tasks associated with each occupation. The vectors illustrate the correspondence between abilities and tasks, with their color indicating the assessed capacity degree of LLMs in the ability for undertaking the task in question: a) negligible (green); b) partial (orange); and b) full (red).

Fig. 5 integrates the above evaluations for all occupations in one graph for the purpose of providing a detailed overview, allowing for comparison and analysis of how LLMs can potentially engage in different roles involved. The capacity of LLMs for performing part or all the task is commensurate with the potential exposure of this task to LLM technology. It is obvious that occupations including several manual tasks, such as “Graders and Sorters, Agricultural Products” (45-2041.00) and “Agricultural Equipment Operators” (45-2091.00) demonstrate negligible exposure LLM technologies, as these roles require hands-on abilities and adaptability to varying physical environments.

In the same vein, resilient to LLMs are the other manual routine occupations, namely “Farmworkers and Laborers, Crop, Nursery, and Greenhouse” (45-2092.00), and “Farmworkers, Farm, Ranch, and Aquacultural Animals” (45-2093.00). The small parts of orange and red within the corresponding rings are attributed to the small need for carrying out some tasks requiring also cognitive abilities that can be partially or entirely performed by LLMs. A larger part is occupied by orange and red regions for “Farm Equipment Mechanics and Service Technicians” (49-3041.00), which although manual in nature integrates some non-routine tasks. In contrast, green color, indicative of negligible exposure to LLMs, starts to subside, when moving towards the center of the graph, corresponding to occupations of mainly cognitive nature. From this qualitative distribution, it can be deduced that more susceptible to LLM exposure is “Precision Agriculture Technicians” (19.4012. 01), who utilize various technologies in agricultural production or management, such as yield mapping and variable-rate irrigation. These analyses usually involve the use of software to analyze and interpret data and images that current LLMs can undertake providing advanced data processing and predictive analytics [3,39].

Fig. 6 consolidates the above results, based on the authors’ assessments, to provide a holistic view of the agricultural labor market landscape. It presents the exposure levels of the entire agricultural domain to current LLMs capabilities. The pie chart is divided into three sections, each illustrating the varying degrees of exposure to LLM integration. The largest section, displayed in green, accounts for 55 % of the

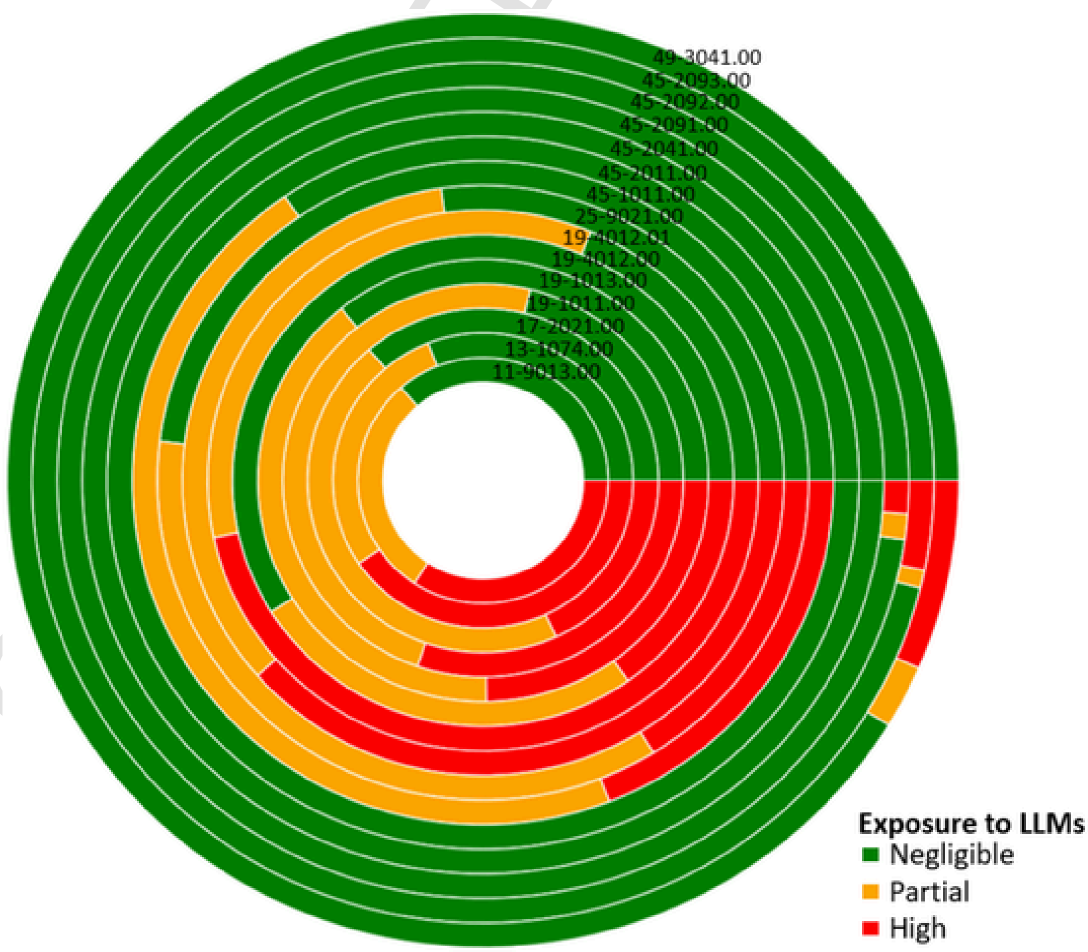


Fig. 5. Qualitative illustration of exposure to current LLM technology for each agricultural occupation.

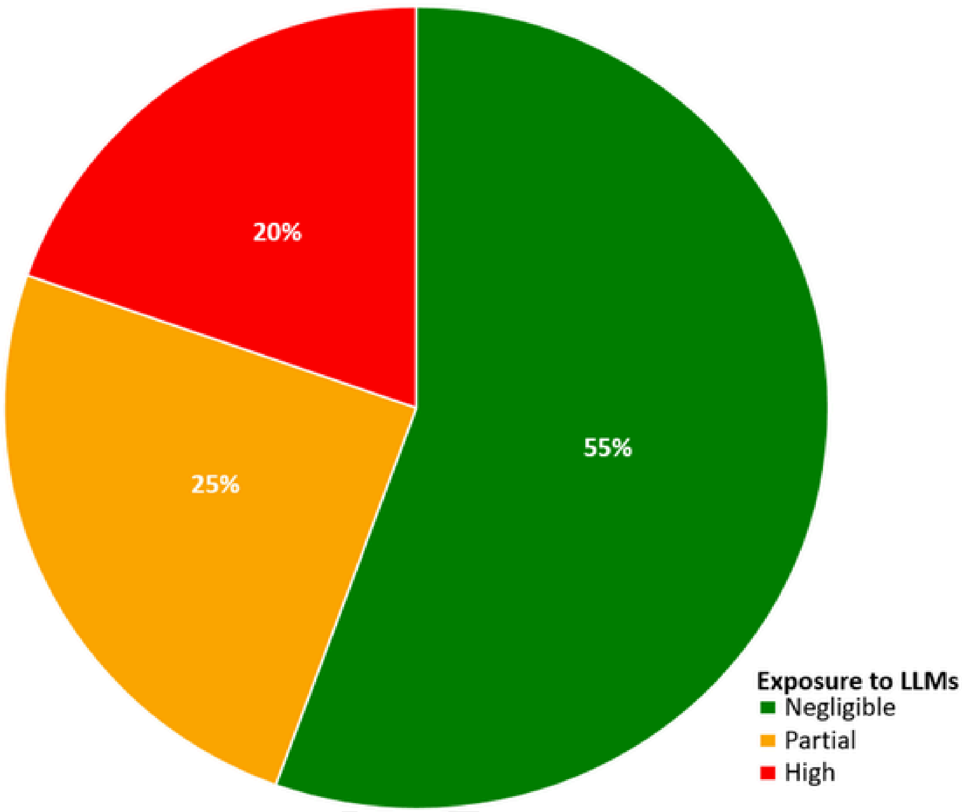


Fig. 6. Exposure to current LLM technology for the entire agricultural labor market.

tasks executed within agricultural occupations. This indicates that over half of tasks within agriculture are likely to experience negligible exposure to LLMs. The orange section, representing 25 % of the tasks, mirrors partial exposure, signifying that LLM technology is capable of moderately influencing only certain tasks. Therefore, while some aspects of the reviewed occupations can be supported by LLMs, there appears to remain a substantial prerequisite for both human involvement and expertise. Finally, the red section, which comprises 20 % of the reviewed cases, indicates high exposure to LLMs. In this instance, a noteworthy portion of tasks are highly susceptible to substitution by LLM technology, marking a potential shift in the workforce dynamics, where these roles may be considerably transformed or even replaced by advanced AI capabilities [40,41].

3.2. Substitution versus complementary potential

3.2.1. Classification of agricultural occupations

In this section, we shift our focus to examine how LLMs might influence the core of occupations, by taking into consideration also the importance of the abilities for executing each of them according to the values summarized in Fig. 3. To predict which occupations are most susceptible to substitution by LLM technology, which may benefit from technological complementarity, and which will not be affected, the average weighted exposure to LLMs, $\hat{\mu}$,and standard deviation, $\hat{\sigma}$, were first calculated. Table 3 presents the resulting values for each occupation.

Towards classifying $\hat{\mu}$ and $\hat{\sigma}$into “low”, “moderate”, and “high”, a method based on the 33rd and 66th percentiles was used, which provides an effective way to segment datasets. Small values are defined as those below the 33rd percentile, moderate values as those between the 33rd and 66th percentiles, and high values as those above the 66th percentile. The resulting values for 33rd and 66th percentiles for $\hat{\mu}$ were approximately 0.044 and 0.099, respectively, whereas for $\hat{\sigma}$ were approximately 0.042 and 0.079, respectively.

Table 3
Summary of the average weighted exposure to LLMs, $\hat{\mu}$, of the reviewed occupations along with the corresponding standard deviation, $\hat{\sigma}$.

O*NET-SOC 2019 Title	O*NET Code	$\hat{\mu}$	$\hat{\sigma}$
Farmers, Ranchers, and Other Agricultural Managers	11-9013.00	0.096	0.107
Farm Labor Contractors	13-1074.00	0.075	0.103
Agricultural Engineers	17-2021.00	0.108	0.092
Animal Scientists	19-1011.00	0.226	0.092
Soil and Plant Scientists	19-1013.00	0.118	0.044
Agricultural Technicians	19-4012.00	0.078	0.073
Precision Agriculture Technicians	19-4012.01	0.202	0.059
Farm and Home Management Educators	25-9021.00	0.13	0.106
First-Line Supervisors of Farming, Fishing, and Forestry Workers	45-1011.00	0.064	0.061
Agricultural Inspectors	45-2011.00	0.096	0.076
Graders and Sorters, Agricultural Products	45-2041.00	0	0
Agricultural Equipment Operators	45-2091.00	0	0
Farmworkers and Laborers, Crop, Nursery, and Greenhouse	45-2092.00	0.002	0.01
Farmworkers, Farm, Ranch, and Aquacultural Animals	45-2093.00	0	0
Farm Equipment Mechanics and Service Technicians	49-3041.00	0.012	0.039

Based on the methodology outlined in Section 2.4, different combinations of $\hat{\mu}$ and $\hat{\sigma}$can classify the occupations into different categories reflecting their substitution or complementarity potential (Fig. 4). Fig. 7 compiles the combinations of $\hat{\mu}$ and $\hat{\sigma}$for all agricultural occupations accompanied by how LLMs might affect occupations. Our analysis demonstrated that the following occupations with both low $\hat{\mu}$ and $\hat{\sigma}$ are considered to be "Not Affected": “Graders and Sorters, Agricultural Products” (45-2041.00); “Agricultural Equipment Operators” (45-

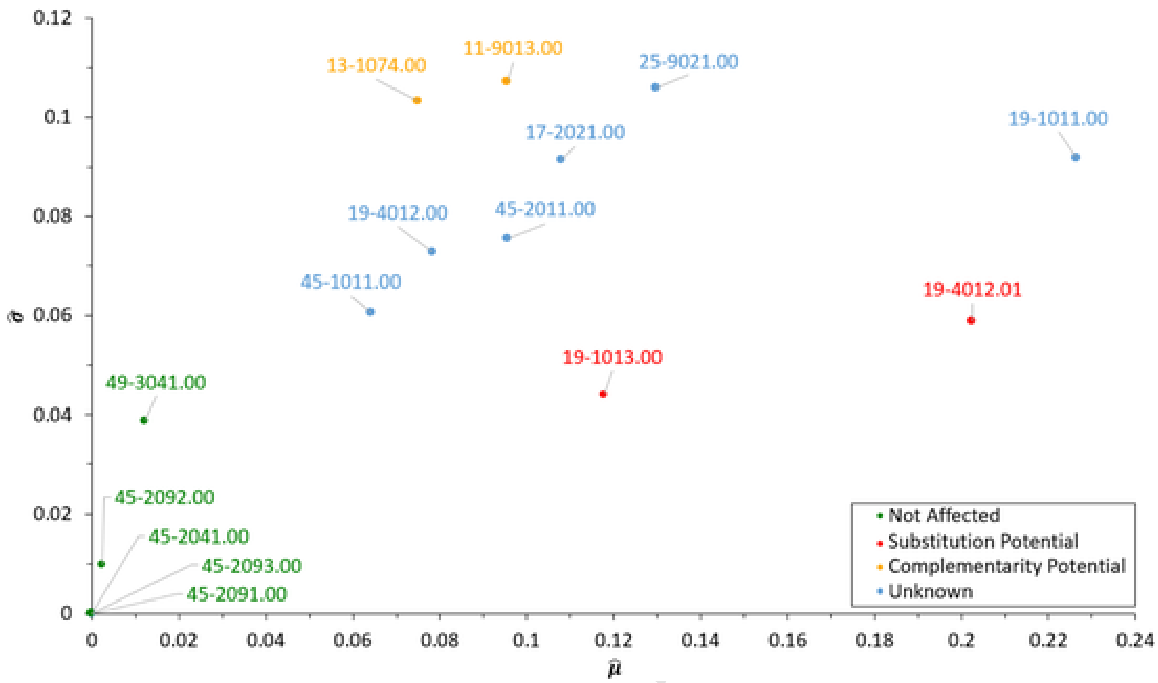


Fig. 7. Standard deviation, $\hat{\sigma}$, versus average weighted exposure to LLM technology, $\hat{\mu}$, for the reviewed agricultural occupations alongside their classification in terms of substitution or complementarity potential.

2091.00); "Farmworkers and Laborers, Crop, Nursery and Greenhouse" (45-2092.00); "Farmworkers, Farm, Ranch, and Aquacultural Animals" (45-2093.00), and "Farm Equipment Mechanics and Service Technicians" (49-3041.00). The core responsibilities in these green-coded occupations involve mainly manual labor and necessitate physical presence. They usually require hands-on responsibilities, such as planting, weeding, and harvesting, and physical engagement with agricultural products, animals, and machinery. These activities are inherently physical and necessitate strength, manual dexterity, and adaptability to varying weather conditions that are beyond the scope of LLMs.

Two occupations were found with moderate to high $\hat{\mu}$ and low $\hat{\sigma}$ as well as high $\hat{\mu}$ and moderate $\hat{\sigma}$ and were classified as having "Substitution Potential". This indicates that most tasks within these occupations have considerable exposure to substitution via LLMs. These red-coded occupations were "Soil and Plant Scientists" (19-1013.00) and "Precision Agriculture Technicians" (19-4012.01). The former occupation examines soil composition, plant growth, and environmental impacts on agriculture. LLMs can support a considerable part of its tasks, by automating, for instance, data analysis, and generations of detailed reports, as well as providing insights based on feed of agricultural and environmental related information [42,43].

Two orange-coded occupations are depicted in Fig. 7, indicative of occupations tending to "Complementarity Potential" by leveraging LLM technology. These occupations are "Farmers, Ranchers, and Other Agricultural Managers" (11-9013.00) and "Farm Labor Contractors" (13-1074.00). In the context of the above occupations, LLMs can serve as powerful tools for enhancing decision-making. For agricultural managers, LLMs can provide data-driven insights for assisting with regulatory compliance and long-term planning. Similarly, for farm labor contractors, LLMs can support the recruitment process and ensure compliance with labor regulations. Potential support of large part of these occupations via LLM, can free up time to address complex challenges and focus more on strategic planning.

As elaborated in Section 2.4, the classification of occupations in those with substitution or complementarity potential and those seen as not to be affected, left a key group of professions positioned between the these regimes, labeled as "Unknowns". The occupations are: "Agricultural Engineers" (17-2021.00); "Animal Scientists (19-1011.00); "Agricultural Technicians" (19-4012.00); "Farm and Home Management Educators" (25-9021.00); "First-Line Supervisors of Farming, Fishing, and Forestry Workers" (45-1011.00); and "Agricultural Inspectors" (45-2011.00). For instance, "Agricultural Engineers" can leverage data-driven insights provided by LLMs to optimize equipment design and support in engineering challenges. "Animal Scientists" can benefit from LLMs in research, by LLM assistance in analyzing large datasets on animal health and productivity. "Agricultural Technicians" can use LLMs to automate data collection and analysis as well as stay updated on the latest research and technological advancements. "Farm and Home Management Educators" can use LLMs to develop personalized training material, while "First-Line Supervisors of Farming, Fishing, and Forestry Workers" can exploit LLMs to analyze performance data and identifying areas for improvement. However, these occupations belong to a group that is not clearly susceptible to either substitution or complementarity. In fact, roles like engineers, scientists, and supervisors involve complex decision-making and adaptability, while technicians and educators rely on hands-on experience and tailored communication. This unique combination of skills highlights their essential human element for technical expertise, human judgment, and creative problem-solving, making them resistant to substitution.

3.2.2. *Relation to cognitive/manual and routine/non-routine nature*

From the above analysis, it appears that the nature of the tasks involved, encompassing cognitive or manual demands as well as routine or non-routine activities, affects the extent to which LLMs can support these roles. These dynamics highlight the importance of recognizing how the specific demands of each role influence the degree to which LLMs can potentially substitute or augment the agricultural workforce. For shedding light on the relation between the substitution/complementarity potential and the overall occupation nature, Fig. 8 is presented. The coordinates of the reviewed occupations in this 2D cognitive/manual versus routine/non-routine space were estimated by Marinoudi et al. [27]. In this paper, this mapping is kept for a common

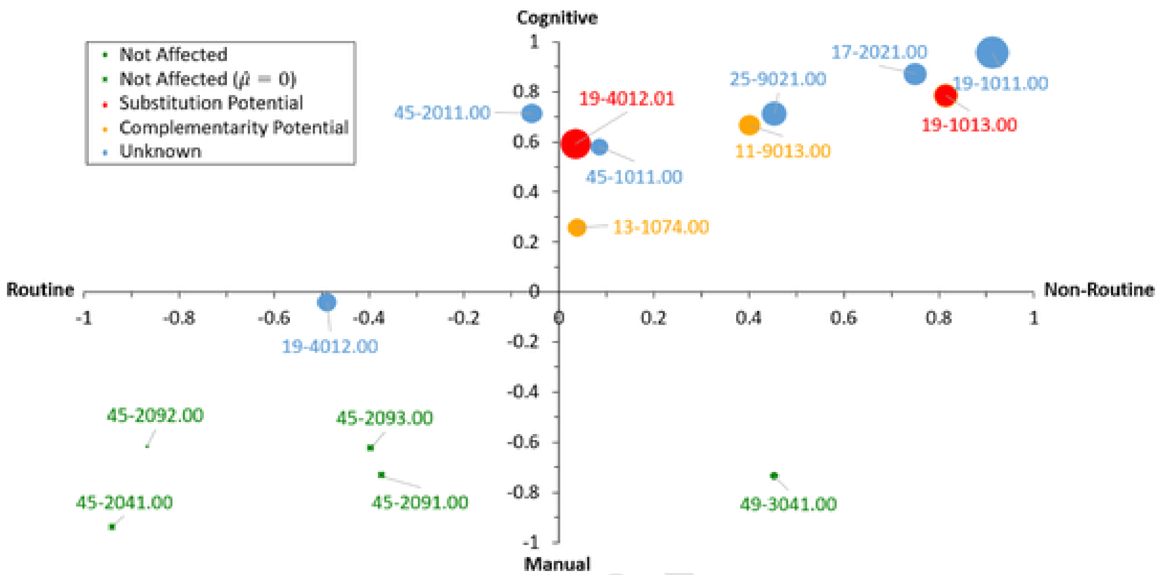


Fig. 8. 2D cognitive/manual versus routine/non-routine space of the agricultural occupations along with their exposure to LLM technology and classification as to the potential for substitution or augmentation.

ground and combined with the assessed average weighted exposure to LLMs, $\hat{\mu}$. As a broad overview, most of the green occupations (classified as "Not Affected") are positioned in the third quadrant characterized from roles normally of manual and routine nature. As analyzed above, tasks that require manual work cannot be undertaken by LLMs. "Farm Equipment Mechanics and Service Technicians" (49-3041.00), belonging also in this group, rely on manual activities, however by requiring more cognitive tasks, thus located in the fourth quadrant. The presence of an "Unknown", namely "Agricultural Technicians" (19-4012.00), in the third quadrant is attributed to the combination of domain-specific knowledge and practical skills [27]. While LLMs excel at data analysis and information retrieval, hands-on expertise required for agricultural technician tasks will still be needed. All contribute to the uncertainty surrounding their future role in the face of advancing AI.

In contrast, occupations having either "Substitution Potential" or "Complementarity Potential" were positioned in the first quadrant, indicative of the cognitive and non-routine nature of most tasks involved. The cognitive and non-routine nature of the majority of tasks in these occupations refers to the complexity and variability involved in the work performed. Cognitive tasks require higher-level thinking processes, such as creativity, problem-solving, and decision-making. These tasks often demand the ability to interpret and process information, adapt to new situations, and develop innovative solutions [44]. The distinction between substitution and complementarity is crucial for understanding the future of work in an AI-driven economy. Occupations with substitution potential may experience significant shifts as technology takes over not only routine but also non-routine tasks, prompting discussions about job workforce adaptation. Conversely, roles with complementarity potential stress the opportunities for collaboration between humans and technology, emphasizing the importance of developing skills that complement AI capabilities.

Finally, the rest of occupations belonging to the "Unknowns" are situated primarily in the quadrants characterized by cognitive and non-routine nature, while the occupation placed in the second quadrant consists of a substantial part of non-routine tasks. The uncertainty surrounding these roles emphasizes the need for further research and analysis to comprehend how advancements in LLM technology might impact them [30]. In other words, as LLM technology continues to advance, the substitution and complementarity potential of various occupations may shift, possibly transforming these professions or giving rise to new occupations, as highlighted above. This evolution reveals the dynamic interplay between technological advancements, including LLMs, and occupational structures within the agricultural sector, highlighting how innovations can reshape traditional roles and workflows. Understanding this interplay is crucial for developing effective strategies that balance technological progress with the need for human expertise and judgment.

3.3. Correlation between large language models exposure and robotization in agriculture

In this fashion, it will be interesting to investigate how the studied LLMs exposure is correlated with the corresponding robotization exposure involving using software or machines to perform tasks automatically without human involvement. In contrast with LLM framework, robotization may involve robots especially designed to carry out mainly repetitive tasks requiring physical exertion with higher speed and precision than humans. These machines often mitigate safety and health risks associated with human labor, making them suitable for fields such as agriculture [37]. However, for non-routine tasks, current AI capabilities can provide support to various aspects, allowing even tasks requiring cognitive flexibility to be managed more efficiently [45]. Towards examining the aforementioned correlation, the average susceptibility rate to robotization, $\hat{s}$, estimated in [27] was used for the same group of occupations associated with agriculture. As can be deduced from Fig. 9, a Pearson's correlation coefficient (r) approximately equal to -0.52 was calculated. This value indicates a moderate negative correlation between exposure to LLMs technology, $\hat{\mu}$, and exposure to robotization, $\hat{s}$. This negative correlation suggests that as exposure to LLMs increases, exposure to robotization tends to decrease, and vice versa. The associated p-value of 0.047 indicates that this correlation is statistically significant at the 5 % level (since p-value < 0.05), emphasizing the interrelated dynamics between these two variables in the context analyzed. This result, qualitatively agrees with [31], and is attributed to the manual nature mainly of the routine tasks and the level of machinery exposure that many agricultural occupations entail. As mentioned above, manual tasks are beyond the scope of LLMs. These tasks often involve hands-on activities, such as physically handling objects, which require physical presence and manual dexterity, capabilities that LLMs cannot provide. LLMs, being software-based models, are typ-

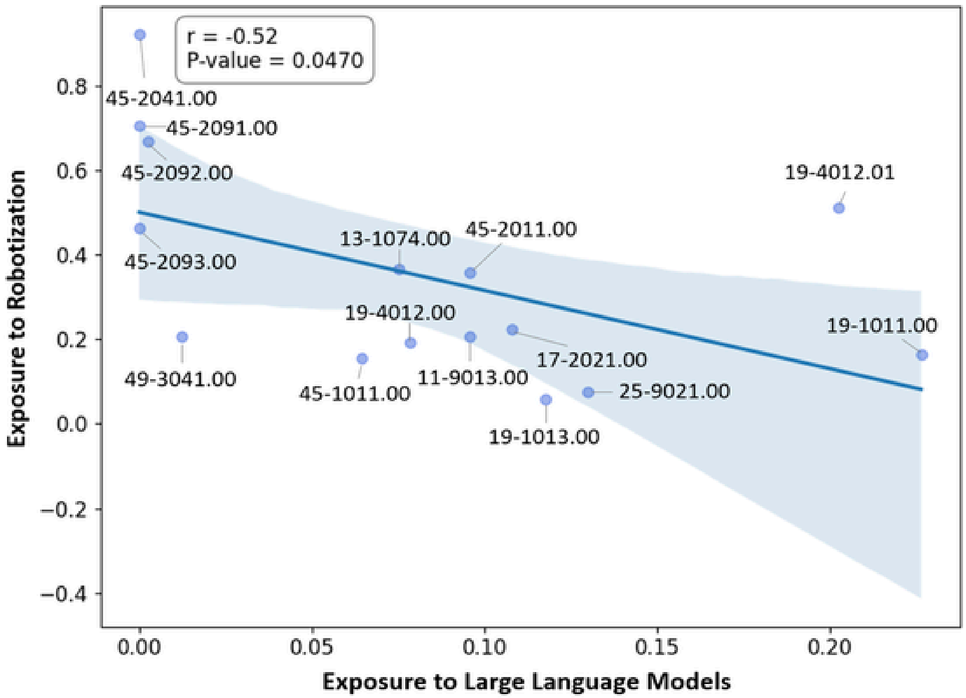


Fig. 9. Correlation between the average weighted exposure to Large Language Models, $\hat{\mu}$,estimated in this study, and to robotization, $\hat{s}$, estimated in [27] both at occupation level.

ically designed to process and generate text, analyze data, and assist with cognitive functions rather than perform physical actions.

4. Discussion

In agriculture, LLMs have the potential to transform traditional practices and synergize with Agriculture 4.0 technologies towards revolutionizing the sector. This study examined the possible implications of LLMs on the agricultural labor market, focusing on how these technologies might affect various occupations. To that end, the cognitive, physical, physicomotor, and sensory abilities required for the execution of each task involved in agricultural occupations were investigated with respect to the potential capacity of current LLMs.

As a first step, the distribution of the 45 abilities, along with their corresponding importance, across the 15 selected agricultural occupations revealed significant insights into how LLMs might influence these roles, with cognitive abilities dominating. Nevertheless, owing to the nature of agricultural domain, which requires physical interaction with a dynamic environment and hands-on involvement, physical, psychomotor and sensory abilities remain critical. Accordingly, while LLMs can enhance cognitive functions, such as data analysis and decision-making through advanced reasoning, they cannot handle the physical and psychomotor facets of agricultural work. Additionally, sensory abilities, like near vision, still remain vital for tasks such as monitoring plant health and detecting pests. As a consequence, although some tasks are partially (25 % out of all tasks) or highly (20 % out of all tasks) susceptible to exposure to LLMs, a significant portion remains largely unaffected (55 % out of total). This varied impact on the agricultural workforce highlights the dual nature of technological progress of LLMs, allowing for intervention in certain roles while preserving traditional roles that rely on human skills.

The classification of agricultural occupations into “Not Affected”, "Substitution Potential", "Complementarity Potential", and “Unknowns” provided also key understandings into how LLMs might reshape agricultural labor landscape. Roles with " Substitution Potential" are characterized by a considerable amount of data-driven tasks, which aligns with the hypothesis that LLMs are highly effective at automating cognitive repetitive functions [46,47]. Occupations with "Complementarity Potential" are anticipated to benefit from LLMs by supporting various aspects of their work, such as report generation and routine administrative tasks. This will enable professionals to focus on more complex and creative tasks, supporting the argument that LLMs can enhance human capabilities rather than fully replace them. This point of view aligns with current perspectives on the complementary role of AI and human expertise [48,49]. As stressed by Jarrahi [49], the symbiosis of humans and AI implies that interaction between them can enhance the intelligence of both over time. Most AI algorithms, including LLMs, can increase their effectiveness with more data and interactions with human partners. Likewise, LLMs can serve as powerful tools that augment human capabilities, allowing for more efficient decision-making with data-driven insights.

Agriculture features considerable diversity not only across different occupations, but also within the same occupation, making it complex to assess how LLMs might reshape these professions. As a consequence, the 40 % of the reviewed occupation fell into the category of “Unknowns”. The uncertainty surrounding these occupations highlights the need for further research to figure out the evolving dynamics between human expertise and LLMs capabilities. This ongoing evolution emphasizes also the necessity for adaptive workforce skills development to ensure that the agricultural labor force can effectively collaborate with LLMs, thus, harnessing their strengths and mitigating potential disruptions. Continuous updating of skill sets is expected to ensure that the integration of LLMs complements human expertise, fostering a symbiotic relationship that maximizes the benefits of both human and AI contributions in the agricultural sector. Finally, the present analysis revealed several key insights into the interplay between LLM exposure and robotization-automation, as notably, a negative correlation between them was found. As the reliance on robotization for repetitive, physically demanding tasks increases, the exposure of LLMs tends to decrease, and vice versa. This outcome suggests that while LLMs can enhance cognitive and data processing tasks, they cannot replace the physical capabilities provided by robotic systems, highlighting the distinct and complementary roles these technologies might play in the agricultural sector.

The integration of LLMs into the agricultural sector has the potential to exacerbate job polarization, where the labor market increasingly splits into high-skill (high-wage jobs) and low-skill (low-wage jobs), with a decline in middle-skill roles [50,51]. As analyzed, LLMs are likely to automate several cognitive routine tasks, disproportionately affecting mid-level occupations that rely on tasks like data handling and report generation. In contrast, high-skill jobs requiring advanced analytical abilities and the integration of LLMs into workflows may grow, whereas low-skill manual roles remain relatively unaffected due to the physical limitations of LLMs. Nonetheless, the extent to which LLMs influence job polarization in agriculture will depend on several factors, including the speed of technological progress, the range of tasks that can be automated, and the adaptability of the workforce to emerging technologies. To address the potential challenges of job polarization, policymakers must prioritize proactive policies and training programs to reduce disparities and ensure equitable access to the opportunities created by these technologies.

Building upon the findings of this work, several potential research directions arise to further explore the integration of LLMs and their impact on the agricultural sector. First, given that the majority of agricultural occupations belong to the "Unknowns" category, future research, mainly under case study approaches, should focus on these roles to deepen the understanding of how LLMs might influence them through identifying areas for possible substitution or complementarity. This presupposes tracking of the evolving dynamics between LLM capabilities and human expertise over time. It would be interesting to apply the current methodology to other sectors, allowing for a broader understanding of how LLMs may impact different industries and occupations, thereby fostering cross-sectoral insights. Identifying timely key skills for enhancing collaboration between human workers and LLMs is of major importance leading to adaptive training programs development. Future policy makers should also consider risks related to the application of LLMs [52–55], such as potential:

Bias: For example, if an LLM is trained on datasets that favor large-scale farming methods, it may prioritize recommendations for high-input, mechanized agriculture over alternative practices suited to smallholders, such as regenerative agriculture [56].

Information 'hallucination': LLMs are prone to generating plausible but factually incorrect outputs. In agriculture, this could have serious consequences which could harm both the environment and crop productivity.

Privacy concerns: As LLMs process vast amounts of sensitive data, there is a risk of unauthorized data sharing without the farmer's consent, undermining trust and exposing farms to unfair competition.

Ethical considerations: Adoption of LLMs, like other technological advancements, may disproportionately benefit larger, technologically advanced farms, further widening the gap between smallholder farmers and agribusinesses [57].

Finally, given the evidence of the fundamental analysis of the relationship between LLMs exposure and robotization, the investigation of their combined effects on agricultural occupations would also be valuable. This analysis can provide understanding on how these technologies can influence various roles within the sector as well as spotting opportunities for optimizing their integration to improve productivity and efficiency in agriculture.

5. Conclusions

In conclusion, this study highlights the nuanced impact of LLMs on the agricultural labor market, emphasizing their potential to replace or augment cognitive functions while being limited in replacing the physical, psychomotor, and sensory demands of agricultural work. The findings suggest that while certain roles, particularly those reliant on data-driven tasks, are more susceptible to substitutions, other occupations will experience a complementary effect, with LLMs supporting cognitive tasks and allowing human workers to focus on more creative responsibilities. However, a significant portion of occupations remains unaffected or uncertain, signaling the need for ongoing research and adaptive workforce development to ensure effective collaboration between human expertise and LLMs.

The insights gained from this work can constitute a valuable foundation for comprehending how these technologies can transform various agricultural occupations and task dynamics. This transformation is expected to lead to a shift towards positions that focus on analytical abilities, as LLMs can support and interface, among others, data processing, decision-making support, and strategic planning. Moreover, a growing demand is anticipated for skilled professionals who can effectively interact with these technologies by exploiting their capabilities to manage and optimize agricultural practices. Accordingly, targeted reskilling initiatives and workforce development programs will be imperative tailored to the emerging technological landscape. Finally, LLMs will be continually advanced and incorporated into various applications. Hence, it is crucial for policymakers to effectively manage biases in training data and ensure ongoing human oversight for maximizing the benefits of LLMs in agriculture while mitigating potential risks.

Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Ethics statement

V Not applicable: This manuscript does not include human or animal research.

If this manuscript involves research on animals or humans, it is imperative to disclose all approval details.

If Yes, please provide your text here:

CRediT authorship contribution statement

Vasso Marinoudi: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lefteris Benos:** Writing – original draft, Methodology, Investigation, Formal analysis. **Carolina Camacho Villa:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Dimitrios Kateris:** Visualization, Validation, Investigation, Data curation. **Remigio Berruto:** Writing – review & editing, Resources, Methodology. **Simon Pearson:** Writing – review & editing, Methodology. **Claus Grøn Sørensen:** Writing – review & editing, Methodology, Formal analysis. **Dionysis Bochtis:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A

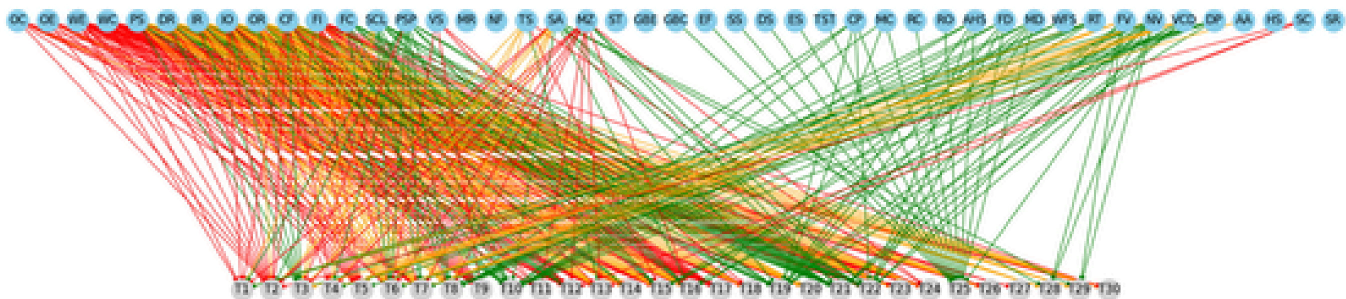
Table A1 presents the short description for each ability according to [29].

Table A1
. Summary of the 45 reviewed abilities along with a short description of their content, [29].

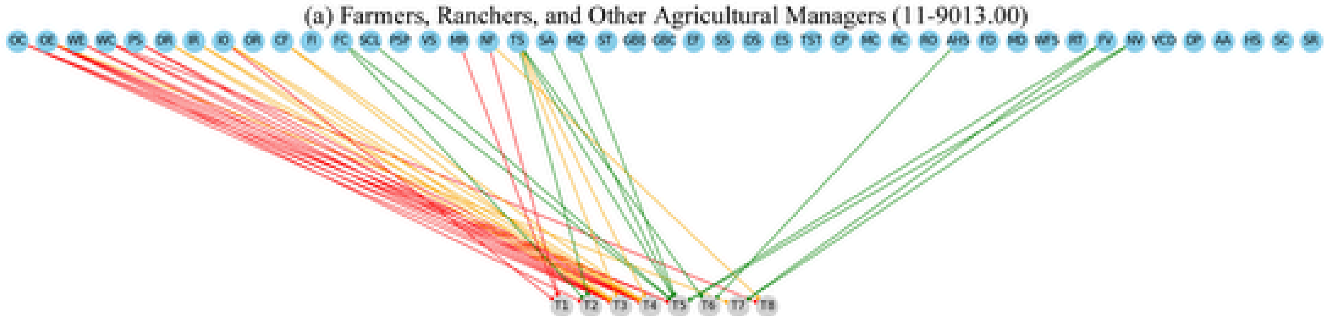
Ability	Description
Oral Comprehension	Listen to and understand information and ideas presented through spoken words and sentences
Oral Expression	Communicate information and ideas in speaking so others will understand
Written Expression	Communicate information and ideas in writing so others will understand
Written Comprehension	Read and understand information and ideas presented in writing
Problem Sensitivity	Tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem
Deductive Reasoning	Apply general rules to specific problems to produce answers that make sense
Inductive Reasoning	Combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events)
Information Ordering	Arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations)
Originality	Come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem
Category Flexibility	Generate or use different sets of rules for combining or grouping things in different ways
Fluency of Ideas	Come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity)
Flexibility of Closure	Identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material
Speed of Closure	Quickly make sense of, combine, and organize information into meaningful patterns
Perceptual Speed	Quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object
Visualization	Imagine how something will look after it is moved around or when its parts are moved or rearranged
Mathematical Reasoning	Choose the right mathematical methods or formulas to solve a problem
Number Facility	Add, subtract, multiply, or divide quickly and correctly
Time Sharing	Shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources)
Selective Attention	Concentrate on a task over a period of time without being distracted
Memorization	Remember information such as words, numbers, pictures, and procedures
Stamina	Exert yourself physically over long periods of time without getting winded or out of breath
Gross Body Equilibrium	Keep or regain your body balance or stay upright when in an unstable position
Gross Body Coordination	Coordinate the movement of your arms, legs, and torso together when the whole body is in motion
Extent Flexibility	Bend, stretch, twist, or reach with your body, arms, and/or legs
Static Strength	Exert maximum muscle force to lift, push, pull, or carry objects
Dynamic Strength	Exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue
Explosive Strength	Use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object
Trunk Strength	Use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without "giving out" or fatiguing
Control Precision	Quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions
Multilimb Coordination	Coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion
Rate Control	Time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene
Response Orientation	Choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part
Arm-Hand Steadiness	Keep your hand and arm steady while moving your arm or while holding your arm and hand in one position
Finger Dexterity	Make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects
Manual Dexterity	Quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects
Wrist-Finger Speed	Make fast, simple, repeated movements of the fingers, hands, and wrists
Reaction Time	Quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears
Far Vision	See details at a distance
Near Vision	See details at close range (within a few feet of the observer)
Visual Color Discrimination	Match or detect differences between colors, including shades of color and brightness
Depth Perception	Judge which of several objects is closer or further away from you, or to judge the distance between you and an object
Auditory Attention	Focus on a single source of sound in the presence of other distracting sounds
Hearing Sensitivity	Detect or tell the differences between sounds that vary in pitch and loudness.
Speech Clarity	Speak clearly so others can understand you
Speech Recognition	Identify and understand the speech of another person

Appendix B

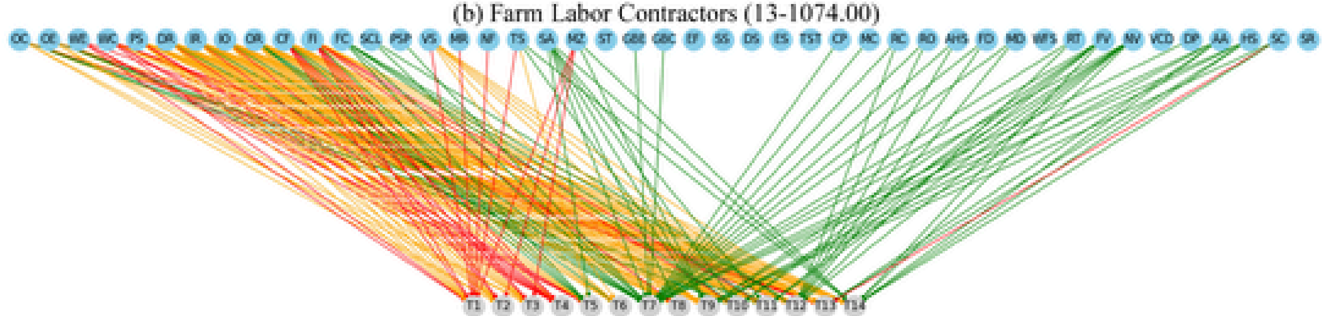
Fig. B1 presents multimode graphs for each agricultural occupation, with light blue circles representing the 45 evaluated abilities, grey circles indicating associated tasks, and colored vectors showing the correspondence between them and the capacity levels of current LLMs.



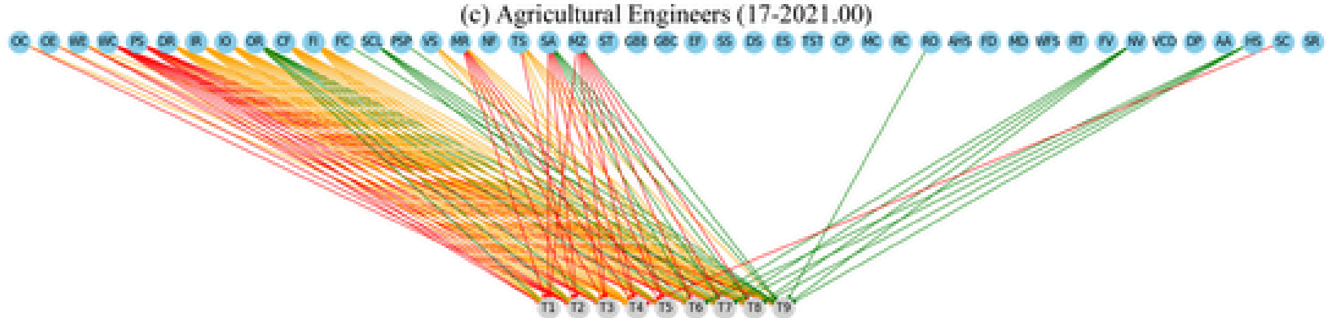
(a) Farmers, Ranchers, and Other Agricultural Managers (11-9013.00)



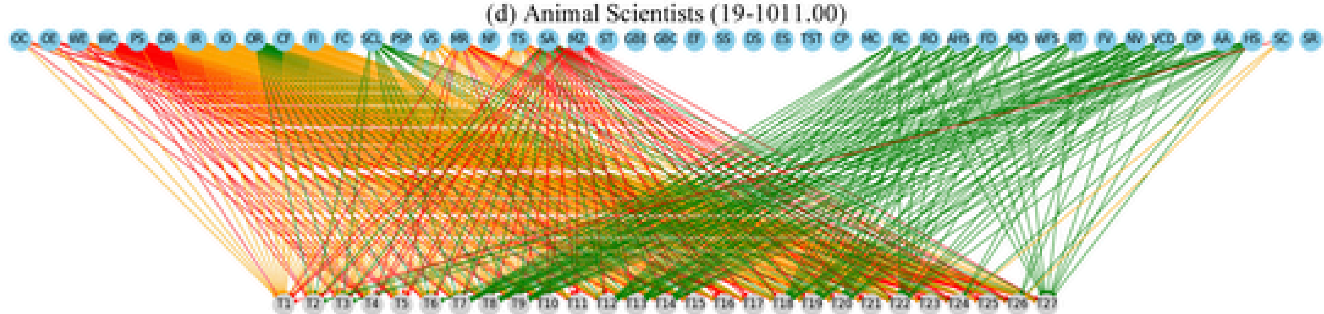
(b) Farm Labor Contractors (13-1074.00)



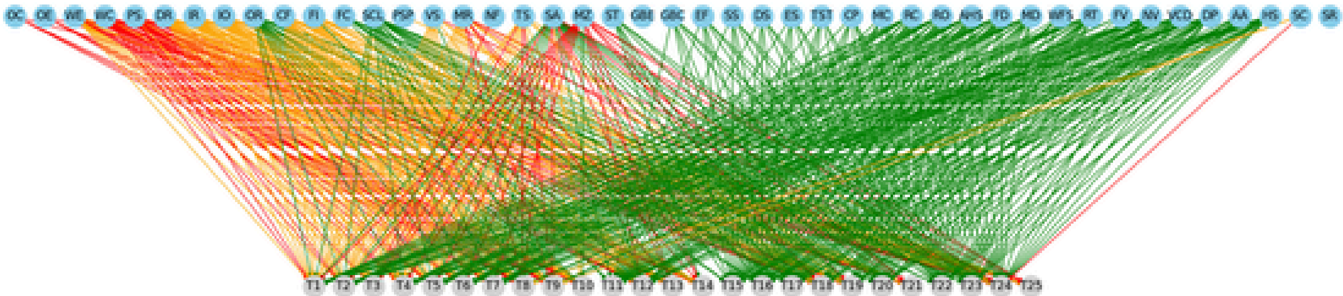
(c) Agricultural Engineers (17-2021.00)



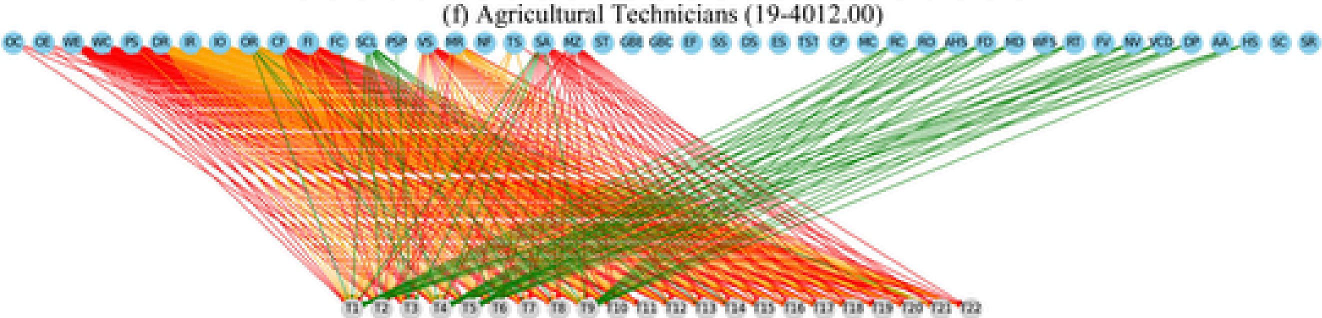
(d) Animal Scientists (19-1011.00)



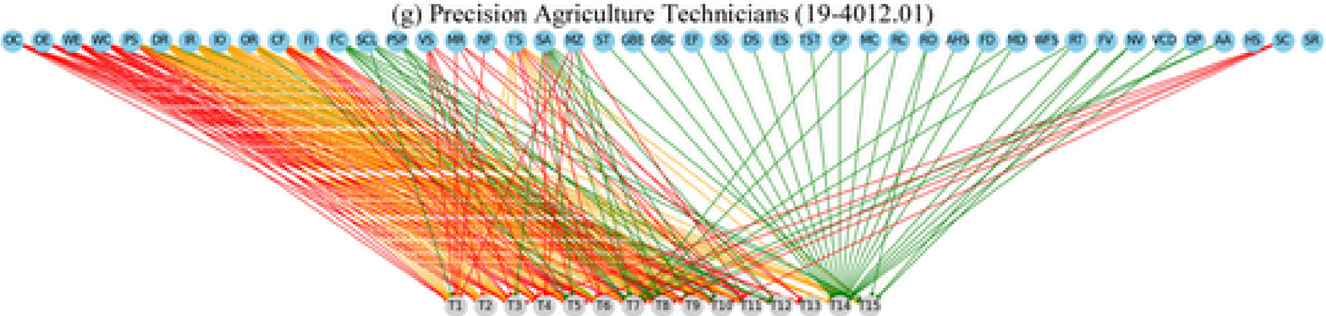
(e) Soil and Plant Scientists (19-1013.00)



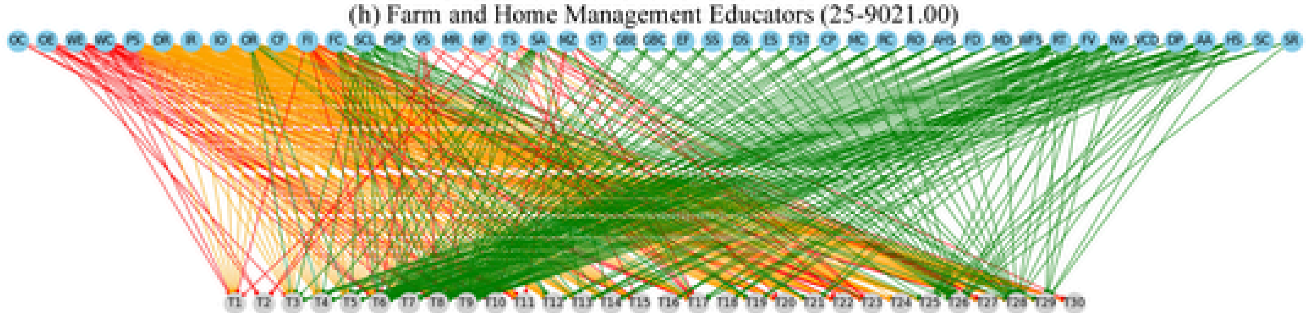
(f) Agricultural Technicians (19-4012.00)



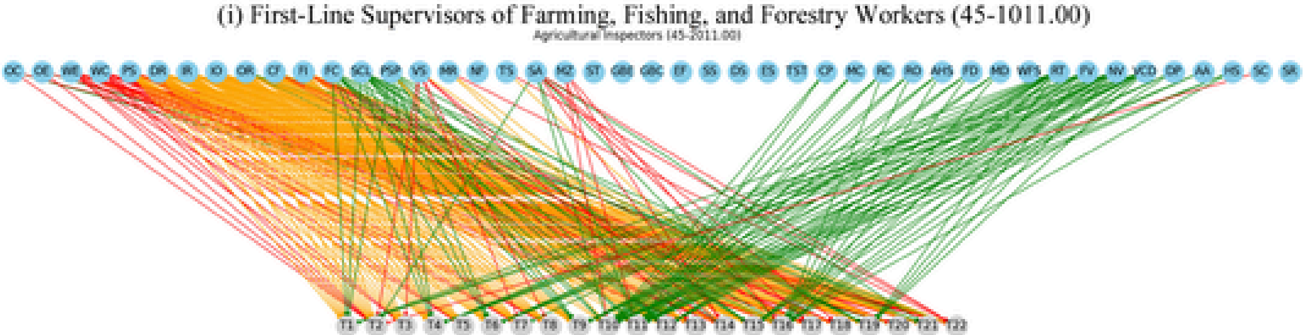
(g) Precision Agriculture Technicians (19-4012.01)



(h) Farm and Home Management Educators (25-9021.00)



(i) First-Line Supervisors of Farming, Fishing, and Forestry Workers (45-1011.00)



(j) Agricultural Inspectors (45-2011.00)

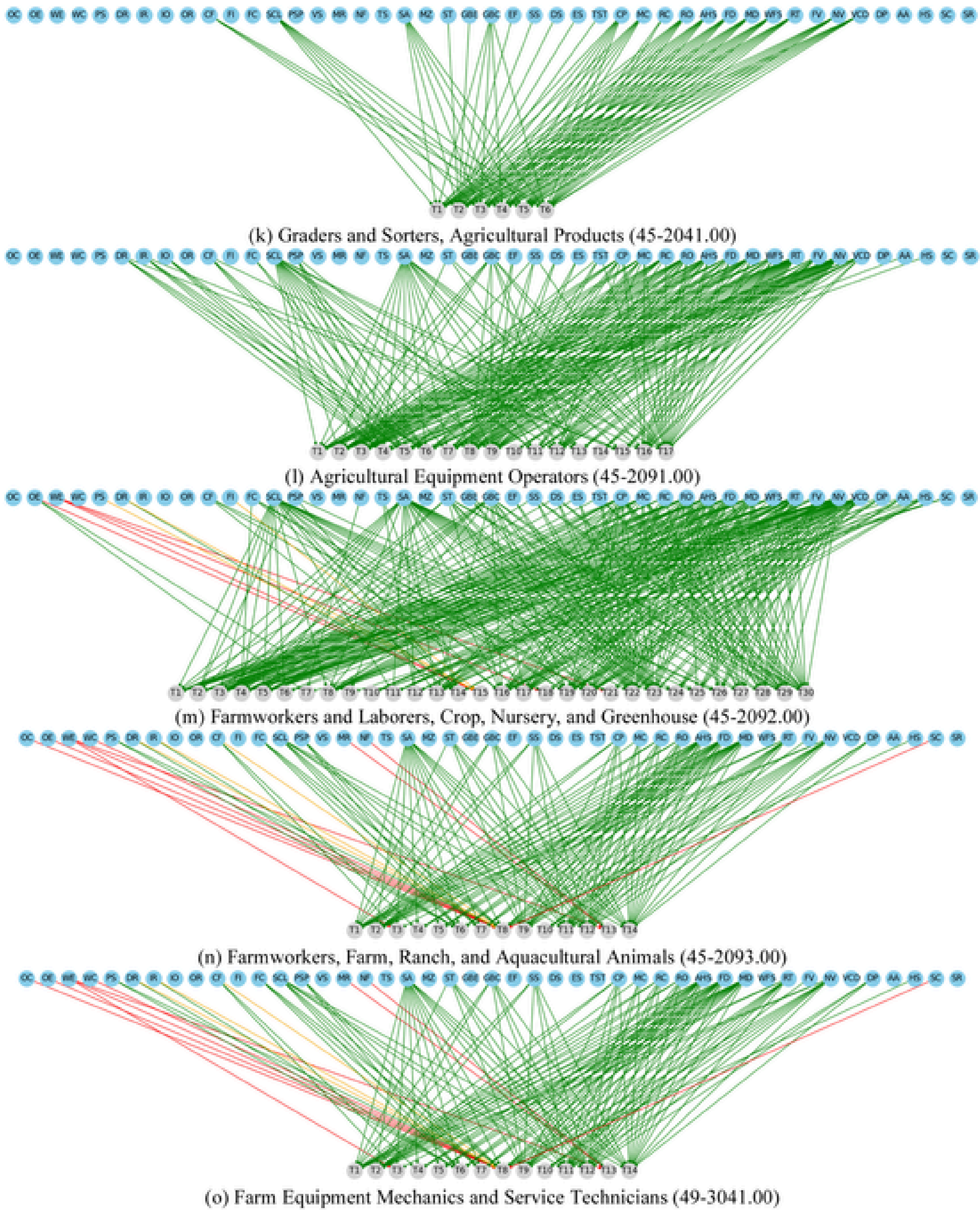


Fig. B1. . Multimode graphs for each agricultural occupation. The main nodes (depicted with light blue circles) represent the ability under assessment, whereas each target node (depicted with grey circles) denotes the reviewed task involved in the occupation at hand. The vectors show which abilities correspond to which tasks, while their colors illustrate the corresponding different level of capacity of current LLMs: negligible (green); partial (orange); full (red).

References

[1] E. Kasneci, K. Sessler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier, S. Krusche, G. Kutyniok, T. Michaeli, C. Nerdel, J. Pfeffer, O. Poquet, M. Sailer, A. Schmidt, T. Seidel, M. Stadler, J. Weller, J. Kuhn, G. Kasneci, ChatGPT for good? On opportunities and challenges of large language models for education, Learn. Individ. Differ. 103 (2023) 102274, https://doi.org/10.1016/j.lindif.2023.102274.

[2] B. Zhao, W. Jin, J. Del Ser, G. Yang, ChatAgri: exploring potentials of ChatGPT on cross-linguistic agricultural text classification, Neurocomputing 557 (2023) 126708, https://doi.org/10.1016/j.neucom.2023.126708.

[3] M.A.K. Raiaan, M.S.H. Mukta, K. Fatema, N.M. Fahad, S. Sakib, M.M.J. Mim, J. Ahmad, M.E. Ali, S. Azam, A review on large language models: architectures, applications, taxonomies, open issues and challenges, IEEE Access 12 (2024) 26839–26874, https://doi.org/10.1109/ACCESS.2024.3365742.

[4] ChatGPT Capabilities Overview, (2024). https://help.openai.com/en/articles/9260256-chatgpt-capabilities-overview (accessed July 17, 2024).

[5] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, in: I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, R. Garnett (Eds.), Adv. Neural Inf. Process. Syst., Curran Associates, Inc., 2017. https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.

[6] OpenAI Platform, Models overview, (n.d.). https://platform.openai.com/docs/models (accessed July 17, 2024).

[7] R. Thoppilan, D. De Freitas, J. Hall, N. Shazeer, A. Kulshreshtha, H.-T. Cheng, A. Jin, T. Bos, L. Baker, Y. Du, Y. Li, H. Lee, H.S. Zheng, A. Ghafouri, M. Menegali, Y. Huang, M. Krikun, D. Lepikhin, J. Qin, D. Chen, Y. Xu, Z. Chen, A. Roberts, M. Bosma, V. Zhao, Y. Zhou, C.-C. Chang, I. Krivokon, W. Rusch, M. Pickett, P. Srinivasan, L. Man, K. Meier-Hellstern, M.R. Morris, T. Doshi, R.D. Santos, T. Duke, J. Soraker, B. Zevenbergen, V. Prabhakaran, M. Diaz, B. Hutchinson, K. Olson, A. Molina, E. Hoffman-John, J. Lee, L. Aroyo, R. Rajakumar, A. Butryna, M. Lamm, V. Kuzmina, J. Fenton, A. Cohen, R. Bernstein, R. Kurzweil, B. Aguera-Arcas, C. Cui, M. Croak, E. Chi, Q. Le, LaMDA: Language Models for Dialog Applications, (2022). https://arxiv.org/abs/2201.08239.

[8] S. Smith, M. Patwary, B. Norick, P. LeGresley, S. Rajbhandari, J. Casper, Z. Liu, S. Prabhumoye, G. Zerveas, V. Korthikanti, E. Zhang, R. Child, R.Y. Aminabadi, J. Bernauer, X. Song, M. Shoeybi, Y. He, M. Houston, S. Tiwary, B. Catanzaro, Using deepspeed and megatron to train megatron-Turing NLG 530B, A Large-Scale Generative Language Model (2022). https://arxiv.org/abs/2201.11990.

[9] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, (2019). https://arxiv.org/abs/1810.04805.

[10] Z. Ghahramani, Introducing PaLM 2, (2023). https://blog.google/technology/ai/google-palm-2-ai-large-language-model/ (accessed July 17, 2024).

[11] Gemini Models, (n.d.). https://deepmind.google/technologies/gemini/ (accessed July 16, 2024).

[12] J.L. Steele, To GPT or not GPT? Empowering our students to learn with AI, Comput. Educ. Artif. Intell. 5 (2023) 100160, https://doi.org/10.1016/j.caeai.2023.100160.

[13] K.I. Roumeliotis, N.D. Tselikas, D.K. Nasiopoulos, LLMs in e-commerce: A comparative analysis of GPT and LLaMA models in product review evaluation, Nat. Lang. Process. J. 6 (2024) 100056, https://doi.org/10.1016/j.nlp.2024.100056.

[14] D. Wang, Y. Wang, X. Jiang, Y. Zhang, Y. Pang, M. Zhang, When large language models meet optical networks: paving the way for automation, Electronics (2024) 13, https://doi.org/10.3390/electronics13132529.

[15] A.J. Thirunavukarasu, D.S.J. Ting, K. Elangovan, L. Gutierrez, T.F. Tan, D.S.W. Ting, Large language models in medicine, Nat. Med. 29 (2023) 1930–1940, https://doi.org/10.1038/s41591-023-02448-8.

[16] E. Westphal, H. Seitz, Generative artificial intelligence: analyzing its future applications in additive manufacturing, Big Data Cogn. Comput 8 (2024), https://doi.org/10.3390/bdcc8070074.

[17] V.T. Hayashi, W.V. Ruggiero, Hardware trojan dataset of RISC-V and Web3 generated with ChatGPT-4, Data 9 (2024), https://doi.org/10.3390/data9060082.

[18] R. Fragomeli, A. Annunziata, G. Punzo, Promoting the transition towards agriculture 4.0: A systematic literature review on drivers and barriers, Sustainability (2024) 16, https://doi.org/10.3390/su16062425.

[19] S.A. Osinga, D. Paudel, S.A. Mouzakitis, I.N. Athanasiadis, Big data in agriculture: Between opportunity and solution, Agric. Syst. 195 (2022) 103298, https://doi.org/10.1016/j.agsy.2021.103298.

[20] L. Benos, V. Moysiadis, D. Kateris, A.C. Tagarakis, P. Busato, S. Pearson, D. Bochtis, Human-robot interaction in agriculture: a systematic review, Sensors (2023) 23, https://doi.org/10.3390/s23156776.

[21] A.C. Tagarakis, L. Benos, G. Kyriakarakos, S. Pearson, C.G. Sørensen, D. Bochtis, Digital twins in agriculture and forestry: a review, Sensors (2024) 24, https://doi.org/10.3390/s24103117.

[22] C. Boix-Fayos, J. de Vente, Challenges and potential pathways towards sustainable agriculture within the European Green Deal, Agric. Syst. 207 (2023) 103634, https://doi.org/10.1016/j.agsy.2023.103634.

[23] A. Tzachor, M. Devare, C. Richards, P. Pypers, A. Ghosh, J. Koo, S. Johal, B. King, Large language models and agricultural extension services, Nat. Food 4 (2023) 941–948, https://doi.org/10.1038/s43016-023-00867-x.

[24] K.P. Seamus McGuinness, P. Redmond, Skills-displacing technological change and its impact on jobs: challenging technological alarmism? Econ. Innov. New Technol. 32 (2023) 370–392, https://doi.org/10.1080/10438599.2021.1919517.

[25] V. Marinoudi, C.G. Sørensen, S. Pearson, D. Bochtis, Robotics and labour in agriculture. A context consideration, Biosyst. Eng. 184 (2019) 111–121, https://doi.org/10.1016/j.biosystemseng.2019.06.013.

[26] E. Filippi, M. Bannò, S. Trento, Automation technologies and their impact on employment: A review, synthesis and future research agenda, Technol. Forecast. Soc. Change 191 (2023) 122448, https://doi.org/10.1016/j.techfore.2023.122448.

[27] V. Marinoudi, L. Benos, C.C. Villa, M. Lampridi, D. Kateris, R. Berruto, S. Pearson, C.G. Sørensen, D. Bochtis, Adapting to the agricultural labor market shaped by robotization, Sustainability (2024) 16, https://doi.org/10.3390/su16167061.

[28] V. Marinoudi, M. Lampridi, D. Kateris, S. Pearson, C.G. Sørensen, D. Bochtis, The future of agricultural jobs in view of robotization, Sustainability (2021) 13, https://doi.org/10.3390/su132112109.

[29] O*NET OnLine, (n.d.). https://www.onetonline.org/ (accessed March 13, 2024).

[30] P. Gmyrek, J. Berg, D. Bescond, Generative AI and jobs: A global analysis of potential effects on job quantity and quality, International Labour Office, Geneva, 2023 ILO Working paper 96. https://www.ilo.org/publications/generative-ai-and-jobs-global-analysis-potential-effects-job-quantity-and.

[31] T. Eloundou, S. Manning, P. Mishkin, D. Rock, GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models, (2023). https://arxiv.org/abs/2303.10130.

[32] F. Carbonero, J. Davies, E. Ernst, F.M. Fossen, D. Samaan, A. Sorgner, The impact of artificial intelligence on labor markets in developing countries: a new method with an illustration for Lao PDR and urban Viet Nam, J. Evol. Econ. 33 (2023) 707–736, https://doi.org/10.1007/s00191-023-00809-7.

[33] D. Xu, H. Yang, M.-A. Rizoiu, G. Xu, From occupations to tasks: a new perspective on automatability prediction using BERT, in: 2023 10th Int. Conf. Behav. Soc. Comput, 2023, pp. 1–7, https://doi.org/10.1109/BESC59560.2023.10386407.

[34] D. Bochtis, L. Benos, M. Lampridi, V. Marinoudi, S. Pearson, C.G. Sørensen, Agricultural workforce crisis in light of the COVID-19 pandemic, Sustainability (2020) 12, https://doi.org/10.3390/su12198212.

[35] A. Agrawal, J.S. Gans, A. Goldfarb, Do we want less automation? Science (80-.) 381 (2023) 155–158, https://doi.org/10.1126/science.adh9429.

[36] D.H. Autor, F. Levy, R.J. Murnane, The skill content of recent technological change: an empirical exploration, Q. J. Econ. 118 (2003) 1279–1333, https://doi.org/10.1162/003355303322552801.

[37] L. Benos, A. Bechar, D. Bochtis, Safety and ergonomics in human-robot interactive agricultural operations, Biosyst. Eng. 200 (2020) 55–72, https://doi.org/10.1016/j.biosystemseng.2020.09.009.

[38] S. Villa, T. Kosch, F. Grelka, A. Schmidt, R. Welsch, The placebo effect of human augmentation: Anticipating cognitive augmentation increases risk-taking behavior, Comput. Human Behav. 146 (2023) 107787, https://doi.org/10.1016/j.chb.2023.107787.

[39] J. Yang, H. Jin, R. Tang, X. Han, Q. Feng, H. Jiang, S. Zhong, B. Yin, X. Hu, Harnessing the power of LLMs in practice: a survey on ChatGPT and beyond, ACM Trans. Knowl. Discov. Data 18 (2024), https://doi.org/10.1145/3649506.

[40] H. Hassani, E.S. Silva, S. Unger, M. TajMazinani, S.Mac Feely, Artificial intelligence (AI) or intelligence augmentation (IA): What is the future? AI 1 (2020) 143–155, https://doi.org/10.3390/ai1020008.

[41] S. Chowdhury, P. Dey, S. Joel-Edgar, S. Bhattacharya, O. Rodriguez-Espindola, A. Abadie, L. Truong, Unlocking the value of artificial intelligence in human resource management through AI capability framework, Hum. Resour. Manag. Rev. 33 (2023) 100899, https://doi.org/10.1016/j.hrmr.2022.100899.

[42] S. Anush Lakshman, D. Ebenezer, Integration of internet of things and drones and its future applications, Mater. Today Proc 47 (2021) 944–949, https://doi.org/10.1016/j.matpr.2021.05.039.

[43] B.I. Akhigbe, K. Munir, O. Akinade, L. Akanbi, L.O. Oyedele, IoT technologies for livestock management: a review of present status, opportunities, and future trends, Big Data Cogn. Comput 5 (2021), https://doi.org/10.3390/bdcc5010010.

[44] V. Marinoudi, M. Lampridi, D. Kateris, S. Pearson, C.G. Sørensen, D. Bochtis, The future of agricultural jobs in view of robotization, Sustainability (2021) 13, https://doi.org/10.3390/su132112109.

[45] C. Angulo, A. Chacón, P. Ponsa, Towards a cognitive assistant supporting human operators in the Artificial Intelligence of Things, Internet of Things 21 (2023) 100673, https://doi.org/10.1016/j.iot.2022.100673.

[46] H.B. Essel, D. Vlachopoulos, A.B. Essuman, J.O. Amankwa, ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs), Comput. Educ. Artif. Intell. 6 (2024) 100198, https://doi.org/10.1016/j.caeai.2023.100198.

[47] Y. Zhuang, Q. Liu, Y. Ning, W. Huang, R. Lv, Z. Huang, G. Zhao, Z. Zhang, Q. Mao, S. Wang, E. Chen, Efficiently Measuring the Cognitive Ability of LLMs: An Adaptive Testing Perspective, (2023). https://arxiv.org/abs/2306.10512.

[48] M.H. Jarrahi, D. Askay, A. Eshraghi, P. Smith, Artificial intelligence and knowledge management: a partnership between human and AI, Bus. Horiz. 66 (2023) 87–99, https://doi.org/10.1016/j.bushor.2022.03.002.

[49] M.H. Jarrahi, Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making, Bus. Horiz. 61 (2018) 577–586, https://doi.org/10.1016/j.bushor.2018.03.007.

[50] O. Charlot, I. Fontaine, T. Sopraseuth, Job polarization and non-standard work: evidence from france, Labour Econ 88 (2024) 102534, https://doi.org/10.1016/j.labeco.2024.102534.

[51] B.M. Fleisher, W.H. McGuire, Y. Su, M.Q. Zhao, Polarization of employment and wages in China, Econ. Transit. Institutional Chang. 32 (2024) 49–71, https://doi.org/10.1111/ecot.12378.

[52] G. Perković, A. Drobnjak, I. Botički, Hallucinations in LLMs: understanding and addressing challenges, in: 2024 47th MIPRO ICT electron, Conv (2024) 2084–2088,

https://doi.org/10.1109/MIPRO60963.2024.10569238.
[53] N. Marques, R.R. Silva, J. Bernardino, Using ChatGPT in software requirements engineering: a comprehensive review, Futur. Internet 16 (2024), https://doi.org/10.3390/fi16060180.
[54] S. Akter, M.A. Hossain, S. Sajib, S. Sultana, M. Rahman, D. Vrontis, G. McCarthy, A framework for AI-powered service innovation capability: review and agenda for future research, Technovation 125 (2023) 102768, https://doi.org/10.1016/j.technovation.2023.102768.
[55] J. Zhou, F. Chen, AI ethics: from principles to practice, AI Soc 38 (2023) 2693–2703, https://doi.org/10.1007/s00146-022-01602-z.
[56] S.G.R.S.K.C. Rebecca Voisin Pierre Horwitz, A. Devine, What goes in and what comes out: a scoping review of regenerative agricultural practices, Agroecol. Sustain. Food Syst. 48 (2024) 124–158, https://doi.org/10.1080/21683565.2023.2270441.
[57] L. Benos, C.G. Sørensen, D. Bochtis, Field deployment of robotic systems for agriculture in light of key safety, labor, ethics and legislation issues, Curr. Robot. Reports (2022), https://doi.org/10.1007/s43154-022-00074-9.