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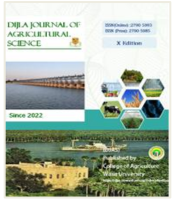

Research article

Current Status and Development Requirements of Artificial Intelligence Applications in Agricultural Extension for Climate Change Adaptation: A Comparative Study between Egypt and Iraq

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ABSTRACT

The study aimed to identify the current state of the use of artificial intelligence technologies in agricultural extension work and their role in addressing climate change, as well as to explore the major obstacles hindering the employment of these technologies. In addition, the study sought to determine the requirements necessary for developing agricultural extension services through the use of artificial intelligence technologies. This was achieved through a comparative study between Sharqia Governorate in the Arab Republic of Egypt and Baghdad Governorate in the Republic of Iraq. The study adopted a comparative descriptive approach, and a questionnaire was used as the primary instrument for data collection. The study population consisted of all agricultural extension agents and personnel working in agricultural extension in the two governorates. The sample included 214 respondents from Egypt and 228 respondents from Iraq, with a total of 442 respondents. A comprehensive census method was employed. Data were analyzed using a range of descriptive statistical techniques, including frequencies, percentages, weighted means, and relative weights. The findings revealed that the use of artificial intelligence technologies in agricultural extension was moderate in both countries, with Iraq recording a higher level than Egypt, where the overall mean score reached 3.14 in Iraq compared with 2.89 in Egypt. Respondents also showed strong positive perceptions regarding the role of AI technologies in addressing climate change impacts, especially in agricultural decision-making, climate prediction, and water resource management, with higher perceptions reported in Iraq. The study identified major obstacles, including weak technological infrastructure, limited funding and governmental support, inadequate training, and shortages of specialized personnel. Furthermore, the findings emphasized that improving smart agricultural extension requires strengthening digital infrastructure, increasing financial and policy support, providing specialized training, and enhancing cooperation between extension and research institutions. The study recommended adopting integrated digital transformation strategies, expanding AI capacity-building programs, and developing smart agricultural extension systems to improve climate adaptation and agricultural sustainability in both Egypt and Iraq.

1. Introduction

The agricultural sector is currently experiencing growing challenges as a result of climate change and its associated impacts, including rising temperatures, fluctuating rainfall patterns, worsening drought

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and desertification, and increasing scarcity of water resources. These challenges have directly affected agricultural production, food security, and the sustainability of natural resources. Consequently, they have become a serious threat to traditional agricultural systems, particularly in developing countries that rely heavily on agriculture as a primary source of food production and national income. In light of these changes, there has been an increasing need to develop agricultural systems that are more capable of adapting to climate-related risks and to adopt modern technologies to improve the efficiency of agricultural resource management and promote agricultural sustainability (Artificial Intelligence for Sustainability, 2024; Sarkar et al., 2023). Other studies have also confirmed that climate fluctuations, such as rising temperatures, irregular rainfall, and the increasing frequency of extreme weather events, reduce the efficiency of traditional agricultural systems and threaten the sustainability of agricultural production, thereby necessitating the adoption of advanced technologies capable of adapting to these climatic changes (Ali et al., 2025; Raihan, 2024).

Agricultural extension is considered one of the most important mechanisms supporting agricultural development processes because of its role in transferring knowledge and modern technologies to farmers and assisting them in adopting agricultural practices suitable for changing environmental and climatic conditions. However, traditional agricultural extension systems are facing increasing challenges related to their limited ability to keep pace with rapid technological developments, difficulties in providing timely access to accurate information, and the rising costs of extension services. In addition, these systems have limited capacity to address the complexities associated with climate change and agricultural risk management (Jarial, 2022; Mushi et al., 2022). Furthermore, the role of agricultural extension has evolved from merely transferring knowledge to providing advisory services based on digital analysis and artificial intelligence. It has become possible to deliver precise and customized extension recommendations tailored to the conditions of each farmer and the characteristics of the surrounding agricultural environment (SAGE, 2025).

In this context, artificial intelligence technologies have emerged as one of the most important approaches for the transition toward smart agriculture and digital agricultural extension because of their advanced capabilities in analyzing agricultural and climatic data, predicting risks, supporting decision-making, and providing accurate and immediate extension recommendations based on field data and local climatic conditions. Furthermore, developments in big data technologies, the Internet of Things, remote sensing, and decision support systems have enhanced the capacity of agricultural extension systems to deliver services that are more efficient, flexible, and responsive to climate-related challenges (Alfa et al., 2023; Jarial, 2022; Rajasathiya & Palanikumar, 2025). Numerous studies have indicated that artificial intelligence applications, such as machine learning and big data analytics, contribute significantly to improving crop management, increasing productivity, and reducing risks associated with climate change (Aijaz, 2025; Mohan et al., 2024). In addition, integrating artificial intelligence into agricultural extension improves access to agricultural information and enhances farmers' decision-making processes through the analysis of agricultural and environmental data and the provision of customized recommendations (Deji et al., 2023; Mmbando et al., 2025).

Many recent studies have further confirmed that artificial intelligence applications can effectively contribute to improving water resource management, predicting agricultural production, selecting suitable crops, monitoring pests and diseases, reducing agricultural losses, and enhancing farmers' ability to adapt to climate change. Smart extension systems based on mobile applications, virtual advisors, and intelligent recommendation systems can also improve the efficiency of extension services and expand access to farmers in rural and remote areas (Gangopadhyay et al., 2019; Joseph et al., 2025; Sarkar et al., 2023). Likewise, remote sensing applications and the Internet of Things contribute to collecting accurate data on crop conditions, soil status, and environmental conditions, thereby improving agricultural management, enhancing water-use efficiency, reducing waste, and increasing agricultural productivity (ICT-AI Platforms, 2025; Raman et al., 2023). Moreover, machine learning models have demonstrated their ability to predict agricultural production, analyze the effects of climate change on crops, and provide accurate recommendations to farmers (Mohan et al., 2024; Wang et al., 2024).

The use of artificial intelligence technologies in agricultural extension contributes directly to achieving the concept of climate-smart agriculture, which relies on employing technology to improve agricultural productivity while reducing environmental impacts. These technologies provide the capability to predict climatic conditions, analyze soil characteristics, and manage water resources more efficiently (Ali et al., 2025; Columbia Climate School, 2024). Artificial intelligence can also contribute to reducing greenhouse gas emissions from the agricultural sector through improved management of agricultural resources and the use of modern technologies in production processes, thereby strengthening the role of agriculture in addressing climate change and achieving environmental sustainability (Ali et al., 2025; SaberiKamarposhti et al., 2024). Recent literature further confirms that artificial intelligence-based smart agriculture represents one of the most significant future directions for achieving agricultural sustainability and improving the efficiency of natural resource utilization (Aijaz, 2025; Chowdhury et al., 2023).

Despite the promising opportunities offered by artificial intelligence technologies for developing agricultural extension, the adoption of these technologies continues to face numerous challenges, particularly in developing countries. Agricultural institutions often suffer from weak digital infrastructure, insufficient funding, a shortage of specialized personnel, inadequate training, and limited awareness of modern technologies. Additional challenges are related to data governance, cybersecurity, and the digital divide between rural and urban areas (Kountios et al., 2025; Luyckx & Reins, 2022; Tumbo et al., 2018). Studies also indicate that the high costs associated with implementing smart technologies, along with the lack of technical skills among farmers and agricultural extension personnel, limit the spread of artificial intelligence applications in developing countries (ICT-AI Platforms, 2025; Raihan, 2024). The literature further emphasizes the importance of governmental policy support, training provision, and institutional capacity building to enhance the use of artificial intelligence in agricultural extension, as the success of these technologies depends largely on the availability of a supportive institutional and legislative environment (Columbia Climate School, 2024; Mmbando et al., 2025).

At the international level, recent studies have focused on integrating artificial intelligence and digital technologies into agricultural extension systems. Bertoglio et al. (2021) indicated that the digital revolution in agriculture, including artificial intelligence and the Internet of Things, plays a significant role in promoting smart agriculture and adapting to climate change. Similarly, Atinaf et al. (2021) demonstrated that developing flexible agricultural information systems contributes to improving the efficiency of agricultural extension, particularly in developing countries facing environmental and technological challenges .

At the Arab regional level, Shehata et al. (2022) found that the use of information technology in agricultural extension significantly improves extension and marketing services, although its application remains limited in developing countries. Abdullah et al. (2025) also revealed that the agricultural extension system in Iraq suffers from irregular extension visits and requires improvements in the content of extension programs. Hamad (2024) pointed to the existence of a gap between scientific research outputs and field implementation, as well as weak institutional coordination in agricultural extension work in Iraq. Likewise, Al-Ajeeli (2022) emphasized the need to restructure the agricultural extension system and strengthen its role in achieving sustainable agricultural development, while Al-Dulaimi et al. (2022) identified substantial knowledge needs among agricultural extension officials, necessitating the implementation of specialized training programs. In addition, Al-Ansari et al. (2020) highlighted weak integration between research and extension institutions in Iraq, whereas Hamdan and Ali (2025) concluded that the role of agricultural extension in addressing climate change remains at a moderate level and requires further development .

In light of the previous literature and studies related to the applications of artificial intelligence in agricultural extension and climate change adaptation, a conceptual framework was developed to illustrate the relationships among the use of artificial intelligence technologies, their role in addressing climate change, the obstacles limiting their adoption, and the requirements necessary for developing smart agricultural extension systems and achieving agricultural sustainability Figure 1.

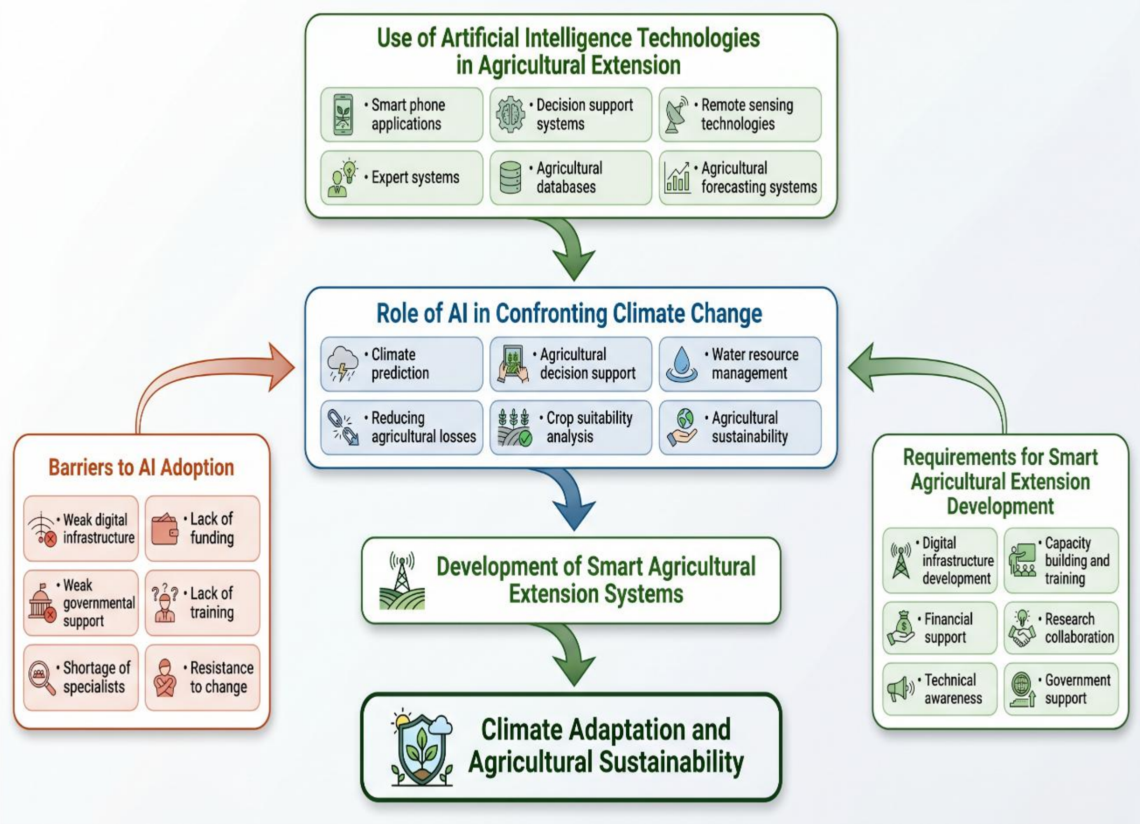

Figure 1. Conceptual Framework for Employing Artificial Intelligence Technologies in Agricultural Extension and Their Role in Addressing Climate Change and Achieving Agricultural Sustainability

The conceptual framework of the study is based on the assumption that the level of use of artificial intelligence technologies in agricultural extension directly influences the ability of the agricultural extension system to address the impacts of climate change through supporting agricultural decision-making and improving the management of agricultural resources. This role is also affected by a set of institutional, technical, and human-related obstacles that limit the efficiency of employing these technologies, in contrast to the presence of several supportive requirements that contribute to the development of smart agricultural extension systems and the achievement of agricultural sustainability.

Based on the foregoing, it becomes evident that artificial intelligence represents a promising tool for developing agricultural extension and enhancing its ability to address climate change. However, achieving this objective requires the integration of technological efforts with supportive policies, training programs, and the development of human and institutional capacities to ensure the optimal utilization of artificial intelligence applications in advancing agricultural extension systems and promoting agricultural sustainability. From this perspective, the importance of the present study emerges, as it seeks to identify the current state of the use of artificial intelligence technologies in agricultural extension work, examine their role in addressing the impacts of climate change, explore the major obstacles hindering their adoption, and determine the key requirements for developing smart agricultural extension systems. This is achieved through a comparative study between Sharqia Governorate in the Arab Republic of Egypt and Baghdad Governorate in the Republic of Iraq, with the aim of providing a scientific perspective that supports the transition toward smarter agricultural extension systems capable of achieving agricultural sustainability and adapting to climate change.

Problem Statement

Agricultural systems in both Egypt and Iraq are facing increasing challenges as a result of climate change and its associated impacts, including rising temperatures, fluctuations in water resources, and growing risks threatening agricultural production and sustainability. These conditions necessitate the development of agricultural extension systems and the adoption of modern technologies, particularly artificial intelligence technologies, to support extension work and improve its efficiency in addressing these challenges. Despite the global expansion in the use of artificial intelligence applications in agriculture, the actual adoption of these technologies in agricultural extension within Arab countries remains uneven. Potential differences also exist between the agricultural and institutional environments in Egypt and Iraq regarding the level of use, available capabilities, obstacles limiting implementation, and the requirements necessary for development. Accordingly, the research problem centers on the need to conduct a comparative study to identify the current state of the use of artificial intelligence technologies in agricultural extension work and their role in addressing climate change, as well as to explore the major obstacles hindering their adoption and the requirements necessary for developing agricultural extension through the use of these technologies in both countries.

Research Questions

1. What is the level of use of artificial intelligence technologies in agricultural extension work in Sharqia Governorate, Egypt, and Baghdad Governorate, Iraq?

2. What is the role of artificial intelligence technologies in addressing climate change in the agricultural sector from the perspective of agricultural extension agents in both Egypt and Iraq?

3. What are the major obstacles facing the adoption of artificial intelligence technologies in agricultural extension in Sharqia and Baghdad Governorates?

4. What are the requirements necessary for developing agricultural extension through the use of artificial intelligence technologies in both Egypt and Iraq?

Research Objectives

1. To identify the level of use of artificial intelligence technologies in agricultural extension work within the study areas.

2. To determine the role of artificial intelligence technologies in addressing climate change in the agricultural sector.

3. To identify the major obstacles facing the employment of artificial intelligence technologies in agricultural extension.

4. To identify the requirements necessary for developing agricultural extension through the use of artificial intelligence technologies.

METHODOLOGY

The study adopted a comparative descriptive approach because of its suitability for the nature of the current research, which aims to identify the current state of the use of artificial intelligence technologies in agricultural extension work and their role in addressing climate change, as well as to determine the major obstacles and requirements associated with the adoption of these technologies, while conducting a comparison between Sharqia Governorate in the Arab Republic of Egypt and Baghdad Governorate in the Republic of Iraq. The study also employed a quantitative approach for data collection and analysis through a questionnaire specifically designed to achieve the objectives of the study and answer its research questions.

Study Population

The study population consisted of agricultural extension agents and personnel working in agricultural extension in Sharqia Governorate, Egypt, and Baghdad Governorate, Iraq. A random sample of respondents was selected, comprising 214 respondents from Sharqia Governorate and 228 respondents from Baghdad Governorate, resulting in a total sample size of 442 respondents Figure 2.

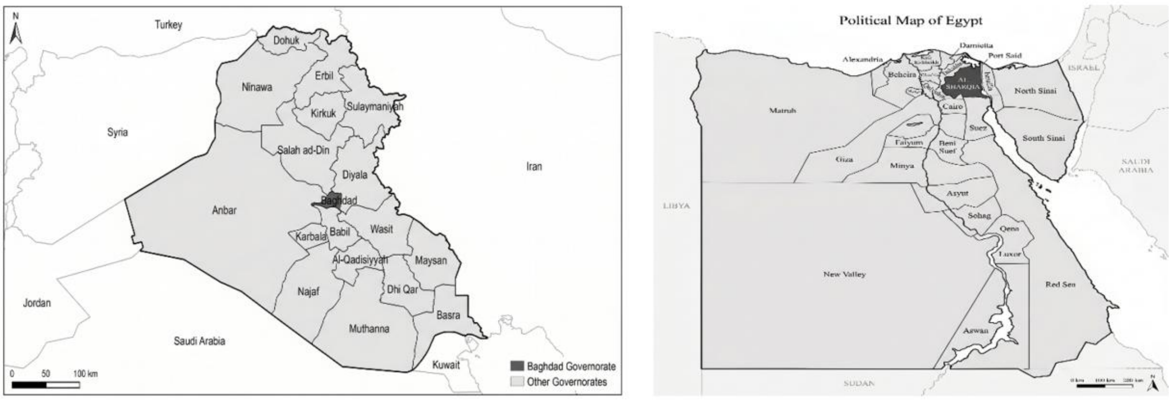

Figure 2. Study Areas in Egypt and Iraq Showing Al Sharqia and Baghdad Governorates

Data Collection Instrument

The study relied on a questionnaire as the primary instrument for data collection because of its suitability for the nature of the study and its effectiveness in achieving the research objectives. The questionnaire was developed based on relevant scientific literature and previous studies related to artificial intelligence applications, agricultural extension, and climate change, in addition to benefiting from the opinions of several specialists and experts in the fields of agricultural extension and modern technologies.

The questionnaire consisted of two main sections:

1. The first section included the respondents' personal characteristics, such as age, place of upbringing, educational qualification, years of experience in agricultural extension work, level of artificial intelligence usage, and participation in technical training programs.
2. The second section covered the main dimensions of the study, namely:

- The use of artificial intelligence technologies in agricultural extension work.
- The role of artificial intelligence technologies in addressing climate change.
- The obstacles facing the adoption of artificial intelligence technologies.
- The requirements for developing agricultural extension using artificial intelligence technologies.

Respondents' answers were measured using a five-point Likert scale, with scores of (1, 2, 3, 4, and 5) assigned respectively to the responses: strongly disagree, disagree, neutral, agree, and strongly agree. Accordingly, the hypothetical mean of the scale was set at 3 points.

Validity and Reliability

To ensure the validity of the instrument, the questionnaire was reviewed by a panel of specialists and experts in the fields of agricultural extension and artificial intelligence technologies in order to verify the clarity of the wording and the appropriateness of the questionnaire items to the objectives of the study.

The reliability of the study instrument was examined using Cronbach's alpha coefficient separately for the Egyptian and Iraqi samples. All values exceeded 0.80, indicating a high degree of internal consistency among the questionnaire items and confirming the suitability of the instrument for field application in both contexts, as shown in Table 1.

Table 1. *Cronbach's Alpha Coefficients for the Questionnaire Dimensions in the Egyptian and Iraqi Samples*

Dimension	Egypt	Iraq
Use of artificial intelligence technologies in agricultural extension work	0.86	0.88
Role of artificial intelligence technologies in addressing climate change	0.88	0.90
Obstacles facing the adoption of artificial intelligence technologies	0.84	0.86
Requirements for developing agricultural extension using artificial intelligence technologies	0.89	0.91
Overall reliability of the questionnaire	0.89	0.90

Statistical Analysis

A set of appropriate statistical methods was employed for data analysis, including frequencies, percentages, weighted means, relative weights, and overall means of the study dimensions. The Statistical Package for the Social Sciences (SPSS) was used to analyze the study data and derive the research findings.

3. RESULTS AND DISCUSSION

First: Respondents' Personal Characteristics

The findings indicate a relative similarity between the Egyptian and Iraqi samples across most personal and occupational variables, reflecting a degree of homogeneity among respondents in both countries and enhancing the objectivity of the comparative analysis. With regard to age, the results showed that the age group of 50 years and above ranked first in both Egypt and Iraq, accounting for 48.6% and 34.6%, respectively. This finding suggests that the majority of agricultural extension personnel possess extensive professional and life experience. The age group of 40 to 49 years ranked second, whereas the 30 to 39 years category recorded the lowest percentages in both countries. Concerning place of upbringing, the results revealed that most respondents came from rural backgrounds, representing 76.6% in Egypt and 74.6% in Iraq. This finding is consistent with the nature of agricultural extension work, which is closely associated with rural communities and agricultural activities.

Regarding educational qualifications, the findings demonstrated that holders of bachelor's degrees in agriculture constituted the largest proportion of respondents in both Egypt and Iraq, followed by holders of agricultural diplomas, while postgraduate degree holders represented the smallest proportion. This reflects the substantial reliance of agricultural extension work on personnel specialized in agricultural sciences.

With respect to years of experience in agricultural extension, the results indicated that respondents with 10 to 20 years of service ranked first in both countries, suggesting that a considerable proportion of respondents possess moderate to extensive professional experience in agricultural extension. The findings also showed that the level of artificial intelligence usage was predominantly moderate in both Egypt and Iraq, accounting for 44.4% and 39.9%, respectively. In contrast, the proportion of respondents reporting a high level of use was relatively limited. This indicates that the adoption of artificial intelligence technologies in agricultural extension work is still at a developmental stage and requires further support and advancement. Concerning technical training, the findings revealed a clear similarity between the two countries, with 53.3% of respondents in Egypt and 44.7% in Iraq having received technical training. This suggests a relative interest in developing the technical capacities of agricultural extension personnel, while also highlighting the continuing need to expand training and qualification programs in modern technologies and artificial intelligence, as shown in Table 2.

Table 2. Distribution of Respondents in Egypt and Iraq According to Personal and Occupational Variables

Variable	Category	Egypt (n)	Egypt (%)	Iraq (n)	Iraq (%)
Age	30-39 years	39	18.2	54	23.7
	40-49 years	71	33.2	95	41.7
	50 years and above	104	48.6	79	34.6
Place of upbringing	Rural	164	76.6	170	74.6
	Urban	50	23.4	58	25.4
Educational qualification	Agricultural diploma	90	42.1	65	28.5
	Bachelor's degree in agriculture	108	50.5	130	57.0
	Postgraduate studies	16	7.5	33	14.5
Years of experience in agricultural extension	Less than 10 years	55	25.7	79	34.6
	10-20 years	102	47.7	92	40.4

	More than 20 years	57	26.6	57	25.0
Level of artificial intelligence usage	Low	87	40.7	108	47.4
	Moderate	95	44.4	91	39.9
	High	32	15.0	29	12.7
Received technical training	Yes	114	53.3	102	44.7
	No	100	46.7	126	55.3
Total	—	214	100.0	228	100.0

Field Data, 2026.

Second: Level of Use of Artificial Intelligence Technologies in Agricultural Extension Work

Table 3 demonstrates a relative variation between Iraq and Egypt regarding the level of use of artificial intelligence technologies in agricultural extension work. The weighted means and relative weights in Iraq were higher than those in Egypt across all dimensions of this axis, indicating a relatively higher level of adoption of modern technologies in agricultural extension work in Iraq compared with Egypt.

In Iraq, the item “use of smartphone applications” ranked first, with a weighted mean of 3.30 and a relative weight of 66.0%, followed by “use of expert systems” with a weighted mean of 3.25, and “use of remote sensing technologies” with a weighted mean of 3.22. This reflects the tendency of agricultural extension personnel to utilize digital applications and modern smart technologies in delivering extension services. In Egypt, the item “use of artificial intelligence applications in agricultural extension” ranked first, with a weighted mean of 3.05 and a relative weight of 61.0%, followed by “use of agricultural forecasting systems” with a weighted mean of 3.00, and “use of remote sensing technologies” with a weighted mean of 2.98. Nevertheless, the overall levels of use remained within the moderate to relatively low range, indicating limited adoption of artificial intelligence technologies in Egyptian agricultural extension work.

The findings also revealed that the item “use of drones in agriculture” ranked last in both countries, with weighted means of 2.95 in Iraq and 2.80 in Egypt. This may be attributed to the high costs of such technologies and the limited availability of the infrastructure and technical support necessary for their implementation. Overall, the general mean score for this dimension reached 3.14, with a relative weight of 62.8% in Iraq, compared with an overall mean of 2.89 and a relative weight of 57.8% in Egypt. These findings indicate that the level of use of artificial intelligence technologies in agricultural extension work remains moderate in both countries, with Iraq demonstrating a relative advantage in this field.

Table 3. Comparison of the Level of Use of Artificial Intelligence Technologies in Agricultural Extension Work Between Iraq and Egypt

No.	Item	Iraq: Weighted Mean	Iraq: Relative Weight (%)	Iraq: Rank	Egypt: Weighted Mean	Egypt: Relative Weight (%)	Egypt: Rank
1	Use of artificial intelligence applications in agricultural extension	3.10	62.0	6	3.05	61.0	1
2	Use of agricultural forecasting systems	3.05	61.0	7	3.00	60.0	2
3	Use of remote sensing technologies	3.22	64.4	3	2.98	59.6	3
4	Use of smartphone applications	3.30	66.0	1	2.92	58.4	4
5	Use of agricultural databases	3.18	63.6	4	2.88	57.6	5
6	Use of decision support systems	3.12	62.4	5	2.85	57.0	6
7	Use of artificial intelligence in data analysis	3.08	61.6	8	2.82	56.4	7

8	Use of drones in agriculture	2.95	59.0	9	2.80	56.0	8
9	Use of expert systems	3.25	65.0	2	2.70	54.0	9
—	Mean	3.14	62.8	—	2.89	57.8	—

Field Data, 2026.

Third: The Role of Artificial Intelligence Technologies in Addressing the Impacts of Climate Change in the Agricultural Sector

The findings presented in Table 4 reveal a clear positive perception among respondents in both Iraq and Egypt regarding the expected role of artificial intelligence technologies in mitigating the impacts of climate change on the agricultural sector. However, this perception was stronger among respondents in Iraq than in Egypt, as reflected in the weighted means and relative weights across all dimensions of the axis.

The findings in Iraq indicate that respondents view artificial intelligence technologies as a strategic tool for supporting smart agricultural management and climate adaptation. The item “supports appropriate agricultural decision-making” ranked first, with a weighted mean of 3.92 and a relative weight of 78.4%, reflecting increasing awareness of the importance of artificial intelligence systems in analyzing agricultural and climatic data and providing more efficient alternatives and decisions under changing climatic conditions. The item “artificial intelligence contributes to predicting climate change” ranked second, indicating recognition of the predictive capabilities of smart technologies in reducing climate-related uncertainty. In contrast, the mean scores in Egypt were relatively lower, although they still reflected an overall positive trend. The item “artificial intelligence contributes to predicting climate change” ranked first, with a weighted mean of 3.50, suggesting that respondents’ perceptions are more strongly focused on the informational and predictive role of artificial intelligence than on its analytical and decision-making functions. This may be explained by the fact that artificial intelligence applications within the Egyptian agricultural environment are still at relatively limited stages of implementation, which affects the level of awareness of their advanced practical capabilities.

The findings also demonstrated that the items related to water resource management, reducing agricultural losses, and selecting suitable crops achieved relatively high mean scores in both countries. This reflects increasing awareness of the relationship between smart technologies and the efficiency of agricultural resource management under the pressures of climate change, particularly in environments facing water-related challenges and elevated climate risks. On the other hand, the item “enhances agricultural sustainability” ranked last in both countries, despite remaining within the moderately high level. This may indicate that the concept of sustainability associated with artificial intelligence is still perceived by some agricultural extension personnel as a long-term or less tangible concept compared with more immediate practical roles, such as climate forecasting or risk reduction. The general mean score for this axis in Iraq reached 3.74, with a relative weight of 74.8%, reflecting a relatively high level of awareness regarding the expected role of artificial intelligence technologies in adapting to climate change. In Egypt, the overall mean reached 3.32, with a relative weight of 66.3%. This variation suggests a relative difference between the two contexts in terms of awareness and exposure to smart applications in the agricultural sector. It may also be associated with the degree of institutional interest, the level of technological infrastructure, and the extent to which modern technologies are integrated into agricultural extension work in each country.

Table 4. Comparison of the Perceived Role of Artificial Intelligence Technologies in Addressing the Impacts of Climate Change in the Agricultural Sector Between Iraq and Egypt.

No.	Item	Iraq			Egypt		
		Weighted Mean	Relative Weight (%)	Rank	Weighted Mean	Relative Weight (%)	Rank
1	Artificial intelligence contributes to predicting climate change	3.85	77.0	2	3.50	70.0	1
2	Helps reduce climate-related agricultural risks	3.78	75.6	3	3.45	69.0	2
3	Supports appropriate agricultural decision-making	3.92	78.4	1	3.38	67.6	3
4	Contributes to improving water resource management	3.74	74.8	4	3.32	66.4	4
5	Assists in selecting crops suitable for climatic conditions	3.70	74.0	5	3.28	65.6	5
6	Contributes to reducing agricultural losses	3.68	73.6	6	3.25	65.0	6
7	Provides farmers with accurate climate information	3.65	73.0	7	3.20	64.0	7
8	Enhances agricultural sustainability	3.60	72.0	8	3.15	63.0	8
—	Mean	3.74	74.8	—	3.32	66.3	—

Field Data, 2026.

Fourth: Major Obstacles Facing the Adoption of Artificial Intelligence Technologies in Agricultural Extension

The findings presented in Table 5 reveal that the challenges associated with employing artificial intelligence technologies in agricultural extension are not merely isolated technical barriers. Rather, they reflect the existence of a structural gap between the requirements of agricultural digital transformation and the institutional and organizational realities of agricultural extension systems in both Iraq and Egypt. The high weighted means across all items in both countries indicate that the implementation of artificial intelligence still faces an incomplete operational environment in terms of infrastructure, human capacities, and institutional support. It is noteworthy that the overall mean score for this axis was higher in Iraq, reaching 3.86 with a relative weight of 77.2%, compared with Egypt, where the overall mean reached 3.52 with a relative weight of 70.4%. This may reflect a higher level of awareness among Iraqi respondents regarding the gap between the theoretical potential of artificial intelligence applications and the actual capacity to employ them within agricultural extension work. This interpretation may also be linked to challenges associated with institutional infrastructure, digital transformation in the agricultural sector, and the stability of technical and technological support systems required for adopting smart applications.

“Weak technological infrastructure” ranked first in both countries, which is highly significant because it indicates that the primary obstacle to implementing artificial intelligence is not a lack of willingness to use such technologies, but rather the absence of a digital environment capable of accommodating them. Agricultural artificial intelligence fundamentally depends on the flow of data, the integration of information databases, the availability of stable communication networks, and digital systems capable of processing, analysis, and prediction. Therefore, weak infrastructure not only hinders the use of technologies but also limits the possibility of building a data-driven agricultural knowledge system. The findings further reveal that economic and institutional constraints constitute a governing dimension in the transition toward smart agricultural extension. In Iraq, “lack of funding” emerged as one of the most prominent challenges, reflecting the capital-intensive nature of agricultural artificial intelligence applications, whether in relation to digital infrastructure, analytical systems, or the updating of hardware and software. In Egypt, however, “weak governmental support” appeared more prominently, suggesting that respondents perceive digital transformation as an issue more closely associated with public policy and institutional governance than merely with the availability of financial resources.

Human and knowledge-related obstacles also emerged as among the most influential dimensions in the study findings. The items “lack of training in modern technologies,” “limited awareness of technologies,” and “shortage of specialized personnel” recorded high levels in both countries. This indicates that the challenge of employing artificial intelligence in agricultural extension is not solely a technical issue, but rather a matter of building human and cognitive capacities capable of understanding and managing digital transformation. Transitioning from traditional extension to smart extension requires reshaping the skills of agricultural extension agents so that they move from being transmitters of information to becoming data analysts and users of intelligent systems for diagnosis, prediction, and decision-making. Furthermore, the prominence of “resistance to change” among the major obstacles indicates the existence of cultural and organizational dimensions influencing technology adoption. Traditional institutions often tend to resist transformations that impose new patterns of work or require the redistribution of roles and expertise within the organization. Consequently, the success of artificial intelligence applications depends not only on the availability of technology but also on the ability of agricultural institutions to manage organizational change and the cultural transformation accompanying digital transformation.

It is also notable that the item “limited availability of modern devices” ranked relatively last, despite maintaining a high mean score. This suggests that the availability of devices in itself is no longer perceived as the most influential challenge when compared with deeper factors such as institutional infrastructure, funding, training, and governmental support. This finding indicates a shift in the nature of challenges from merely lacking tools to a broader systemic integration crisis involving policies, capacities, and operational structures. Overall, the findings demonstrate that the implementation of artificial intelligence technologies in agricultural extension in both Iraq and Egypt faces what may be described as an “agricultural digital transformation gap.” This gap results from the imbalance between the rapid advancement of smart technologies and the slow development of institutional and human structures capable of effectively accommodating and utilizing these technologies. Accordingly, the transition toward smart agricultural extension requires adopting a comprehensive approach that extends beyond the mere introduction of technology to include rebuilding the institutional, cognitive, and organizational environment that supports agricultural digital innovation.

Table 5

Comparison of the Obstacles Facing the Adoption of Artificial Intelligence Technologies in Agricultural Extension Between Iraq and Egypt

		Iraq			**Egypt**		
No.	**Item**	**Weighted Mean**	**Relative Weight (%)**	**Rank**	**Weighted Mean**	**Relative Weight (%)**	**Rank**
1	Weak technological infrastructure	4.05	81.0	1	3.70	74.0	1
2	Lack of funding	3.95	79.0	2	3.58	71.6	3
3	Lack of training in modern technologies	3.90	78.0	3	3.42	68.4	7
4	Limited awareness of technologies	3.82	76.4	4	3.55	71.0	4
5	Resistance to change	3.75	75.0	5	3.50	70.0	5
6	Shortage of specialized personnel	3.88	77.6	4	3.45	69.0	6
7	Weak governmental support	3.80	76.0	6	3.62	72.4	2
8	Limited availability of modern devices	3.70	74.0	7	3.35	67.0	8
—	Mean	3.86	77.2	—	3.52	70.4	—

Field Data, 2026.

Fifth: Requirements for Developing Agricultural Extension Using Artificial Intelligence Technologies

The findings presented in Table 6 reveal a general consensus among respondents in both Iraq and Egypt regarding the high importance of the requirements necessary for developing agricultural extension through the use of artificial intelligence technologies. However, the nature of the priorities identified in each country reflects differences in perspectives concerning the requirements for transitioning toward smart agricultural extension. These differences are largely associated with the institutional, technological, and economic contexts within which agricultural extension systems operate in both countries.

In Iraq, all weighted means were relatively high, and the overall mean for this dimension reached 3.94, with a relative weight of 78.8%, indicating a strong awareness of the importance of building an integrated environment for agricultural digital transformation. The item “providing digital infrastructure” ranked first, with a weighted mean of 4.10, reflecting respondents’ perception that digital infrastructure constitutes the fundamental starting point for any attempt to apply artificial intelligence in agricultural extension. This finding demonstrates awareness of the nature of smart technologies, which depend on the availability of communication networks, databases, information analysis platforms, and digital systems capable of supporting agricultural forecasting and decision-making processes. The item “training agricultural personnel” ranked second, reflecting a clear understanding that the success of the transition toward smart agricultural extension depends not only on the availability of technology but also fundamentally on developing human capacities capable of understanding and effectively utilizing these technologies. This also indicates increasing awareness of the need to redefine the role of agricultural extension agents, transforming them from transmitters of information into users of intelligent systems and analysts of agricultural and climatic data.

In Egypt, however, the ranking of priorities differed relatively. The item “providing funding” ranked first, with a weighted mean of 3.72 and a relative weight of 74.4%, followed by “cooperation with research institutions” with a weighted mean of 3.68, and “governmental support for modern technologies” with a weighted mean of 3.60. This ranking reflects that respondents in Egypt view economic and institutional challenges as the primary gateway to developing smart agricultural extension, rather than focusing mainly on purely technical aspects. The prominence of funding in the Egyptian context indicates recognition that agricultural artificial intelligence applications involve relatively high costs related to digital infrastructure, software, training, and maintenance, making financial resources a fundamental prerequisite for agricultural digital transformation. The high importance assigned to “cooperation with research institutions” also reflects increasing awareness of the knowledge-based nature of artificial intelligence and that the success of agricultural applications depends on integration between extension institutions, research centers, and universities in producing digital knowledge and developing predictive models and smart solutions suitable for local agricultural conditions.

The findings also reveal a relative difference in the ranking of “training agricultural personnel,” which occupied an advanced position in Iraq but a relatively lower position in Egypt. This may reflect differences in the level of human readiness or variations in national priorities between the two countries. While respondents in Iraq view capacity building as a fundamental entry point for digital transformation, respondents in Egypt appear to consider addressing financial and institutional constraints as a higher priority preceding the expansion of training programs. Furthermore, the items “spreading technological awareness,” “developing training curricula,” and “gradual introduction of modern technologies” reflect a shared understanding in both countries that the transition toward smart agricultural extension is not merely a process of introducing technical tools. Rather, it represents a broader cultural, organizational, and cognitive transformation that requires restructuring extension thinking, work methods, and training systems within agricultural institutions.

These findings indicate that the requirements for developing agricultural extension through artificial intelligence technologies in Iraq are more strongly oriented toward addressing technical and human capacity gaps related to infrastructure and digital competencies. In contrast, development priorities in Egypt are more concentrated on financial, institutional, and research integration aspects. This reflects differences in the nature of challenges and institutional contexts in the two countries, despite their shared recognition that the transition toward smart agricultural extension constitutes a strategic necessity for addressing climate change and achieving agricultural sustainability.

Table 6. *Comparison of the Requirements for Developing Agricultural Extension Using Artificial Intelligence Technologies Between Iraq and Egypt*

		Iraq (n = 228)			**Egypt (n = 214)**		
No.	**Item**	**Weighted Mean**	**Relative Weight (%)**	**Rank**	**Weighted Mean**	**Relative Weight (%)**	**Rank**
1	Providing digital infrastructure	4.10	82.0	1	3.55	71.0	4
2	Training agricultural personnel	4.05	81.0	2	3.45	69.0	7
3	Governmental support for modern technologies	3.98	79.6	3	3.60	72.0	3
4	Providing funding	3.95	79.0	4	3.72	74.4	1
5	Spreading technological awareness	3.90	78.0	5	3.50	70.0	5
6	Developing training curricula	3.88	77.6	6	3.48	69.6	6
7	Cooperation with research institutions	3.85	77.0	7	3.68	73.6	2
8	Gradual introduction of modern technologies	3.80	76.0	8	3.40	68.0	8
—	Mean	3.94	78.8	—	3.55	71.0	—

Field Data, 2026.

CONCLUSIONS

The findings of the study revealed that the level of use of artificial intelligence technologies in agricultural extension work in both Baghdad Governorate, Iraq, and Sharqia Governorate, Egypt, remains within the moderate range, with Iraq showing a relative advantage over Egypt. This indicates that artificial intelligence applications in agricultural extension have not yet reached a level consistent with global developments in smart agriculture, despite increasing awareness of the importance of these technologies in developing extension work and improving its efficiency. The study also demonstrated a high level of positive perception among agricultural extension personnel regarding the role that artificial intelligence technologies can play in addressing the impacts of climate change, particularly in the areas of climate forecasting, agricultural decision-making support, water resource management, and the reduction of agricultural risks and losses. This perception was more pronounced among respondents in Iraq than in Egypt, reflecting a relative difference in the level of awareness or exposure to smart applications in the agricultural sector between the two countries.

The findings further revealed that the obstacles facing the adoption of artificial intelligence technologies in agricultural extension are not limited to technical aspects alone, but also extend to institutional, organizational, and human dimensions. The most prominent obstacles included weak digital infrastructure, insufficient funding, limited governmental support, inadequate training, and a shortage of specialized personnel, in addition to limited technological awareness and resistance to change. These findings indicate the existence of a clear gap between the rapid advancement of smart technologies and the capacity of agricultural extension institutions to absorb and effectively utilize these technologies.

The study also demonstrated that developing agricultural extension through the use of artificial intelligence technologies requires the establishment of an integrated environment that includes strengthening digital infrastructure, providing the necessary funding, supporting governmental policies, building human capacities, developing training programs and educational curricula, and enhancing cooperation between extension and research institutions. The findings further confirmed that the success of the transition toward smart agricultural extension depends on the integration of technology, knowledge, policies, and institutions. The comparison between Egypt and Iraq also revealed relative differences in development priorities. Respondents in Iraq placed greater emphasis on the importance of digital infrastructure and human capacity development, whereas respondents in Egypt focused more on financial aspects, governmental support, and cooperation with research institutions. This reflects differences in institutional and economic contexts as well as variations in the level of digital readiness between the two countries.

The study confirms that artificial intelligence technologies represent a promising approach for improving the efficiency of agricultural extension and enhancing the agricultural sector's ability to adapt to climate change. However, achieving this objective requires the adoption of comprehensive strategies for agricultural digital transformation based on developing infrastructure, building human capacities, supporting agricultural innovation, and strengthening the integration between technology and extension work in ways that contribute to achieving smart agriculture and agricultural sustainability in both Egypt and Iraq.

RECOMMENDATIONS

Based on the findings and conclusions of the study, a set of practical recommendations can be proposed for the relevant authorities, including the Ministry of Agriculture and its affiliated institutions, as follows:

1. Develop digital infrastructure in the agricultural sector by improving communication networks and establishing agricultural and climatic databases that support the application of artificial intelligence technologies in agricultural extension work.
2. Implement specialized training programs for agricultural extension agents to enhance their competencies in using smart technologies, analyzing agricultural and climatic data, and employing these technologies in supporting agricultural decision-making.
3. Increase governmental support and funding allocated to agricultural digital transformation in order to provide the modern technologies, equipment, and software necessary for applying artificial intelligence in agricultural extension.
4. Strengthen cooperation between agricultural extension institutions, universities, and research centers to develop smart applications that are compatible with the needs of the agricultural sector and the challenges posed by climate change.

5. Promote awareness of the importance of artificial intelligence technologies and their role in addressing the impacts of climate change and achieving agricultural sustainability among agricultural extension personnel and farmers.
6. Adopt a gradual and well-organized implementation of artificial intelligence technologies within the agricultural extension system, taking into consideration the readiness of institutions, human capacities, and infrastructure in both Egypt and Iraq.

Limitations of the Study

1. The study was geographically limited to Sharqia Governorate in the Arab Republic of Egypt and Baghdad Governorate in the Republic of Iraq, which may restrict the generalizability of the findings to all governorates or other agricultural environments within the two countries.
2. The study relied solely on the perspectives of agricultural extension agents and personnel working in agricultural extension, without including other groups such as farmers, policymakers, or technical specialists. This may limit the comprehensiveness of the interpretation of the actual use of artificial intelligence technologies in the agricultural sector.
3. The study focused on a specific set of artificial intelligence dimensions related to agricultural extension and climate change and did not address in detail advanced technical aspects or specialized application models of agricultural artificial intelligence.

Future Research Directions

Future studies are recommended to expand the investigation of artificial intelligence applications in agricultural extension by including additional agricultural regions and different categories of stakeholders, particularly farmers, policymakers, and agricultural technology specialists in both developing and developed countries. Further research may also focus on evaluating the actual effectiveness of specific artificial intelligence applications, such as expert systems, remote sensing technologies, decision support systems, and smart mobile applications, in improving agricultural extension performance, agricultural productivity, and climate change adaptation.

Future research could also examine the institutional readiness and digital transformation capacities of agricultural extension organizations, as well as the economic feasibility of adopting artificial intelligence technologies within agricultural extension systems. Comparative studies between countries with different technological and institutional contexts may provide broader insights into the factors affecting the adoption of smart agricultural extension systems.

Moreover, future studies are needed to explore the long-term role of artificial intelligence technologies in supporting climate smart agriculture, improving water resource management, reducing agricultural risks and losses, and enhancing agricultural sustainability. Longitudinal studies may further contribute to understanding the long-term impacts of artificial intelligence technologies on agricultural extension efficiency and farmers' adaptive capacities under climate change conditions.

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