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ARTIFICIAL INTELLIGENCE IN AGRICULTURE: EMPLOYEES' PERCEPTION OF OCCUPATIONAL HEALTH AND SAFETY RISKS

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Abstract. *The increasing adoption of Artificial Intelligence (AI) in agriculture is transforming farming practices while introducing new challenges related to occupational health and safety (OHS). AI technologies have the potential to improve productivity, optimize resource utilization, support decision-making, and automate repetitive or hazardous tasks. However, their successful implementation depends not only on technological capabilities but also on employees' awareness, acceptance, and perception of the associated occupational risks. This study investigates employees' perceptions of AI implementation and its potential impact on workplace safety in agricultural small and medium-sized enterprises (SMEs). The research was conducted in* ***35 agricultural enterprises*** *from Timiș County, Romania, representing crop production, fruit cultivation, and livestock farming. A structured questionnaire was administered to* ***223 respondents*** *to evaluate their knowledge of AI, confidence in its implementation, perceived occupational risks, expected consequences, and preferred preventive measures. The collected data were statistically processed using Microsoft Excel and STATGRAPHICS, while Analysis of Variance (ANOVA) was applied to assess the statistical significance of the results. The findings indicate that only* ***17%*** *of respondents considered themselves sufficiently informed about AI applications, whereas more than half expressed the need for additional information and training. Workforce reduction, deterioration of interpersonal relationships, and the need for continuous professional development were identified as the main concerns associated with AI adoption. The results emphasize the importance of combining technological innovation with effective OHS management, employee training, and a human-centered approach to support the safe and sustainable implementation of AI in agriculture. The study provides practical insights for managers, OHS specialists, and policymakers involved in the digital transformation of agricultural SMEs, contributing to the development of safer and more resilient workplaces.*

Keywords*: Artificial Intelligence, occupational health and safety, agricultural SMEs, employee perception, risk perception*

INTRODUCTION

Agriculture is currently undergoing a profound digital transformation driven by the rapid development of advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), robotics, machine learning, autonomous systems, and precision agriculture. These technologies are changing traditional agricultural practices by improving productivity, optimizing resource use, supporting data-driven decision-making, and increasing the sustainability of farming systems. AI applications are becoming increasingly common in crop monitoring, livestock management, disease detection, yield prediction, irrigation management, and autonomous agricultural machinery, contributing to the modernization of agricultural production systems.

Despite these technological advances, the successful implementation of AI in agriculture depends not only on technical performance but also on human factors. Employees remain central to agricultural production, and their acceptance, understanding, and trust in AI technologies directly influence the effectiveness of digital transformation. The introduction of

AI into the workplace may generate concerns related to job security, changes in work organization, increased monitoring, new training requirements, and the interaction between workers and intelligent systems. Consequently, understanding employees' perceptions has become an essential component of sustainable AI implementation.

Occupational Health and Safety (OHS) represents one of the most important aspects affected by digitalization in agriculture. While AI technologies can reduce workers' exposure to hazardous environments by automating repetitive or dangerous tasks, they may also introduce new categories of occupational risks. These include increased psychological stress, reduced human interaction, overreliance on automated systems, information overload, and the need for continuous adaptation to rapidly evolving technologies. For this reason, recent research has emphasized the importance of adopting a human-centered approach to AI implementation, ensuring that technological innovation is accompanied by adequate training, effective risk management strategies, and active employee involvement.

Small and medium-sized enterprises (SMEs) represent the dominant organizational structure within the agricultural sector in Romania and throughout Europe. Compared with large enterprises, SMEs often have limited financial resources, reduced access to specialized training, and lower levels of technological maturity, making the adoption of AI more challenging. Evaluating employees' perceptions within these organizations is therefore essential for identifying potential barriers to AI implementation and developing appropriate occupational health and safety measures.

Although numerous studies have investigated the technical applications of AI in agriculture, relatively few have focused on employees' awareness, perception of occupational risks, and acceptance of AI technologies in agricultural workplaces. Understanding these aspects is fundamental for supporting the transition toward Agriculture 5.0, where technological innovation is integrated with human-centered principles, sustainability, and safe working environments.

The objective of this study is to evaluate employees' perceptions regarding the implementation of Artificial Intelligence in agricultural SMEs, with particular emphasis on occupational health and safety risks. The research is based on a questionnaire survey conducted among employees from crop production, fruit cultivation, and livestock enterprises in Timiș County, Romania. The collected data were statistically analysed to identify the main concerns, perceived risks, and training needs associated with AI adoption, providing useful information for managers, occupational health and safety specialists, and policymakers involved in the digital transformation of agriculture.

MATERIAL AND METHODS

The present study was designed to investigate employees' perceptions regarding the implementation of Artificial Intelligence (AI) in agricultural small and medium-sized enterprises (SMEs), with particular emphasis on occupational health and safety (OHS) issues. A questionnaire-based survey was selected as the primary research method because it provides an efficient and reliable approach for collecting information related to employees' awareness, attitudes, perceived risks, and expectations concerning the adoption of AI technologies in agricultural workplaces.

The research focused on identifying how workers perceive the potential benefits and challenges associated with AI implementation, as well as their level of confidence in these technologies and the preventive measures considered necessary for ensuring a safe working environment. In addition, the study examined whether factors such as enterprise size,

agricultural activity, age, and job position influence employees' perceptions toward AI applications.
The methodological framework was organized into five sequential stages. The first stage involved a comprehensive literature review to identify the main research directions related to AI, Agriculture 5.0, and occupational health and safety. The second stage consisted of designing and validating the questionnaire based on the identified research objectives. The third stage included the selection of agricultural enterprises and the administration of the questionnaire to employees. During the fourth stage, the collected responses were verified, coded, and statistically processed. Finally, the fifth stage focused on data interpretation and the identification of relationships between respondents' characteristics and their perceptions regarding Artificial Intelligence in agriculture.

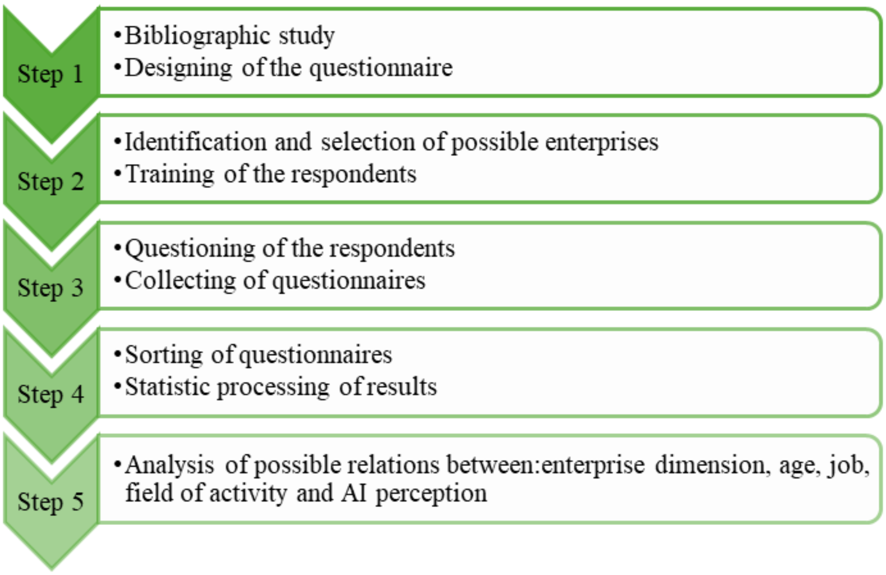

Figure 1. Methodological workflow of the research.

The research was conducted in Timiș County, located in the western part of Romania, one of the country's most important agricultural regions. The area is characterized by extensive agricultural activities, including cereal production, horticulture, and livestock farming, making it representative for analysing the implementation of innovative technologies within agricultural SMEs. A total of 35 agricultural enterprises participated in the study. The enterprises were selected to represent the main agricultural sectors according to the Romanian Classification of Economic Activities (CAEN): crop production (CAEN 011), fruit cultivation (CAEN 012), and livestock production (CAEN 014). The selected companies also represented different organizational sizes, including micro, small, and medium-sized enterprises, according to the European Commission classification.

The questionnaire was completed by 223 respondents, including workers and managerial personnel directly involved in agricultural activities. The diversity of participants allowed the analysis of AI perception from multiple organizational perspectives.

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Data collection was carried out through direct distribution of printed questionnaires within the selected agricultural enterprises. Before completing the questionnaire, respondents received a brief explanation regarding the objectives of the research and the confidentiality of the collected information. Completed questionnaires were checked for completeness and consistency before being included in the statistical database. Responses containing incomplete or inconsistent information were excluded from further analysis.

After validation, all responses were coded numerically and centralized using Microsoft Excel to facilitate statistical processing. The collected data were analysed using **Microsoft Excel** and **STATGRAPHICS** software.

Initially, descriptive statistical indicators were calculated by determining the percentage distribution of responses for each questionnaire item. The percentage weights allowed the identification of the most significant perceptions regarding Artificial Intelligence implementation and occupational health and safety.

Subsequently, inferential statistical analyses were performed to investigate the influence of enterprise size, agricultural sector, respondent age, and occupational position on AI perception. The statistical significance of the observed differences was evaluated using **Analysis of Variance (ANOVA)**, while **Multiple Range Tests** were applied to identify homogeneous groups among the analysed variables. Statistical significance was considered at a confidence level of **95% ($p < 0.05$)**. The adopted methodology combines descriptive survey techniques with inferential statistical analysis to obtain a comprehensive evaluation of employees' perceptions regarding Artificial Intelligence in agricultural SMEs.

The proposed methodological approach provides both quantitative information regarding respondents' opinions and statistical evidence concerning the influence of organizational and demographic factors on AI acceptance. This framework offers a reliable basis for identifying potential barriers to AI implementation and supports the development of appropriate occupational health and safety strategies for the digital transformation of agriculture.

RESULTS AND DISCUSSIONS

The survey included responses from 223 participants employed in 35 agricultural SMEs operating in Timiș County, Romania. The selected enterprises represented the main agricultural production sectors, namely crop production, fruit cultivation, and livestock farming. Most respondents were workers directly involved in agricultural activities, while only a limited number occupied managerial positions. Therefore, the statistical analysis mainly reflects the perceptions of operational personnel regarding the implementation of Artificial Intelligence in agriculture.

The selected sample ensured a representative distribution across different enterprise sizes and agricultural sectors, allowing the comparison of employees' perceptions according to organizational characteristics.

Before performing the statistical analyses, all completed questionnaires were verified for completeness and consistency. The responses were subsequently coded and centralized in a Microsoft Excel database, creating a structured dataset suitable for descriptive and inferential statistical analyses. Table 1 presents a representative excerpt from the centralized database, illustrating the coding system adopted for respondents' demographic characteristics and questionnaire responses. This database served as the basis for calculating the response frequencies, percentage distributions, and the subsequent statistical analyses carried out using ANOVA and Multiple Range Tests.

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Table 1

Sequence from centralized results of answers in Microsoft Excel

	Enterprise		Act.,	Age,	Q3-Familiary concepts										Q4 -confidence in the					Q5- Negative impact										Q6- Consequences										Q7- Protection Eff.							Q8- Level Inf.			
No.	Dim.	Poz.	A	G	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	1	2	3	4
1	1	w	3	4						1		1				1																															1			
2	1	w	3	4						1							1										1						1																1	
2	1	w	3	3									1			1				1															1						1								1	
2	1	w	4	4						1						1				1														1										1					1	
3	1	w	3	4	1		1	1	1			1							1	1																		1			1							1		
3	1	w	3	3	1		1					1							1			1								1					1	1					1					1		1		
3	1	w	3	4	1		1					1							1			1														1	1				1					1		1		
3	1	w	3	4	1		1					1	1											1												1					1					1				1
3	1	w	3	4	1		1					1							1			1														1	1									1		1		
3	1	w	3	4	1		1	1	1			1							1	1																		1			1							1		
3	1	w	3	4	1		1					1							1										1	1																1		1		
3	1	w	3	4	1		1					1					1							1												1				1							1			
3	1	w	3	3	1		1					1	1	1					1			1	1			1					1	1			1	1	1				1					1		1		
4	2	w	4	4			1	1	1			1				1				1																	1			1			1	1				1		
4	2	w	4	2	1	1	1	1	1		1	1	1	1		1						1		1		1		1	1			1		1				1	1	1			1	1	1	1		1		
4	2	w	4	2	1		1	1	1	1	1	1	1	1	1					1				1					1	1		1	1				1			1		1	1	1	1	1	1			
5	3	w	2	2	1		1			1	1	1	1	1			1			1		1		1			1	1	1					1				1		1								1		
5	3	w	2	3	1		1			1	1	1	1	1			1			1		1		1			1	1	1				1	1	1			1	1	1		1	1	1					1	

No.- number of enterprise, Dim.- dimension of enterprise, Act.- type of activity,

Because 96.86% from respondents were workers, the influence of other work positions categories (managers, specialists) was not interesting for studies.
The weight of answers, pWi, were calculated with next formula:

$$pWi = 100 * \frac{ni}{227},$$

where ni - the number of answers at specific question.
Also, because, after centralizing of answers, few respondents activate in other fields (5.4 %), and no person aged under 18 years or over 65 years, these categories of factors were not included in statistical processing.
The results of calculated weight of answers for Q3, Q4 and Q5 are presented in Table 2 and the results of calculated weight of answers for Q6, Q7 and Q8 are presented in Table 3.

Table 2

Results of calculated weight of answers for Q3, Q4 and Q5

Fac-tors	**pWi at Q3-Familiary concepts, [%]**										**pWi at Q4 – confidence in AI, [%]**					**pWi at Q5- Negative impact, [%]**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PT	**84.8**	**13**	**67.3**	**17**	**30**	**25**	**40**	**85.7**	**47**	**17**	**1.3**	**11**	**35**	**37**	**17**	**70**	**0.9**	**22**	**7.2**	**45**	**3.1**	**12**	**13**	**26**	**61**
pMC	72.5	5.9	64.7	16	7.8	14	22	80.4	37	20	0	24	33	18	24	51	0	27	3.9	18	2	24	9.8	12	33
pSM	98.8	4.9	93.8	23	73	21	73	93.8	79	6	1.2	3.7	20	63	12	93.8	0	11	6.2	77	2.5	8.6	7.4	33	94
pMD	79.1	25	45.1	12	3.3	34	22	81.3	24	24	2.2	9.9	48	24	16	59.3	2.2	27	9.9	32	4.4	7.7	20	29	47
PT	**84.8**	**13**	**67.3**	**17**	**30**	**25**	**40**	**85.7**	**47**	**17**	**1.3**	**11**	**35**	**37**	**17**	**70**	**0.9**	**22**	**7.2**	**45**	**3.1**	**12**	**13**	**26**	**61**
pA1	85	15	70	20	10	15	25	85	20	25	0	15	35	40	10	65	0	25	15	30	5	15	15	25	55
pA2	96.3	0	90.1	21	65	16	86	92.6	79	7	1.2	1.2	22	64	12	91.4	0	20	1.2	79	4.9	4.9	14	47	91

pA3	78.2	21	50	11	5.5	30	8.2	81.8	27	18	0.9	14	45	19	20	57.3	0.9	24	11	24	1.8	15	12	12	42
PT	**84.8**	**13**	**67.3**	**17**	**30**	**25**	**40**	**85.7**	**47**	**17**	**1.3**	**11**	**35**	**37**	**17**	**70**	**0.9**	**22**	**7.2**	**45**	**3.1**	**12**	**13**	**26**	**61**
pV2	70.8	13	66.7	33	33	33	67	91.7	50	38	4.2	13	38	21	29	83.3	0	33	0	63	0	21	33	46	71
pV3	90.2	16	68.3	20	35	22	45	87.8	49	16	2.4	7.3	33	44	13	67.1	1.2	21	8.5	52	4.9	7.3	12	30	62
pV4	84.2	12	66.7	12	25	24	32	83.3	46	12	0	12	34	36	17	70.2	0.9	20	7	36	2.6	12	9.6	20	59

Table 3

Results of calculated weight of answers for Q6, Q7 and Q8

Fac-tors	**pWi at Q6- Consequences, [%]**										**pWi at Q7- Protection Eff., [%]**							**pWi at Q8- Level Inf., [%]**			
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**
PT	**22**	**5.8**	**21**	**20**	**18**	**15**	**7.2**	**8.5**	**46**	**13**	**35**	**47**	**9.9**	**40**	**22**	**20**	**16**	**17**	**29**	**54**	**0.4**
pMC	24	3.9	27	25	7.8	18	14	16	25	7.8	49	24	9.8	20	24	25	22	16	41	47	2
pSM	22	6.2	15	4.9	15	8.6	7.4	11	74	16	21	70	2.5	73	16	17	14	1.2	15	84	0
pMD	22	6.6	22	30	26	19	3.3	2.2	32	13	40	40	16	22	26	19	15	32	35	32	0
PT	**22**	**5.8**	**21**	**20**	**18**	**15**	**7.2**	**8.5**	**46**	**13**	**35**	**47**	**9.9**	**40**	**22**	**20**	**16**	**17**	**29**	**54**	**0.4**
pA1	35	20	30	20	10	15	5	15	40	30	40	60	35	25	25	40	25	20	45	55	0
pA2	4.9	1.2	4.9	20	21	9.9	0	1.2	83	6.2	21	74	6.2	74	14	4.9	1.2	12	8.6	79	0
pA3	32	7.3	31	20	16	20	13	11	24	14	44	26	8.2	18	24	25	24	20	41	36	0.9
PT	**22**	**5.8**	**21**	**20**	**18**	**15**	**7.2**	**8.5**	**46**	**13**	**35**	**47**	**9.9**	**40**	**22**	**20**	**16**	**17**	**29**	**54**	**0.4**
pV2	17	0	25	33	42	17	0	4.2	54	8.3	58	42	17	54	33	17	13	21	46	33	0
pV3	16	4.9	23	16	16	16	7.3	7.3	46	15	30	52	9.8	44	21	15	12	26	22	54	0
pV4	28	7.9	18	19	15	13	8.8	11	44	13	33	46	8.8	35	19	25	20	11	32	59	0.9

Analysis of the results presented in Table 2 shows that respondents were generally familiar with traditional occupational health and safety concepts. Approximately 85% recognized the concepts of Work Security and OHS Training, while 67% were familiar with Risk Factors, 47% with Work Stress, 40% with Occupational Health and Safety Management (MOHS), and 30% with the Internet of Things (IoT). Familiarity with AI-related concepts was considerably lower, indicating that digital technologies are still relatively new to many agricultural employees. ANOVA and Multiple Range Tests revealed no statistically significant differences ($p \geq 0.05$) between enterprise size, field of activity, or age groups regarding familiarity with these concepts. Regarding employees' confidence in their organization's readiness to implement AI (Question Q4), 37% reported a low level of confidence, 35% a moderate level, 17% no confidence, 11% high confidence, and only 1.3% very high confidence. Statistical analysis showed that these perceptions were not significantly influenced by enterprise size, activity sector, or respondents' age.

The main perceived negative effects of AI implementation (Question Q5) were workforce reduction (70%), deterioration of interpersonal relationships (61%), loss of interest in traditionally human activities (45%), the need to acquire new knowledge (26%), and increased productivity pressure (22%). The remaining factors received relatively low percentages, indicating that they were considered less relevant by respondents.

Regarding the perceived consequences of AI implementation (Question Q6), the most frequently identified issue was the continuous and rapid increase in work-related information

(46%), followed by work equipment risks (22%), insufficient knowledge of work equipment (21%), frequent changes in work tasks (20%), and work-related stress (18%). These concerns were more frequently reported in micro and small enterprises, particularly in crop production and horticulture. Concerning preventive measures (Question Q7), respondents considered the limited use of AI whenever alternatives are available (47%), collective protection measures (40%), and adequate work instructions (35%) to be the most effective actions. Additional measures, including AI risk awareness, specific training, and managerial supervision, were also considered important by approximately one-fifth of respondents.

Finally, responses to Question Q8 showed that only 17% of participants considered themselves sufficiently informed about AI, while 29% reported insufficient knowledge and 54% expressed the intention to obtain additional information. These findings emphasize the need for continuous training and awareness programmes to support the safe implementation of Artificial Intelligence in agricultural SMEs.

CONCLUSIONS

The rapid digital transformation of agriculture is creating new opportunities for improving productivity, optimizing resource management, and supporting more sustainable farming systems. However, the successful implementation of Artificial Intelligence depends not only on technological progress but also on employees' acceptance, awareness, and ability to adapt to new working environments. Social factors, organizational culture, and employees' perceptions play a fundamental role in determining the success of AI adoption within agricultural enterprises.

The results of this study indicate that, although respondents recognize the potential benefits of Artificial Intelligence, significant concerns remain regarding its impact on employment, interpersonal relationships, and occupational health and safety. At the same time, the relatively low level of knowledge about AI technologies highlights the need for continuous education and specialized training programs that enable workers to understand both the opportunities and the risks associated with digital transformation. The transition toward Agriculture 5.0 requires a balanced integration of technological innovation and human-centered principles.

Artificial Intelligence should be implemented as a decision-support tool that complements human expertise rather than replacing it. Ensuring transparency, maintaining employee involvement, and providing appropriate occupational health and safety measures are essential conditions for increasing confidence in AI technologies and facilitating their acceptance within agricultural SMEs.

The present study provides an overview of the current perception of Artificial Intelligence among employees working in agricultural SMEs in western Romania. The findings may support managers, occupational health and safety specialists, and policymakers in developing strategies that encourage responsible AI adoption while protecting workers' well-being and promoting sustainable digital transformation in agriculture.

Future research should include larger samples from different agricultural regions and investigate changes in employees' perceptions as AI technologies become more widely adopted. In addition, comparative studies between different categories of agricultural enterprises could provide a deeper understanding of the organizational factors influencing the successful implementation of Artificial Intelligence.

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