Research

Smart Fields, Smarter Minds: Exploring Agricultural Experts' Adoption of Artificial Intelligence

Masoud Yazdanpanah
405 College Station Road, Athens, GA 30602
706- 542-8935
Department of Agricultural Leadership, Education and Communication, University of Georgia, Athens, Georgia, USA. my55713@uga.edu

Yousof Azadi
Department of Agricultural Extension and Communication, Zanjan University, Zanjan, Iran. azadi.yousof@gmail.com

J. Renee Martin
Department of Agricultural Leadership, Education and Communication, University of Georgia, Athens, Georgia, USA. reneemartin@uga.edu

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Introduction

Artificial Intelligence (AI) has emerged as a transformative technology with the potential to reshape how agricultural knowledge is produced, processed, and delivered to farmers (Olawumi et al., 2025). AI offers innovative solutions for knowledge dissemination, decision support, and resource management in agriculture, thereby enhancing productivity, reducing environmental impacts, and improving farmers' livelihoods (Ibrahim, 2023). However, one of the main challenges in integrating AI into agriculture is ensuring that farmers are willing and able to adopt and use these technologies (Kai et al., 2025). Agricultural extension services serve as a key mechanism for supporting farmers through the transfer of improved practices, technologies, and innovations developed by agricultural research institutions (Olawumi et al., 2025). In this process, extension agents and experts play a vital role in translating research into practice, providing tailored advice, and building trust among farmers (Lawani et al., 2025). Clearly, the anticipated economic and environmental benefits of AI in agriculture can only be realized if extension agents and farmers are willing to adopt these technologies (Mohr & Kühl, 2021). Therefore, it is essential to identify the factors influencing agricultural experts' and extension agents' behavioral intention to use AI technologies.

Conceptual Framework

The Technology Acceptance Model (TAM) provides a robust theoretical framework for understanding how individuals adopt new technologies and has been validated across various technologies and populations (Jaipong et al., 2022). In this model, two core constructs—perceived usefulness and perceived ease of use—play critical roles in determining technology adoption and continued use of AI (Jaipong et al., 2022; Mohr & Kühl, 2021). These constructs shape users' attitudes toward the technology. Davis (1993) argued that perceived usefulness influences perceived ease of use, but not vice versa. Moreover, perceived usefulness directly affects an individual's behavioral intention to use a technology (Jaipong et al., 2022), while user attitude also significantly shapes this intention (Chen et al., 2024). To account for the influence of social context, social influence was incorporated into the TAM (Ji et al., 2019). Social influence is defined as the degree to which an individual perceives that important others approve of their engagement in a particular behavior (Verma & Sinha, 2017).

Purpose and Research Objectives

The present study aims to examine the factors influencing agricultural experts' and extension agents' behavioral intention to use artificial intelligence (AI) in the agricultural sector, using the Technology Acceptance Model as the theoretical framework.

Research Methodology

This study employed a cross-sectional design. The statistical population consisted of agricultural experts and extension agents in Khuzestan Province, Iran. Based on the Krejcie-Morgan table, a total of 174 participants were selected. Data were collected using a questionnaire, the content validity of which was confirmed by experts. The reliability of the questionnaire was measured using Cronbach's alpha, and all values were within acceptable ranges. All variables were measured using a five-point Likert scale. Data analysis was conducted using SPSS 26 and SmartPLS 4.

Results

The demographic analysis revealed that 53.4% of respondents were female (n=93) and 46.6% were male (n=81), with an average age of 41.71 years (SD = 6.86).
Structural equation modeling results showed that perceived ease of use had a positive and significant effect on both perceived usefulness ($\beta = 0.564$, $p = 0.001$) and attitude toward AI use ($\beta = 0.402$, $p = 0.001$). Perceived usefulness also positively influenced attitude ($\beta = 0.272$, $p = 0.039$) and behavioral intention ($\beta = 0.193$, $p = 0.009$). Attitude, in turn, had the strongest positive direct effect on behavioral intention ($\beta = 0.725$, $p = 0.001$).
Social influence had a significant positive effect on perceived ease of use ($\beta = 0.661$, $p = 0.001$) but not on perceived usefulness ($\beta = 0.162$, $p = 0.152$).
Indirect effect analysis indicated that social influence significantly affected perceived usefulness ($\beta = 0.372$, $p = 0.001$), attitude ($\beta = 0.411$, $p = 0.001$), and behavioral intention ($\beta = 0.401$, $p = 0.001$). Perceived usefulness also had a positive and significant indirect effect on behavioral intention ($\beta = 0.197$, $p = 0.041$), whereas the indirect effect of perceived ease of use on attitude was not significant ($\beta = 0.153$, $p = 0.069$). However, perceived ease of use indirectly influenced behavioral intention significantly ($\beta = 0.511$, $p = 0.001$).

Conclusions & Implications

The findings confirm the suitability of the extended TAM as a strong theoretical framework for understanding the determinants of AI adoption among Iranian agricultural experts and extension agents, aligning with the results of Bagheri et al. (2024). The inclusion of social influence in the model significantly enhanced its explanatory power for predicting attitude and behavioral intention toward AI use, accounting for 38.3% and 71.4% of their variance, respectively. Attitude emerged as the most influential direct predictor of behavioral intention. To strengthen experts' and extension agents' intention to use AI, policymakers should focus on providing the necessary infrastructure, training, and support to enhance their awareness, perceived usefulness, and ease of use of AI technologies. Future studies are encouraged to explore additional psychological and contextual variables such as AI awareness and AI-related anxiety to gain deeper insights into adoption behavior

References

Bagheri, A., Tarighi, J., Emami, N., & Szymanek, M. (2024). Extension experts 'intentions to use precision agricultural technologies, a test with the technology acceptance model. *Acta Technologica Agriculturae*, *27*(2), 84–91.

Chen, X., Zhang, X., & Chen, J. (2024). TAM-Based study of Farmers' live streaming E-Commerce adoption intentions. *Agriculture*, *14*(4), 518.

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies*, *38*(3), 475–487.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003.

Ibrahim, U. (2023). Artificial Intelligence in Agricultural Extension for Sustainable Development. *International Journal of Applied and Scientific Research*, *1*(3), 259–268. https://doi.org/10.59890/ijasr.v1i3.740

Jaipong, P., Sriboonruang, P., Siripipattanakul, S., Sitthipon, T., Kaewpuang, P., & Auttawechasakoon, P. (2022). A review of intentions to use artificial intelligence in Big Data Analytics for Thailand agriculture. *Review of Advanced Multidisciplinary Science, Engineering & Innovation*, *1*(2), 1–8.

Ji, Z., Yang, Z., Liu, J., & Yu, C. (2019). Investigating users' continued usage intentions of online learning applications. *Information*, *10*(6), 198.

Kai, C., Ping, W., Siyu, K., & Chunzhen, Z. (2025). Breaking through the bottleneck in the promotion of artificial intelligence in agriculture: an analysis of the moderating role of individual's heterogeneity among farmers in Shandong Province. *Frontiers in Sustainable Food Systems*, *9*, 1621832.

Lawani, A., de Koff, J., Muriuki, J., & Ihuhwa, A. (2025). Determinants of Knowledge and Usage of Generative Artificial Intelligence in Agricultural Extension: Evidence From Tennessee Extension Personnel. *Agribusiness*.

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture*, *22*(6), 1816–1844.

Olawumi, A. O., Oyediji, B. I., Bamidele, J., Eleke, U. P., Olaitan, M. A., & Sennuga, S. O. (2025). Artificial Intelligence in Agricultural Extension for Sustainable Livelihoods among Rural Farmers in Abuja, Nigeria. *Global Academic Journal of Agriculture and Bio Sciences*, *7*(3), 47–57.

Verma, P., & Sinha, N. (2017). Role of attitude as mediator of the perceived ease of use and behavioural intention relationship. *International Journal of Management Concepts and Philosophy*, *10*(3), 227–245.