

Research article

Artificial Intelligence in Smart Agriculture: Perceptions of Agricultural Employees in Nineveh Governorate

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ABSTRACT

This research aims to identify the perceived importance of artificial intelligence (AI) in smart agriculture from the perspective of agricultural employees, rank its roles, examine correlations with independent variables including gender, age, training courses, and participation in activities, and determine key obstacles. To collect data, a questionnaire comprising personal information and a 20-item scale with a high reliability coefficient of 0.98 was administered to a simple random sample of 200 agricultural employees, representing 61 percent of the total population of 329 employees across the Nineveh Agriculture Directorate and its 32 affiliated divisions. The results revealed that the perceived importance of AI in smart agriculture was high, driven by its significant role in increasing production, improving living standards, eradicating poverty, and achieving food security. Among the items, the statement regarding smart irrigation systems helping provide necessary water quantities ranked first with a weighted average of 4.17 and a percentage weight of 83.40 percent. Furthermore, statistical analysis showed a significant correlation at the 0.01 level between the perceived importance of AI and both gender and participation in AI-related activities, as well as a significant correlation at the 0.05 level with AI training courses, while age showed no significant correlation. Finally, the study identified major obstacles facing employees, particularly concerns regarding the responsibility of using AI, difficulties in understanding the technology, and time constraints. Consequently, the researcher recommends providing intensive training courses for agricultural workers to enhance their expertise and promote AI adoption to support food security.

1. Introduction

In recent decades, the global agricultural sector has undergone rapid digital transformation to address escalating challenges such as climate change, water scarcity, rising production costs, and growing food demand driven by population growth (Monteiro et al., 2021). Within this context, smart agriculture has emerged as a vital framework integrating advanced technologies—such as the Internet of Things (IoT), drones, remote sensing, big data analytics, and artificial intelligence (AI)—to optimize resource management and promote environmental sustainability (Wolfert et al., 2017; Samar, 2022). While developed countries have successfully integrated these tools into routine farm

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operations (Creed & Dens, 2024), developing nations face systemic barriers, including weak infrastructure and a shortage of specialized training (Elijah et al., 2018).

In Iraq, agriculture remains a vital economic pillar, yet the sector struggles heavily with severe water scarcity, desertification, and limited technological adoption (U.S. Department of Agriculture, n.d.). Nineveh Governorate, one of the country's primary agricultural regions, exemplifies these hurdles (Nadia & Dalila, 2023). Although agricultural employees play a crucial role in guiding farmers and executing development programs, their readiness and attitudes toward AI integration remain largely undocumented (Khaldi, 2024).

Research Gap and Problem Statement

While previous studies have predominantly focused on the technical applications of AI, exceptionally limited attention has been given to agricultural employees' perceptions, awareness, and adoption challenges, particularly within the context of Iraq [MF2]. Field observations in Nineveh Governorate indicate a notable disparity in workers' familiarity with AI tools, coupled with institutional hurdles such as insufficient training programs and scarce technical resources (Liakos et al., 2018).

Addressing this gap is critical for designing targeted development policies. Therefore, this study investigates the role of artificial intelligence in smart agriculture from the perspective of agricultural employees in Nineveh Governorate. Specifically, the research aims to:

1. Determine employees' level of awareness regarding the importance of AI in smart agriculture.
2. Explore the relationship between employee adoption and key personal and professional variables (such as age, gender, AI training courses, and participation in related activities).
3. Identify the primary obstacles hindering agricultural employees from utilizing AI applications in their professional work.

Accordingly, the research problem can be formulated through the following questions:

1. What is the importance of artificial intelligence in smart agriculture from the perspective of agricultural employees in Nineveh Governorate?
2. What is the relative importance of the various aspects of the role of artificial intelligence in smart agriculture?
3. Is there a relationship between the role of artificial intelligence in smart agriculture and some independent variables, namely gender, age, training courses, and participation in AI-related agricultural activities?

What are the most significant obstacles facing agricultural employees in using artificial intelligence in agricultural work?

Research Objectives

1. To identify the level of importance of artificial intelligence (AI) in smart agriculture from the perspective of agricultural employees in general.
2. To rank the various aspects of the role of AI in smart agriculture from the perspective of agricultural employees according to their relative importance.
3. To establish a significant correlation between the role of AI in smart agriculture and several independent variables, namely: gender, age, participation in AI-related training courses, and participation in AI-related agricultural activities.
4. To identify the most significant obstacles facing agricultural employees in using AI in agricultural work.

Research Materials and Methods

This study employed a descriptive-analytical cross-sectional research design to investigate the role of artificial intelligence in smart agriculture from the perspective of agricultural employees.

The research population comprised agricultural employees across the Nineveh Agriculture Directorate and its affiliated agricultural divisions, encompassing a total of (32) divisions with an initial population of (329) respondents. A simple random sample of (200) respondents was selected, representing (61%) of the accessible population.

Data were collected using a structured questionnaire divided into two main sections:

- Part I: Personal and professional characteristics of the respondents, including gender, age, training courses in artificial intelligence, and participation in AI-related agricultural activities.
- Part II: A scale designed to measure the importance of artificial intelligence in smart agriculture, consisting of (20) items developed through a comprehensive review of relevant literature.

Validity and Reliability: Face validity was established by submitting the scale to a panel of academic and field experts. To assess reliability, a pilot sample of (30) respondents was randomly selected from the population and subsequently excluded from the final analysis. Internal consistency was evaluated using Cronbach's alpha, yielding a high coefficient of (0.98), indicating excellent reliability.

Measurement and Statistical Analysis: Responses for the scale items were measured using a five-point Likert scale (very important, important, moderately important, slightly important, not important), assigned numerical values ranging from (1) to (5). Following data collection, tabulation, and preliminary data screening, tests for normality revealed that the data distribution deviated from normality. Consequently, appropriate **non-parametric statistical methods** were utilized for data analysis via SPSS software.

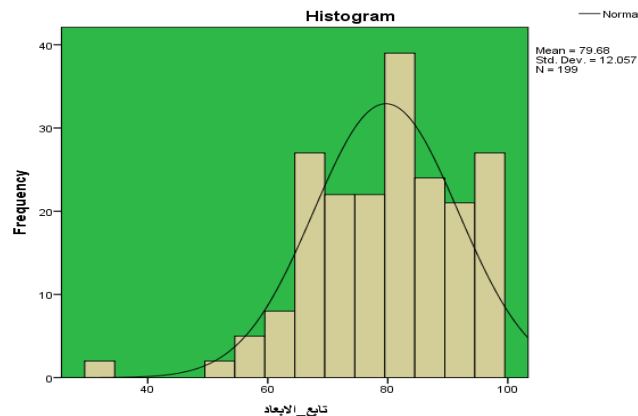


Figure (1) illustrates the data distribution

Results and Discussion

First: Identifying the level of importance of artificial intelligence in smart agriculture from the perspective of agricultural employees in general.

The results showed that the highest numerical value obtained by the respondents, representing the importance of artificial intelligence in smart agriculture from their perspective, was (100), while the lowest numerical value obtained by the respondents was (20). The range and class size were used, which was (27), as shown in Table (1).

Table (1) illustrates the importance of artificial intelligence in smart agriculture in general

No.	Categories	Frequency	%	Average Importance
1	20-46	15	7.5	39.541
2	47-73	66	33	70.321
3	74-100	119	59.5	90.211
Total		200	100	
Overall Arithmetic Mean: 77.800				
Standard Deviation: 14.101				

Table (2) shows that (59.5%) of agricultural employees considered artificial intelligence (AI) to be of great importance in smart agriculture. This indicates that AI has become one of the most important and effective modern technologies for developing agricultural processes and improving production efficiency. This, in turn, has increased awareness among agricultural employees of the importance of AI in the agricultural sector, especially given the challenges facing traditional agriculture. This has made AI one of the most important modern solutions capable of achieving sustainable agricultural development.

Second: Ranking the items related to the role of AI in smart agriculture from the perspective of agricultural employees according to their relative importance.

To achieve this objective, the weighted arithmetic mean and percentage were calculated for each item related to AI, and they were then ranked according to their importance, as shown in Table (2).

Table (2): Ranking of items related to AI in smart agriculture according to their importance

Seq. in Questionnaire	Items	Weighted Mean	Percentile Weight	Rank
1	Improving crop quality and reducing waste through precision agriculture	4.12	82.40	2.5
2	Using drones to provide accurate aerial images for farmers	4.04	80.80	4
3	Helping to provide the necessary amounts of water through smart irrigation systems	4.17	83.40	1
4	Identifying disease and pest-affected areas through crop monitoring devices	4.12	82.40	2.5
5	Using intelligent robots to harvest fruits and sort them individually	3.76	75.20	18
6	Using intelligent robots in agriculture to perform tasks such as harvesting, planting, and fertilizing	3.67	73.40	20
7	Analyzing soil fertility and its nutritional requirements	3.90	78.00	8
8	Analyzing and collecting big data from farms using sensors	3.85	77.00	12.5
9	Using self-driving tractors to draw efficient routes, saving time and increasing the efficiency of agricultural operations	3.90	78.00	8
10	Monitoring animals to track vital and behavioral aspects of the animal	3.87	77.40	10.5
11	Analyzing data using intelligent algorithms to provide accurate predictions on how to improve productivity	3.90	78.00	8

12	Using machine learning to predict future climatic conditions and best agricultural practices	3.84	76.80	14
13	Analyzing genetic data to provide recommendations for animal breeding and enhancing their quality	3.78	75.60	17
14	Using satellites to monitor agricultural fields, helping to detect changes in environmental conditions	3.82	76.40	15
15	Using robots and automated machines to remove harmful weeds	3.73	74.60	19
16	Using automated harvesters to pick fruits and vegetables with high precision, reducing waste and damage	3.85	77.00	12.5
17	Using blockchain in tracking crops from planting to harvest, providing farmers with crop quality	3.81	76.20	16
18	Detecting harmful weeds that infect and destroy crops	3.91	78.20	6
19	Crop forecasting helps farmers in effective planning for agricultural seasons	3.87	77.40	10.5
20	Training on modern techniques for using artificial intelligence	3.95	79.00	5

Table (2) shows that the item "Helps provide the necessary quantities of water through smart irrigation systems" ranked first with a weighted arithmetic mean of (4.17) and a percentage weight of (83.40%). This indicates that smart irrigation systems are among the most important applications of artificial intelligence in agriculture, given their significant role in rationalizing water consumption and providing the appropriate quantities for agricultural crops according to their actual needs. Furthermore, agricultural employees recognized the importance of using artificial intelligence to address environmental and agricultural challenges, which contributes to achieving agricultural sustainability and food security. The item "Using smart robots in agriculture to perform tasks such as

harvesting, planting, and fertilizing" ranked last with a weighted arithmetic mean of (3.67) and a percentage weight of (73.40%). This indicates that agricultural employees recognized the limited adoption of these technologies in the local agricultural environment, as most agricultural operations still rely heavily on traditional methods. This results in agricultural employees having less exposure to robotic applications and less awareness of their practical benefits in the agricultural field.

Third: To establish a significant correlation between the role of artificial intelligence (AI) in smart agriculture and several independent variables, namely gender, age, participation in AI training courses, and involvement in AI-related agricultural activities.

To determine the significant correlation between the perceived importance of AI in smart agriculture from the perspective of agricultural staff, non-parametric methods were employed due to the non-normal distribution of the data. Spearman's rank correlation coefficient was used to identify the correlation, as shown in Table (3).

Table (3) shows the correlation between artificial intelligence and some research variables

Variables	N	Percentage	Spearman Correlation Coefficient	Significance
Gender				
Male	132	66	0.612**	Significant
Female	68	34		
Total	200	100		
Age				
(Less than 30 years)	20	10	0.285	Not Significant
(30 - 39 years)	78	39		
(40 - 49 years)	78	39		
(50 years and above)	24	12		
Total	200	100		
Training Courses in Artificial Intelligence				
Did not train	109	54.5	0.149*	Significant

One course	36	18		
Two courses	27	13.5		
Three courses or more	28	14		
Total	200	100		
Participation in Agricultural Activities Related to Artificial Intelligence				
Participant in activities	118	59		
Non-participant in activities	82	41	0.216**	Significant
Total	200	100		

(*) Significant at the 0.05 level

(**) Significant at the 0.01 level

Table (3) shows a significant correlation between the level of importance of artificial intelligence in smart agriculture and gender at a significance level of (0.01), where the value of Spearman's correlation coefficient was approximately (0.612**). This means that the majority of respondents were male, numbering (132) respondents, representing (66%), compared to females, numbering approximately (68) respondents, representing (34%). This indicates that males in the agricultural sector often have greater opportunities to engage with modern technologies and advanced agricultural practices, due to the nature of the work and field tasks they perform, which increases their level of knowledge and interest in artificial intelligence applications in the agricultural field. While the results showed no significant correlation between the perceived importance of artificial intelligence (AI) in smart agriculture and age, this indicates that the awareness of the importance of AI applications is no longer tied to a specific age group. Rather, it stems from the nature of agricultural work and the tasks of agricultural employees, who are responsible for increasing and improving agricultural production and quality, as well as the common challenges faced by all agricultural workers regardless of age. The results also showed a significant correlation at the 0.05 level between the perceived importance of AI in smart agriculture and AI training courses, with a Spearman's coefficient of approximately 0.149. This means that although most agricultural employees are not formally trained, they recognize the importance of AI training courses as a key factor in enhancing their understanding and ability to use AI in agricultural work. Even if they haven't actually received training, they feel a strong need for it and believe it contributes to developing their skills and improving their professional competence in their job duties related to using AI in agriculture to improve crop yields. The results also showed a significant correlation between the perceived importance of artificial intelligence (AI) in smart agriculture and participation in AI-related agricultural activities at a significance level of 0.01. This indicates that agricultural employees who recognize the importance of AI are more likely to understand that the future of the agricultural sector is moving towards its use. Therefore, their participation in smart agriculture activities is a crucial

strategic step in developing their personal skills to raise awareness among farmers about the importance of using smart agriculture to increase agricultural production and achieve food security. Fourth: Identifying the most significant obstacles facing agricultural employees in using AI in agricultural work.

To achieve this objective, the arithmetic mean and standard deviation were calculated for each item of obstacles facing agricultural employees in using AI, and these were ranked according to their importance, as shown in Table (4).

Table (4) shows the ranking of the most significant obstacles facing agricultural employees according to their importance.

No.	Barriers	Arithmetic Mean	Standard Deviation	Rank
1	The cost of adopting artificial intelligence in agriculture is high	3.615	0.639	7
2	Lack of staff training on using artificial intelligence in agricultural work	3.690	0.637	2
3	Lack of an electronic network between agricultural staff administrations	3.635	0.602	6
4	Weak English language skills among most agricultural staff to access artificial intelligence websites	3.655	0.630	5
5	Slow internet speed at the workplace of agricultural staff	3.595	0.702	9
6	Lack of incentives to encourage agricultural staff regarding the adoption of artificial intelligence in smart agriculture	3.575	0.675	10
7	Lack of local and accurate environmental data is considered an obstacle to the accuracy of predictive models	3.605	0.656	8
8	Lack of the necessary technical skills to deal with modern technology regarding how to use artificial intelligence	3.670	0.618	4
9	Weak or non-existent infrastructure in some rural areas, leading to malfunction of smart systems related to smart agriculture	3.685	0.589	3
10	Agricultural staff fear of bearing responsibility for using artificial intelligence, especially in rural areas	3.740	0.551	1

No.	Barriers	Arithmetic Mean	Standard Deviation	Rank
	where they find it difficult to understand this technology which requires long-term use			

Table (4) shows that the item “Agricultural employees’ fear of taking responsibility for using artificial intelligence, especially in rural areas where they find it difficult to understand this technology, which requires a long time to use” ranked first with an arithmetic mean of (3.740). This means that agricultural employees struggle to easily adopt these artificial intelligence technologies in agriculture and may need a lot of time, effort, and continuous work to understand these technologies and their benefits in increasing production and improving living standards. Meanwhile, the item “Lack of incentive to encourage agricultural employees to adopt artificial intelligence in smart agriculture” ranked last with an arithmetic mean of (3.575). This means that agricultural employees are tasked with convincing farmers to use artificial intelligence in smart agriculture, whether there are incentives or not, as they are performing their job duties. Therefore, this item was considered the least of the obstacles that agricultural employees might face in their work.

Conclusions

Based on the empirical findings of this study, the following in-depth conclusions and broader implications are drawn:

- 1. Evolution of Professional Consciousness and Institutional Readiness:** The findings reveal that agricultural employees have moved beyond basic familiarity to develop a substantive conviction regarding AI's role in smart agriculture. This heightened awareness indicates a critical psychological readiness within the workforce, suggesting that institutional resistance to digital transformation is diminishing. However, translating this internal conviction into practical, field-level impact requires structured administrative frameworks to bridge the gap between employee awareness and actualized farm-level deployment.
- 2. Strategic Alignment with Regional Environmental Crises:** The strong prioritization of water conservation and waste reduction as the primary benefit of AI highlights a pragmatic alignment between employee perceptions and Iraq's acute environmental realities. Because water scarcity and desertification pose existential threats to regional agriculture, employees naturally view AI through the lens of resource preservation. This underscores the potential for targeted digital interventions focused specifically on smart irrigation and water management, as local stakeholders already recognize this as the most urgent area for technological integration.
- 3. The Catalyst Effect of Continuous Professional Development:** The significant correlation between participation in specialized training courses and enhanced comprehension of AI underscores the limitations of passive technology introduction. A superficial familiarity with AI is insufficient for driving adoption; rather, structured, hands-on extension activities and continuous professional development are foundational catalysts. Building institutional capacity must therefore rely on systemic training programs rather than sporadic workshops to ensure long-term competency and confidence among agricultural staff.

4. **Systemic Friction and the Novelty Paradox:** The identification of major obstacles—stemming from the novelty of AI and the heavy effort required for adoption—points to a "novelty paradox" within developing agricultural sectors. While employees recognize the theoretical value of digital tools, the absence of robust technological infrastructure and localized technical support creates a friction point that stalls transition. Overcoming these barriers requires moving past individual training to address systemic deficits, ensuring that institutional resources, user-friendly interfaces, and ongoing technical backup are established to ease the burden on both employees and the farmers they guide.

Recommendations

1. It is important to prepare intensive training courses for agricultural employees on the importance of developing their expertise and intensifying their efforts to support and promote the use of AI to achieve food security.
2. The Ministry of Agriculture should focus on increasing practical application of AI by agricultural employees in the field of smart agriculture to develop and increase agricultural production.
3. Agricultural institutions, in cooperation with the Directorate of Agriculture, should implement pilot projects in model demonstration fields to continuously apply artificial intelligence in smart agriculture, encouraging its adoption and future reliance.
3. 4. The Ministry of Higher Education should include topics on artificial intelligence and smart agriculture in the curricula of agricultural colleges. This will contribute to translating theoretical knowledge into practical applications that meet the needs of the labor market.
4. 5. A similar study should be conducted on this topic using other independent variables, such as years of service, agricultural information sources related to smart agriculture, and the attitudes of agricultural employees towards using artificial intelligence in smart agriculture.

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