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RESEARCH ARTICLE
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The Role of Artificial Intelligence in Enhancing the Agricultural Extension and Marketing

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ABSTRACT

Artificial Intelligence (AI) is a groundbreaking tool in agricultural extension and marketing that offers new ways to enhance productivity and efficiency. The study investigates the application of AI in the development of agricultural practice in Jordan from the perspectives of key stakeholders like farmers, agribusiness professionals, extension officers, and technology consultants. A cross-sectional survey with 380 participants was used to evaluate AI performance in agricultural decision-making and operational performance. The findings indicate moderate-to-high consensus on applying AI to increase productivity with mean ratings of 3.47-3.63. AI's role in agricultural extension registered high consensus with mean ratings of 4.65-4.78 for its benefits, indicating its significant role in knowledge dissemination and resource use. Structural Equation Modeling (SEM) findings validate the efficacy of the model in forecasting high composite reliability (0.988) and high correlation (r = 0.884) of AI adoption to better agricultural extension services. The findings are promising, even if the study recognizes limitations as data being cross-sectional in nature and self-report biases. In conclusion, for the realization of the full potential of AI in agriculture, investment is advised in AI training, infrastructure, and policy. The future research needs to analyze regionally and gender-differentiated gaps and identify the long-term implications of AI use in agriculture to ensure that there is sustainable development in agriculture.

Keywords: Artificial Intelligence, Agricultural Extension, Marketing, Technology Adoption, Jordan, Structural Equation Model, Agriculture.

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INTRODUCTION

Combining Artificial Intelligence (AI) with farming is a revolution that increases efficiency, precision, and decision-making based on knowledge in agricultural extension services and marketing. AI-driven approaches like machine learning, data analytics, and computer vision optimize the utilization of resources, increase productivity, and recast agricultural marketing strategies. With the complexity of agricultural systems on the rise in the contemporary period, AI presents new answers that enable stakeholders to make decisions with data, thus improving efficiency and competitiveness in the market (Victoire, 2023). AI applications in agriculture extend beyond automation since it enables predictive analytics, precision agriculture, and improved marketing strategies that capture consumer patterns and market demand. By employing AI-insights, agribusiness companies can anticipate market trends, streamline supply chain logistics and implement targeted marketing strategies that enhance profitability and sustainability.

AI can provide large-scale data analysis on crop yields, market trends and consumer behavior, allowing agribusiness companies to develop effective marketing strategies. AI models dissect real-time agricultural data to determine trends, forecast market trends, and optimize supply chain logistics. Farmers and agribusinesses formulate their marketing strategies with AI-based information so that they are in accordance with economic and sustainability goals. Victoire (2023) is to the point that AI enhances agricultural decision-making authority and facilitates sustainability as it maximizes the use of resources and minimizes waste. AI application in agricultural marketing enables firms to improve consumer

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behavior understanding, leading to niche marketing strategies that enhance customer satisfaction and responsiveness to the market.

AI's contribution to the value of the economy in agriculture transcends increased productivity, influencing price strategies, supply chain management, and market positioning. Sahoo & Sharma (2023) recognize the employment of AI to make the value chain in agriculture more efficient, particularly by enhancing production and distribution systems. Applications of AI in predictive analytics help agribusinesses predict change in demand, coordinate marketing plans in response, and maintain competitive pricing mechanisms. Artificial intelligence software allows for the automation of inventory management, maintaining the production process in check and loss prevention. AI makes agricultural businesses more responsive to emerging market trends, altering consumer preferences.

AI hugely drives the modernization of agribusiness marketing through automation and personalization. AI-driven CRM and chatbots enable direct interactions between farmers and consumers, enhancing engagement and service quality. Shaik (2023) maintains that artificial intelligence (AI)-based automation facilitates marketing communication, providing the consumer with punctual and proper information regarding agri-products. AI-powered algorithms analyze consumer habits, segment the consumer base, and generate tailored campaigns that boost customer loyalty. Babatunde et al. (2024) also mention the capability of AI to tailor the marketing message, leading to improved conversion rates as well as effective customer retention in agricultural markets.

Supply chain optimization is one of the most impactful uses of AI in agricultural marketing. Machine learning and predictive analytics deliver supply and demand in real time, aiding in optimal inventory management and preventing farm wastage. AI logistics platforms use weather, historical patterns of sales, and transportation restrictions to optimize routing. Such facilities are of maximum use in products with perishable farm life, low storage, and short delivery. Successful AI-driven supply chain systems harmonize levels of production to meet consumer demand, reducing losses and profitability. Successful distribution networks enhance supply chain resilience, farm products reaching markets with little cost and delay inefficiency.

Sustainability is an inherent aspect of AI-driven agricultural marketing. AI technologies render farming activities environmentally friendly by conserving water, minimizing the use of chemicals, and promoting sustainable crop rotation methods. Mor et al. (2021) highlight the use of AI to foster sustainability, i.e., minimizing carbon footprints through data-driven decision-making. AI precision agriculture technologies improve resource utilization efficiency by facilitating site-specific application of fertilizers and pesticides, preventing environmental degradation. Green consumers are sustainable applications of AI in agri-marketing, improving market positioning and creating long-term consumer loyalty. AI is used in green agriculture in carbon monitoring and climate risk analysis that assists agribusinesses in coming into compliance with global sustainability regulations.

Though revolutionary as the application of AI is to agricultural development, there are gigantic impediments to its use. Exclusionary cost of use, absence of specialized technical expertise, and data privacy concerns are impediments to the mass use of AI in agriculture. Kulykovets (2023) finds that although the initial cost of adopting AI is high, long-term benefits overrule expenses. Greater productivity from AI resulting in lowering costs of market inefficiency over a period makes AI technology all the more desirable for the players in agriculture. Furthermore, research improvements towards developing tailor-made AI machinery specifically towards the cultivation sector assist in making it more and more accessible, dis-linking technical obstacles once AI is adopted. Governments and business stakeholders play a key role in enabling AI access through investments in specific sectors, capacity building, and building digital infrastructure.

Empirical evidence verifies the contribution of AI to agricultural marketing performance. Javaid et al. (2023) point out the function of AI in enhancing data-driven decision-making for agribusiness firms in analyzing past sales data and making market strategies simpler. Machine learning techniques are a significant support towards increasing the accuracy of demand forecasts, minimizing uncertainty in farm planning. Λιάκος et al. (2018) demonstrate how predictive analytics with AI supports superior market segmentation to enable agribusiness companies to create future-oriented marketing plans for niche consumer segments. Such data-driven functionalities represent the contribution of AI towards stimulating innovation, optimizing marketing effectiveness, and enhancing operational efficiencies in agriculture.

The constant advancement of AI technologies offers new chances for agro-extension services and marketing. AI platforms provide real-time analysis of data to enable agribusiness firms to respond to changing market conditions. Oliveira & Silva (2023) further argue that the use of AI exposes market competition due to the fact that agribusiness firms with the use of AI possess a better strategic location than others in order to realize consumers' needs. AI application development by agricultural companies speeds up to drive further investment in AI-enabled research and development. Advanced AI algorithms provide predictive modeling, risk assessment, and automation, further streamlining decision-making in a dynamically changing agricultural ecosystem. With AI-enabled farming marketing, firms maximize efficiency, maximize sustainability, and drive innovation.

This current study aims to examine the role of Artificial Intelligence in enhancing efficiency in agricultural extension and marketing, specifically its impact on decision-making, sustainability, and consumer engagement. Based on stakeholder attitudes and analysis of AI strategies, the report presents the main opportunities and challenges in applying AI in agriculture. The research contributes to the broader understanding of how AI will enhance resource utilization, increase market competitiveness, and transform the agricultural sector into an information-driven one. The research also clarifies the necessity of minimizing technical capabilities, infrastructural constraints and ICT competencies to achieve maximum potential in AI, thereby transforming the agricultural extension and marketing industry.

MATERIALS & METHODS

Study Design and Participants

This study employed a cross-sectional survey design to ascertain the perception of agricultural stakeholders towards the capacity of Artificial Intelligence (AI) to enhance agricultural extension and marketing in Jordan. A Victoire (2023) structured questionnaire was adapted to suit the study objectives and to make it suitable for the research environment. The survey had three main parts: demographic and personal information, i.e., years of experience, age, and gender; use and familiarity with AI, in which the intensity of AI utilization in agricultural extension and marketing was measured; and knowledge of AI's impact, in which AI's contribution to farm efficiency, decision-making, and sustainability was measured.

Pilot testing was carried out on 30 participants, who were various agricultural roles to guarantee clarity and reliability. Feedback from the pilot test resulted in slight adjustments that were made to guarantee more clarity in a few of the questions as well as to better match them with the study aims. This ensured that the questionnaire was appropriate for the target population to collect accurate and meaningful data.

Sampling Methodology

A systematic random sampling method was used to obtain a representative sample of different agricultural stakeholders. The study had 380 participants, comprising farmers, agribusiness specialists, agricultural extension agents, and technology specialists. The Ministry of Agriculture in Jordan provided an official list of potential stakeholders, and to ensure randomness and avoid selection bias, every third number from the list was selected. This ensured a representative sample from different sectors of agriculture.

Participants' age ranged between 20 to 65 years, with the average age of 42.5 years. The gender ratio was relatively equal, with 51.1% male and 48.9% female participants. There was also diversity in professional years of experience for the sample, so that there was a broad representation of perceptions on AI implementation and its implications on farming processes.

For consistency, the participants were visited at their work places where they were given a clear explanation of the purpose of the study and the voluntary nature of their participation. Written informed consent was obtained from all the respondents before data collection. For reliability of data, all the questionnaires were completed on the day they were given to avoid response bias and inconsistencies.

Study Area and Location Map

To provide the geographical context of this study, Fig. 1 indicates the most significant agricultural regions in Jordan where data were gathered. The regions—Jordan Valley, Irbid, Mafraq, Madaba, Karak, and Azraq—were selected for their agricultural significance and potential AI uptake. The Jordan Valley is among the most significant agricultural regions in the nation, with intensive cropping and advanced irrigation systems. Although Irbid, Mafraq, Madaba, Karak, and Azraq are engaged in diverse farming activities and agribusiness activities, representing different agricultural landscapes and market situations, the map is a descriptive measure of the research sites, hence enabling a clearer understanding of AI-based agricultural extension and marketing activities.

Questionnaire Development and Literature Support

The questionnaire for the survey was designed after a thorough literature review to ensure that it can analyze the pertinent facts of AI implementation in agricultural extension and marketing. Section 1 on AI and knowledge application drew inspiration from Maraveas (2022) who had analyzed the application of AI in smart greenhouses and how the productivity of farms is impacted. Section 2, concerning AI utilization in agricultural extension and marketing, was influenced by Saiz-Rubio & Rovira-Más's (2020) reflection upon how one works towards Agriculture 5.0 and the resulting implication for data-centered agricultural management. Section 3, concerning responsibility and accountability of AI utilization and accountability of AI utilization in agriculture, was written after consulting Dara et al. (2022) on responsible AI utilization guidelines in digital agriculture.

Recent studies have shown the capability of AI to revolutionize sustainable agriculture. El Jarroudi et al. (2024) explained the ways edge AI technologies are to be utilized in order to make agriculture practices more robust, and Olufemi-Phillips et al. (2024) explained the ways predictive analytics are to be utilized for monitoring food supply chains. AI has also helped enhance market access for farm produce, as indicated in studies like Anyadike et al. (2024) on AI use in Nsukka yellow pepper production. General impacts of AI on farm industries, particularly in agro-based economies, were extensively examined by Kumar & Pal (2024).

The use of AI in green agriculture is also well-established, with studies such as Maraveas et al. (2023) looking at resource management through greenhouses and how these are able to be utilized in an effort to supply zero greenhouse gas emissions. More broadly, intelligent production technologies based on AI have been explored through research into sustainability, with Cioffi et al. (2020) reporting on the use of AI technology within industrial transitions. Also explored was the intersection of AI and sustainable development, as per Goralski & Tan (2020).

Based on the current data, the survey was done to determine the current AI applications in agriculture in a way that it would be able to identify the changing challenges and opportunities of AI-based agricultural extension and marketing services.

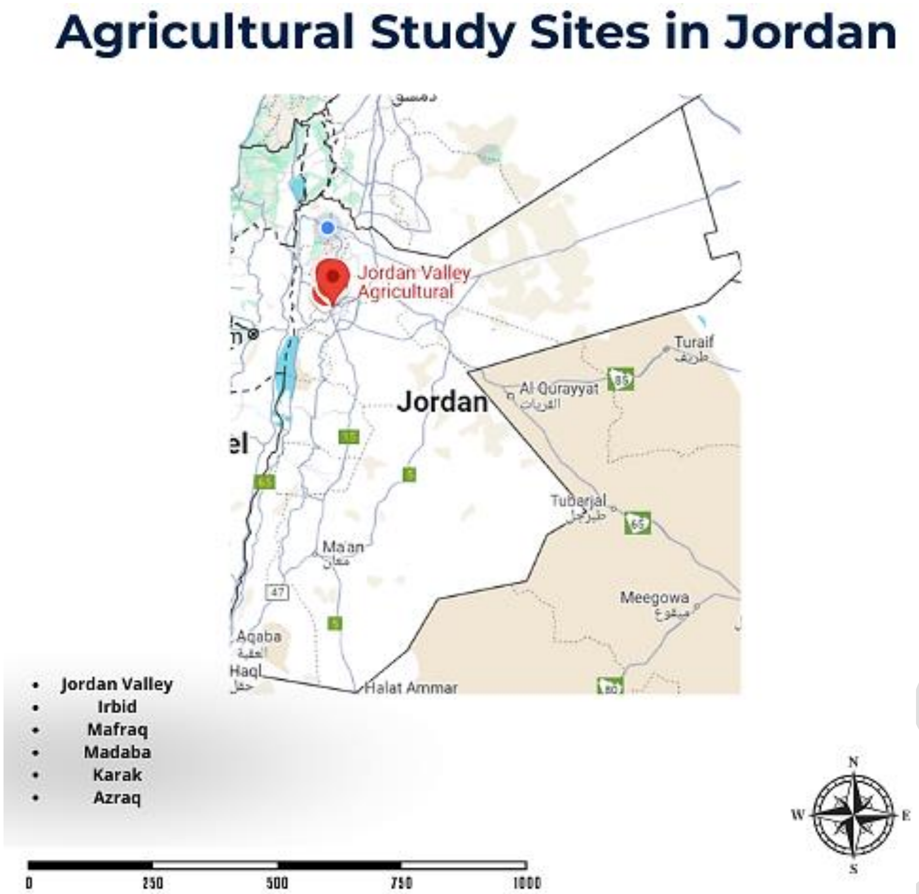

Fig. 1: Agricultural Study Sites in Jordan. (Source By Author).

Statistical Analysis

SPSS (version 26) was utilized to analyze data to perform descriptive and inferential statistical analysis. Cronbach's alpha was applied to test the reliability of the questionnaire to validate internal consistency across sections. Findings confirmed that the instrument was reliable and sufficient to measure constructs of interest.

For analysis of the relationship between adoption of AI and perceived effect, Pearson correlation analysis was conducted that demonstrated to what level AI influences efficiency, sustainability, and improvement of operations in agriculture extension and marketing. Additionally, Structural Equation Modeling (SEM) was also performed using AMOS (version 26) for examining direct as well as indirect effects of adoption of AI on agricultural decision-making and market performance. The SEM strategy facilitated a better understanding of the role of AI through the simulation of the relationships between AI integration, stakeholder involvement, and farming productivity.

To assess the stability of the results, certain fit indices of the model were evaluated, including Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). The fit indices provided the justification of the accuracy of the SEM model, which reported that the statistical relationships between the implementation of AI and agricultural extension outcomes were correct. The results demonstrated that AI adoption significantly influences marketing efficiency and stakeholder engagement, supporting the broader hypothesis that AI can enhance agricultural extension and sustainability.

RESULTS

The demographic profile of the study participants, as shown in Table 1, highlights a balanced gender distribution, with 48.9% female (186 participants) and 51.1% male (194 participants) out of 380 respondents. The data on years of experience indicates that a significant portion of the participants, 34.7%, have between 6 to 10 years of experience, followed closely by 33.2% with 11 to 15 years, and 23.4% with 0 to 5 years, suggesting a well-rounded mix of early to mid-career professionals. Only 8.7% of respondents have more than 16 years of experience, representing a smaller but experienced group. The current work positions of participants reflect the diverse nature of

Table 1: Demographic Profile

Categories	Sub-categories	Frequency	Percentage
Gender	Female	186	48.9
	Male	194	51.1
	Total	380	100.0
Years of Experience	0-5 years	89	23.4
	6-10 years	132	34.7
	11-15 years	126	33.2
	16 years or more	33	8.7
	Total	380	100.0
Current Work Position	Farmer	54	14.2
	Agricultural Extension Officer	67	17.6
	Agribusiness Specialist	70	18.4
	Researcher	40	10.5
	Data Analyst	37	9.7
	Technology Consultant	42	11.1
	Policy Advisor	3	0.8
	Educator/Trainer	44	11.6
	Market Analyst	23	6.1
	Total	380	100.0

agricultural roles in Jordan: Agribusiness Specialists (18.4%) and Agricultural Extension Officers (17.6%) are the most represented categories, followed by Farmers (14.2%), Educators/Trainers (11.6%), and Technology Consultants (11.1%). Roles such as Policy Advisors and Market Analysts are less common, comprising 0.8% and 6.1%, respectively, demonstrating a wide array of expertise contributing to the agricultural sector.

The analysis of AI's role in agricultural practices, as depicted by the statistics, reveals moderate to high levels of agreement among participants regarding AI's effectiveness. The mean values for the various AI-related items range from 3.47 to 3.63, indicating a generally positive perception of AI's impact on agricultural processes, though not overwhelmingly strong. The highest scoring item has a mean of 3.63 and thus suggests somewhat greater positive recognition in the case of this statement than any other regarding the contribution of AI. The lowest mean, 3.47, indicates a positive assessment but with more reservation. The standard deviations range from 1.221 to 1.376, and this would suggest a variability of opinion across participants that, while many see AI as something helpful to stakeholders, there is a range of opinion on its scope or influence. This range puts forward the indication that agricultural professional perception is somewhat nuanced, AI is seen to have potential benefits but at the same time might create challenges or areas of uncertainty when implemented.

Results for the section on Enhancing Agricultural Extension and Marketing show a strong and consistent agreement from the respondents about the effectiveness of AI in this area. The mean values for all items are substantially high, ranging from 4.65 to 4.78, which shows a robust consensus that AI greatly enhances agricultural extension and marketing practices. The highest mean score, 4.78, represents very strong endorsement in regard to a particular aspect, while even the lowest mean points to 4.65 as considerable support. It should be noted that the low standard deviation, 0.530 to 0.589, indicates little dispersion in response, i.e., all of the respondents are aware of the benefit of AI in enhancing communication, enhanced resource allocation, and market strategy. These findings indicate AI's transformative potential in streamlining agricultural extension and marketing, making them more data-intensive and market-responsive.

To ensure the robustness of the study model, Table 2 presents the most critical indicators, including Composite Reliability (CR), Average Variance Extracted (AVE), Maximum Shared Variance (MSV), and Maximum Reliability Estimate (MaxR(H)). CR is an indicator of each construct's internal consistency, ensuring the reliability of the scale. AVE is a measure of the variance explained by a construct over measurement error, and values greater than 0.5 are acceptable. MSV is used to compare the common variance between constructs for discriminant validity purposes, with constructs being different from one another. MaxR(H) provides the highest possible reliability estimate, reinforcing construct stability. Additionally, the correlation coefficient (*), denoting statistical significance at $p < 0.001$, confirms a strong association between AI Role and Agricultural Extension and Marketing. These indicators collectively validate the study model, ensuring reliability and discriminant validity.

Results of reliability and validity analyses (Table 2): The study model is internally consistent and demonstrates good construct validity. The CR values in the two constructs, AI Role and Agricultural Extension and Marketing are very high, reflecting excellent reliability; hence, confirmation is obtained that items within each construct set consistently measure the same concept. Also, the values of AVE are strong: 0.890 for AI Role and 0.827 for Agricultural Extension and Marketing, both above the threshold of acceptability of 0.5. This means that convergent validity is very strong; the underlying constructs can account for a big part of the method variance in the observed items. Similarly, MSV stands at 0.781, indicating a highly related but still distinct relationship between the constructs. The correlation coefficient between AI Role and Agricultural Extension and Marketing is 0.884, marked as highly significant (***), reinforcing the constructs' strong and meaningful association. The MaxR(H) values, 0.990 for AI Role and 0.988 for Agricultural Extension and Marketing, further support the model's robustness, confirming the constructs' high reliability and stability. The analysis validates the study model's reliability and the strong interconnection between AI's role and the enhancement of agricultural extension and marketing practices.

The distribution of participants by current work position and gender, as shown in Table 3, provides an insightful look into gender representation across

Table 2: Reliability and Validity Analysis of the study model

	CR	AVE	MSV	MaxR(H)	AI role	Agricultural Extension and Marketing
AI role	0.988	0.890	0.781	0.990	0.943	
Agricultural Extension and Marketing	0.988	0.827	0.781	0.988	0.884***	0.910

Note: CR = Composite Reliability, AVE = Average Variance Extracted, MSV = Maximum Shared Variance, MaxR(H) = Maximum Reliability Estimate. (*) indicates statistical significance at p < 0.001.*

Table 3: Distribution of Participants by Current Work Position and Gender (N=380)

Current Work Position	Total n (%)	Males n (%)	Females n (%)	P value
Farmer	54 (14.2)	30 (7.9)	24 (6.3)	0.05
Agricultural Extension Officer	67 (17.6)	35 (9.2)	32 (8.4)	0.03
Agribusiness Specialist	70 (18.4)	38 (10.0)	32 (8.4)	0.02
Researcher	40 (10.5)	20 (5.3)	20 (5.3)	0.06
Data Analyst	37 (9.7)	19 (5.0)	18 (4.7)	0.07
Technology Consultant	42 (11.1)	22 (5.8)	20 (5.3)	0.04
Policy Advisor	3 (0.8)	2 (0.5)	1 (0.3)	0.09
Educator/Trainer	44 (11.6)	24 (6.3)	20 (5.3)	0.05
Market Analyst	23 (6.1)	12 (3.2)	11 (2.9)	0.08

various roles in the agricultural sector. Among the 380 participants, Farmers represent 14.2% of the sample, with a slightly higher percentage of males (7.9%) compared to females (6.3%), and the gender difference is marginally significant (P = 0.05). Agricultural Extension Officers make up 17.6% of the participants, with a nearly equal distribution of males (9.2%) and females (8.4%), reflecting a significant gender difference (P = 0.03). Agribusiness Specialists comprise the largest group at 18.4%, with males (10.0%) slightly outnumbering females (8.4%), and this difference is statistically significant (P = 0.02). The Researcher category shows an equal split between males and females, both at 5.3%, with no significant gender disparity (P = 0.06). Data Analysts and Technology Consultants show similar gender distributions, with non-significant P-values of 0.07 and 0.04, respectively. Policy Advisors are the least represented group (0.8%), with a slight male predominance (0.5%) but no significant difference (P = 0.09). Educators/Trainers and Market Analysts show a balanced gender distribution, with P-values of 0.05 and 0.08, respectively. Overall, these findings highlight gender variations across different roles, with some positions showing statistically significant differences, indicating potential areas for addressing gender equity in the agricultural sector.

Goodness-of-fit measures of the Structural Equation Modeling (SEM) model described in Table 4 is a global indicator of how well the observed data fit the model. Normed Chi-Square (CMIN/DF) at 3.074 marginally crosses the mentioned cut-off boundary of less than 3.0, pointing to a medium degree of fit. Incremental Fit Index (IFI) = 0.953, and this is above the acceptable threshold of above 0.9, demonstrating a perfect fit of the model. The same can be said of Tucker Lewis Index (TLI), also 0.948, more than the break point of 0.9, in favor of the efficiency of the model. The Comparative Fit Index (CFI) matches the IFI at 0.953, further confirming a good fit of the model to the data. However, the Root Mean Square Error of Approximation (RMSEA) is at the boundary of acceptability, recorded at 0.08, which is the maximum permissible value for a well-fitting model. Despite the RMSEA being on the higher end, the overall fit indices suggest that the SEM model has an adequate fit, with most metrics comfortably within the recommended range, indicating that the model provides a reasonable representation of the data.

Table 4: The Goodness of Fit Indices for SEM model

Index	Abbreviation	Model	Cut-off Value
Normed chi-square	CMIN/DF	3.074	<3.0
Incremental Fit Index	IFI	0.953	>0.9
Tucker Lewis index	TLI	0.948	>0.9
Comparative fit index	CFI	0.953	>0.9
Root mean square error of approximation	RMSEA	0.08	<0.08

Fig. 1 presents the Structural Equation Model (SEM) illustrating the relationships between the latent constructs “AI Role” and “Agricultural Extension and Marketing.” The model demonstrates how various observed variables (indicated as AI1 to AI10 and AEM1 to AEM17) are associated with the respective latent constructs. The standardized factor loadings for the observed variables linked to the “AI Role” construct range from 1.00 to 1.23, suggesting strong relationships between these indicators and the latent construct. The error terms (e1 to e10) associated with these observed variables have relatively low values, indicating that a large proportion of the variance in the indicators is explained by the latent construct.

The "Agricultural Extension and Marketing" construct is associated with 17 observed variables, AEM1 to AEM17, whose standardized factor loadings are mostly close to or above 1.00, indicating that these measures are densely related to their respective constructs. Similarly, error terms, e11 to e27 associated with these indicators, are also small, indicating high reliability of the measures. Notably, it shows a very significant path coefficient of 0.90 between the two latent constructs. This indicates that there is a strong positive association between both-meaning an increase in the perceived role of AI relates to improvement in agricultural extension and marketing practices. Besides, some of the error terms have covariance paths to each other, such as e20 and e21 and e23 and e24, indicating latent relationships between these specific observed variables not captured by the model.

In the model, the ensuing benefits from Agricultural Extension indeed point to the immense improvement AI can pose in agricultural practices. From the result, a high loading on the factors related to Agricultural Extension and Marketing shows strong ties and points out that with AI technologies, communication is enhanced, more knowledge is effectively disseminated, and farmers make data-based decisions. These range from efficiency in resource allocation, better market access, to the application of agricultural practices according to specific needs. The overall model adopted here demonstrates how the integration of AI at Agricultural Extension promotes more precise, efficient, and effective extension services for sustainable agriculture, so as to make agriculture more competitive in respective markets.

Overall, Fig. 2 depicts the strong and significant associations of AI's role with the improvement of agricultural extension and marketing, thus showing that the measurement model has a high degree of reliability and validity. Accordingly, SEM results suggest that AI is significantly contributing to enhancing agricultural practices, evinced by high factor loadings and a compelling relationship between the two constructs.

DISCUSSION

This paper contributes to the expanding empirical literature on the transformative potential of artificial intelligence (AI) in revolutionizing farming practices, particularly in extension services and agricultural marketing. The results are consistent with existing literature showing the contribution of AI to business performance and innovation in agriculture (Avasthi et al., 2025; Ryan, 2023). AI-based marketing initiatives have greatly contributed to decision-making, operational effectiveness, and resource distribution towards promoting sustainable agriculture (Chelliah et al., 2024). Nguyen et al. (2023) emphasize that AI empowers agricultural business outcomes through enhancing market forces and human resource competencies

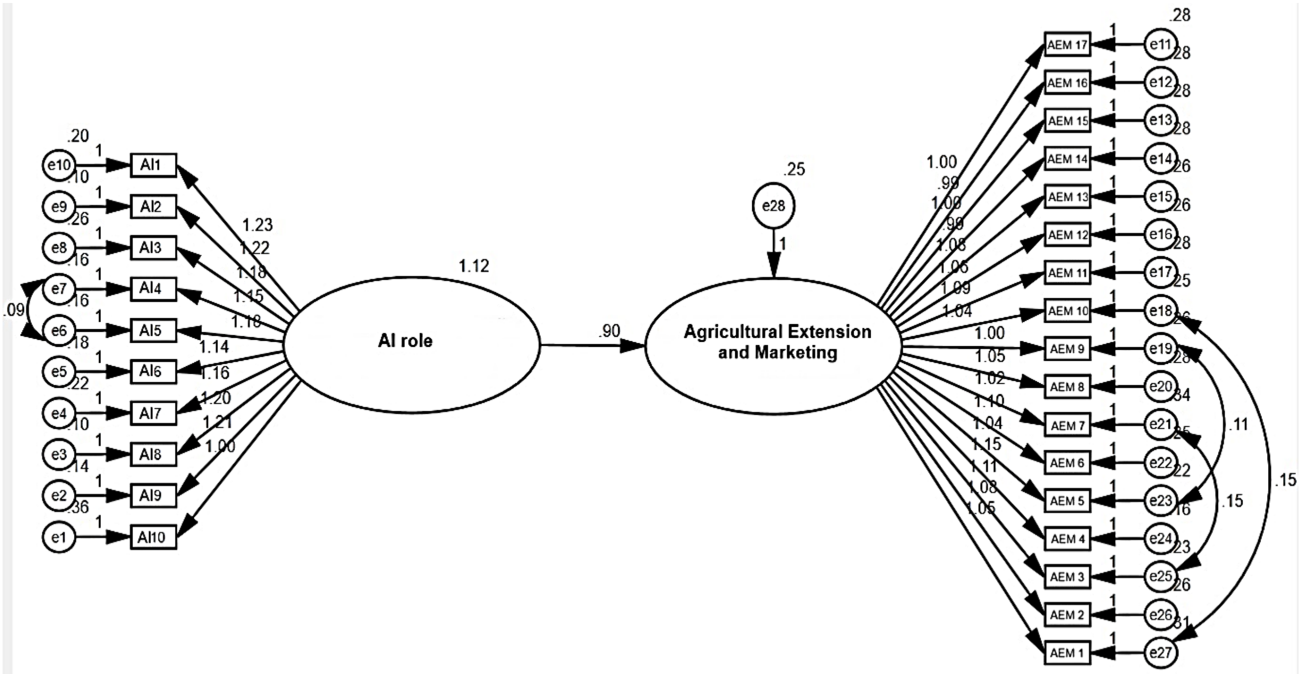

Fig. 2: Research SEM Model.

that exert a determining impact on business performance in agriculture. Their work in the Vietnamese environment points to the economic significance of AI, particularly in optimizing production efficiency and marketing, in favor of the argument that AI adoption has notable economic and operational benefits for agricultural firms.

The empirical findings are further substantiated by studies examining the structural and institutional factors influencing agricultural research and technological adoption. Buttel & Goldberger (2002) found that gender differences do not strongly impact scientists' commitment to significant agricultural research goals, though structural disparities exist in other domains of agricultural science. Their research underscores that institutional innovation systems remain a critical factor in shaping agricultural transformations. Pound & Conroy (2017) theorize that systemic interventions using AI technologies are a central impetus for driving rural agriculture forward. Their argument aligns with this study's affirmation that AI-enabled collaboration between diverse agricultural actors enhances agricultural extension services, improves productivity, and optimizes marketing strategy (Bisht & Roy, 2024).

While AI's undisputed strengths in agricultural extension are present, its application is determined by socio-economic factors, specifically gender inequalities. Limited access to extension services restricts technology dissemination, reinforcing inequities. Ciampi (2021) highlighted how entrenched gender norms in Zimbabwe impact extension effectiveness, while Ragasa et al. (2013) found that women farmers receive less access to quality agricultural advice, limiting AI adoption. Their lack of access to knowledge-sharing platforms worsens inequalities, reducing the overall impact of AI. This research is consistent with existing literature, emphasizing inclusive AI approaches that provide equal access and maximize technology-driven gains for all stakeholders in agriculture (Meinzen-Dick et al., 2012; Vishnoi & Goel, 2024).

Validity and reliability of the findings in this research are assured by a satisfactory model fit measure, validating the validity and reliability of the proposed SEM. SEM models have equally been used commonly in agricultural research, particularly, complex, transdisciplinary integration of information on high-technology agriculture research with climate change adaptation intervention and AI (SS et al., 2024). SEM has been cautioned by Smith et al. (2014) as an optimal tool to simulate interdependence in numerous interdependent variables in decision-making through AI, agricultural extension and advertising efficiency. This assertion is most appropriate for this current study with the highly significant correlations built for AI adoption and improved agricultural extension services and marketing (Uddin et al., 2024). Highly significant composite reliability (CR) values built in this current research also ascertain the validity of measurement items through building evidence of validity of results.

The research adds to the general debate of the revolutionary effects of AI in agricultural production by providing empirical evidence of the advantages of AI-supported agricultural extension and marketing (Dara et al., 2022). The positive relationships among the SEM model constructs validate that AI is an important facilitator of innovation, efficiency, and responsiveness in agriculture (Vishnoi & Goel, 2024). The outcomes point towards investing in AI technology and training to be able to gain the complete potential of AI (Chelliah et al., 2024). Crossing over socio-economic problems, such as gender gap and technical know-how shortage, continue to be vital to spur extreme adoption of AI. The research sheds light on the reality that although AI technology holds vast potential for increasing farm productivity, it is essential to break down systemic barriers to reach its full potential (Ryan, 2023).

Despite the key role that it plays, the research has limitations in some ways that must be realized. The cross-sectional nature of the research prevents the ability to determine causality between AI adoption and expanded agricultural extension and marketing. Because data cover just a point in time, it is hard to make assessments on long-term trends and on the changing influence of AI (Avasthi et al., 2025). Future research also needs to consider longitudinal methods tracking AI take-up and impact over longer timescales to provide more comprehensive views on AI-facilitated transformation of agriculture. Second, the self-reporting data collection also poses potential bias in that social desirability bias and recall bias can be determinants of responses given by the respondents (Dara et al., 2022). Steps were taken to ensure the reliability of the data, and subject biases could not be completely eliminated.

In addition, variations in participants' experiences and exposure to AI technologies can have influenced participants' attitudes towards AI adoption in agriculture. The study is cognizant of the possibility of heterogeneity in AI solution technological capability and online information access influencing perceived success (Bisht & Roy, 2024). Closing this gap requires further work on heterogeneity in AI uptake by different segments of the agriculture sector and population groups. Subsequent research will need to investigate the impact of AI training on the willingness of farmers to adopt AI technology and the impact of education interventions on AI-based decision-making in agricultural extension services and marketing (Uddin et al., 2024).

Given that AI technology is evolving every day, subsequent research will need to take into account new applications of AI in precision agriculture, supply chain management, and climate-resilient agriculture (SS et al., 2024). The integration of artificial intelligence (AI) and Internet of Things (IoT) devices, remote sensing technology, and blockchain networks provides promising avenues for raising agricultural data analysis, risk estimation, and market forecasting (Vishnoi & Goel, 2024). Also, exploring the regulatory and ethical aspects of AI in agriculture is a continuously developing point of investigation, namely, in the area of preserving privacy of data, justice and transparency of AI-based agricultural policy (Ryan, 2023).

In general, this study provides empirical proofs for the employment of AI within agricultural extension services and marketing strategy transformations. The results emphasize the importance of gender-responsive AI uptake frameworks that can bridge the gap of gender inequality, enhance the access to technology, and accelerate sustainable agricultural progress (Avasthi et al., 2025). The study is an addition to the current argument on agricultural revolutions via AI because it demonstrates that the application of AI reconfigures decision-making in agriculture, utilization of resources, and competition in the market (Bisht & Roy, 2024). Nevertheless, it requires policy intervention targeted at such impasses for the implementation of AI, additional investment in AI research, and even coordination among stakeholders (Dara et al., 2022). By overcoming these challenges, AI can reshape the future of agriculture so that it is achievable to attain efficiency, sustainability, and economic resilience in global food systems (Uddin et al., 2024).

Limitations

Though interesting evidence regarding the use of Artificial Intelligence (AI) to enhance agricultural extension and marketing emerges from this study, a number of limitations need to be mentioned. First, the cross-sectional design of the study restricts causality between AI adoption and agricultural practice change. Since data were taken at a single point in time, it is impossible to tell if integration of AI produces long-term benefits or if extraneous factors create the observed trends. Longitudinal methods must be employed in subsequent research to trace the adoption of AI over the long term and ascertain its evolving impacts on agricultural efficiency and sustainability.

Second, the study relies on self-report data, which would introduce potential biases such as social desirability bias and recall bias. Respondents may have overstated or understated the extent of AI adoption and its benefits, affecting the validity of the findings. Despite taking measures to ensure data reliability, such as pilot testing and structured questionnaire design, future research studies would be well advised to incorporate objective measures such as field observation and monitoring of AI adoption to complement self-reported opinions.

A second limitation refers to the geographic scope of the study. The study targets only agricultural stakeholders in Jordan, and this could confine the findings' generalizability to other countries with various technological infrastructures, policy structures, and socio-economic environments. Although the results provide significant implications for AI use in agriculture, comparative research among various countries or agricultural systems would yield a richer understanding of the role of AI in varied settings.

In addition, differences between participants' technological familiarity with AI technologies can have impacted responses. There can be low exposure to AI application in agriculture in some of the participants, leading to diverse understandings of its effectiveness. Further research must examine the impact of AI education and training on uptake percentages and establish the role of diverse technological familiarity levels on realized advantages of AI in agriculture.

Finally, although this research lays out the future of AI in agricultural extension and marketing, it does not extensively examine issues of ethics, regulation, and economics that are brought forth by the use of AI. Data privacy issues, algorithmic bias, and cost constraints remain important concerns for further research. By unearthing these limitations, it is possible to develop policies and regulatory frameworks that push forward the responsible adoption of AI while ensuring equitable access to its benefits.

Conclusions

This research theorizes and evaluates the transformative impact of AI in enhancing agricultural extension and marketing activities. The findings indicate a highly favorable perception of the role of AI, with agreement on its worth in enhancing communication, optimizing the utilization of resources, and developing data-driven market strategies. The model used is highly reliable and valid, corroborating the robust association between AI adoption and agricultural advancement.

Optimization of the potential of AI integration necessitates high investment in AI training for the creation of technical capacity among agricultural stakeholders. Provision for equitable access to AI technologies, elimination of gender biases from agricultural professions, and creation of the necessary infrastructure are essential for the realization of AI implementation. Interactions between governments, agricultural institutions, and technology providers will drive innovation to deliver scalable, accessible, and customized AI solutions responding to the evolving needs of the sector.

Implications and Recommendations

The study presents major findings regarding the role of Artificial Intelligence (AI) in transforming agricultural extension services and market strategies, emphasizing its potential to enhance efficiency, sustainability, and decision-making in the agricultural sector. The findings have several theoretical, practical, and policy implications that guide both scholarly research and business operations.

Theoretical Implications

The study contributes to the burgeoning literature in the area of AI application in agriculture by empirically verifying the impacts of AI solutions on agricultural extension services and marketing. The study employs a Structural Equation Modeling (SEM) approach and provides evidence of the relationships between AI adoption, farm productivity, and responsiveness in the market. These findings support and add to previous work (Nguyen et al., 2023; Ryan, 2023), which affirms that AI improves business sense, operations, and the use of resources in agriculture further. Further, the study highlights gender inclusivity in AI-driven agriculture transformation, which aligns with previous research on the socio-economic challenges of technology adoption.

Practical Implications

The study findings indicate that AI technologies can significantly improve decision-making for extension agents, policymakers, farmers, and agribusiness companies, which will lead to effective supply chain management, predictive analytics-based demand forecasting, and targeted marketing campaigns. Farmers' enterprises and extension workers can leverage AI-powered data analytics to reduce inefficiency, wastage, and boost productivity. Further, the strong nexus between AI and agricultural extension services emphasizes the need for AI literacy programs and training programs to equip farmers and agribusiness professionals with appropriate technical skills.

In addition, rural communities and smallholder farmers would also benefit from AI-based agricultural innovation, yet the unavailability of AI technologies and digital illiteracy could prove to be adoption hindrances. Thus, interventions must be implemented to mitigate the digital divide such that the all the stakeholders, especially marginalized groups, enjoy equal access to AI innovation.

Policy Recommendations

For the true potential of AI in agriculture to be actualized, policymakers will have to introduce end-to-end programs that guarantee adoption of AI-based technologies into farm work. AI infrastructure funding should rank among their top agendas, with governments and private entities collaborating on enhancing AI-aided farmwork. This entails investing in research, digitalization projects, and infrastructure development to facilitate the use of AI across the industry.

And although so, capacity building and training in AI is also required. Extension officers, agribusiness experts, and farmers will be supported with technical training courses in applying AI technology. Public-private partnerships can cause AI literacy and knowledge bridging that will lead to mass utilization of AI-based agri-solutions.

The second region of policy priority concerns the creation of standards of regulation for ethical adoption of AI. Policymakers must develop data safety, privacy, and ethical adoption of AI regulations so that AI adoption by farmers will be transparent, equitable, and inclusive to all the stakeholders. This is particularly crucial as AI programs are progressively making decisions, and regulatory intervention is inevitable in an attempt to prevent biases as well as defend farmers' rights to data.

Apart from this, gender disparities in the adoption of AI need to be addressed half-way as regards maximising equal access to technology. Gender-sensitive AI policies need to be developed for empowering women farmers and providing them an equal opportunity like men for adopting AI-facilitated farm technologies. This may include tailored AI training programs and digital solutions that are specifically designed for addressing the specific challenges of women farmers.

Affordability is one of the main barriers to the adoption of AI, particularly by smallholder farmers as they lack the ability to pay for installing AI technology. The barrier can be mitigated by incentives in the form of subsidies, grants, and low-interest loans from governments and financial institutions. These financial tools will be able to lower the price of AI tools and make them accessible and affordable to small and medium farms, hence all the stakeholders in agriculture will be able to gain from technology.

Second, AI applications must be climate-resilient agriculture practice-oriented in order to promote sustainability and green accountability. Funding for AI-based sustainability initiatives will enhance resource efficiency, enable precision agriculture, and assist in reducing the carbon footprint of agricultural activities.

Future Research

While this study provides valuable contributions, there are certain aspects that require further research in the application and understanding of AI in agriculture. Future studies must investigate longitudinal approaches to ascertain long-term impacts of AI on agricultural extension services and marketing. By tracking AI over time, researchers can more accurately quantify its evolving impact on productivity, efficiency, and sustainability.

Other than that, studies on the barriers of AI adoption in different socio-economic settings should be conducted so that it can be realized how farmers in other settings will probably be subject to different barriers. Studies in different geo-economic, economical, and technical settings will shed more light into determinants of the availability and effectiveness of AI.

Furthermore, the integration of AI with other frontier technologies such as the Internet of Things (IoT), blockchain, and remote sensing should also be researched further to support decision-making in agriculture. All of these technologies, put together, can potentially make supply chains more efficient, enhance predictive analytics, and drive more efficiency into farm operations.

Furthermore, the regulatory and ethical concerns should be researched even deeper, i.e., data privacy, algorithmic fairness, and the regulation of AI in agriculture. Enabling more research in these fields of utmost importance will render AI for agriculture transparent, fair, and effective.

With such policy direction and broader research field, AI can re-engineer farming in ways that are more efficient, sustainable, and adaptable to global risk.

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