Advancements in Agricultural Development
Volume 7, Issue 2, 2026
agdevresearch.org

Artificial Intelligence and Digital Technologies in Agricultural Development Research and Practice

T. G. Roberts[1]

Abstract

Advancements in Agricultural Development hosted its second symposium, centered on the theme of "*Applications of Artificial Intelligence and Digital Technologies in Agricultural Development Research and Practice*," co-hosted by the University College Dublin School of Agriculture and Food Science, on October 13 and 14, 2025. Invited experts from Auburn University, Digital Green, Harper Adams University, International Food Policy Research Institute, the University of Florida, University College Dublin, and Utah State University shared papers that advanced our understanding of the role of these emerging technologies in our extension and teaching efforts. This article summarizes each of the papers presented. We are proud of this special issue and hope the agricultural development community finds it useful.

Article History

Received: January 5, 2026
Accepted: January 5, 2026
Published: January 26, 2026

Keywords

Teaching; extension; advisory services; SDG 2: Zero Hunger; SDG 4: Quality Education

Introduction

Advancements in Agricultural Development hosted its second symposium, centered on the theme of "*Applications of Artificial Intelligence and Digital Technologies in Agricultural Development Research and Practice*," co-hosted by the University College Dublin School of Agriculture and Food Science (https://www.ucd.ie/agfood/), on October 13 and 14, 2025. We would like to thank Professor Jim Kinsella and his colleagues for their warm hospitality.

The goal of this symposium was to document new and innovative agricultural development methods, including research methods (e.g., data collection, analysis, etc.) and development approaches (e.g., education, extension, communication, participatory approaches, adoption/diffusion, etc.). We invited a small number of experts from North American universities, European universities, and CGIAR centers. In the end, we had nine papers presented, with authors from Auburn University, Digital Green, Harper Adams University, International Food Policy Research Institute, the University of Florida, University College Dublin,

1. T. Grady Roberts, University of Florida, 220 Rolfs Hall, PO Box 110540, Gainesville, FL 32611 groberts@ufl.edu, https://orcid.org/0000-0001-7618-78502.

and Utah State University. In addition to the invited papers, students at UCD presented posters on their work.

Summary of Papers

Extension and Advisory Services

Ahn et al. (2026) conducted a systematic review of agricultural technology adoption research published between 2021 and 2025, analyzing 571 cases from 531 publications. Guided by Rogers's diffusion of innovation theory and employing Random Forest (RF), a supervised machine learning technique within the AI toolkit, the study identified key predictors of adoption outcomes. The methodology integrated systematic bibliometric searches, rigorous textual coding, numerical conversion, and RF modeling to synthesize diverse empirical evidence into actionable insights. The RF model demonstrated strong predictive performance, revealing extension access, climate risk awareness, and perceived relative advantage as the most influential factors, alongside perceived simplicity and participation in training programs. Education, or innovation literacy, was significant in localized contexts but less impactful across all cases, while peer networks exhibited moderate, context-dependent effects. These findings underscore the importance of extension strategies that emphasize clear benefits, manageable complexity, and climate-related risk information tailored to farmers' needs. Overall, this integrated approach offers robust, data-driven guidance for agricultural development policy, extension programming, and future research, advancing both methodological rigor and practical relevance in technology adoption studies.

Hill and Narine (2026) examined the applicability and effectiveness of a low-cost artificial intelligence (AI) foundational model (FM) in agricultural extension services. Their research involved developing and evaluating a custom GPT system, *Utah PeachBot*, which utilized OpenAI's GPT platform to support real-time, evidence-based advisory services for Extension agents working with small-scale peach producers in Utah. The model was trained with curated, research-based horticultural resources and assessed by an expert panel of six Extension agents. Findings revealed that the GPT demonstrated high reliability and accuracy in responding to general inquiries about peach cultivation. However, limitations were identified, including inconsistencies in regional specificity and the practicality of certain recommendations. Expert feedback emphasized the need for iterative fine-tuning through continuous input and integration of localized, context-specific data. Based on these results, the study recommends a phased implementation of customized GPT systems within agricultural advisory frameworks. This approach aims to enhance information dissemination, improve the quality of decision-making, and increase operational efficiency across extension systems. Overall, their research highlighted the potential of AI-driven tools to transform agricultural extension, underscoring the importance of contextual adaptation and ongoing refinement to meet the diverse needs of producers.

Jones-Garcia et al. (2026) examined strategies for designing and evaluating generative AI (GAI) tools for agricultural extension in a socially responsible manner. While GAI systems offer scalable and personalized advisory services, they frequently overlook the lived realities of smallholder farmers, particularly women, due to reliance on generic datasets and rigid evaluation metrics. To address these gaps, their research employed three complementary methods: (a) adversarial testing to identify gendered and contextual blind spots in model outputs; (b) deliberative stakeholder engagement using the C-H-A-T framework to uncover value tensions and design trade-offs; and (c) field-level insights from extension officers to highlight trust-building, diagnostic reasoning, and social intelligence absent from static chatbot interactions. Findings indicated that responsible GAI development extends beyond technical accuracy, requiring participatory design processes that prioritize user realities, challenge stakeholder assumptions, and incorporate social and institutional contexts. Recommendations included creating gender-responsive benchmarks, embedding reflexive and participatory design practices, and modeling advisory reasoning based on real-world extension experiences. Overall, this study contributes to the growing discourse on responsible AI by emphasizing the need to align GAI tools not only with technical objectives but also with the cultural, social, and political environments in which they operate.

Singh et al. (2026) shared an example of how Digital Green is overcoming an inherent limitation of most large language models (LLMs), which lack training data representing diverse agroecological contexts, often resulting in generic or locally misaligned recommendations. To address this gap, Digital Green implemented Reinforcement Learning from Human Feedback (RLHF) to enhance agricultural advisory services, creating *Farmer.Chat*, an AI assistant serving over 670,000 farmers across India, Kenya, Ethiopia, and Nigeria. This tool delivers text, image, and voice-based content tailored to regional needs. The RLHF process involved a web-based annotation platform, multi-phase implementation, and rigorous quality assurance. Through the development of more than 25,000 expert-reviewed question-and-answer pairs, the system achieved substantial improvements in response accuracy, tone, contextual relevance, and cultural appropriateness, particularly for region-specific queries. Their paper also discussed lessons learned, cost and equity considerations, and strategies for replication. It advocates for collaborative efforts among researchers, governments, and NGOs to share validated Q&A datasets, thereby strengthening global AI systems for agriculture. Future directions include advancing multimodal RLHF, integrating image, voice, and video, to build an inclusive, evidence-based ecosystem for AI-driven agricultural advisory services worldwide.

McGrath et al. (2026) documented participatory approaches in digital agricultural innovation by examining the application of design thinking to the development of a digital animal health tool. Specifically, the research reported practical insights from implementing the first three phases of the design thinking process. Design thinking proved highly effective in fostering direct engagement with end users through focus groups and a co-design workshop, while employing techniques such as user personas and “How might we…?” questions. These strategies enabled the identification of critical user needs and the co-creation of tailored solutions, which informed the tool’s design. The study also offered context-specific considerations for researchers seeking to replicate participatory approaches in agricultural settings. Key recommendations included accounting for the farming calendar to ensure stakeholder availability, addressing environmental factors during on-farm engagement, and utilizing boundary objects to promote mutual understanding and facilitate rich dialogue. These findings underscore the importance of integrating participatory design principles into agricultural innovation processes to enhance relevance, usability, and stakeholder ownership. Overall, their research demonstrates that design thinking provides a structured yet flexible framework for aligning technological development with the practical realities and priorities of agricultural end users.

Stapleton et al.'s (2026) study focused on farmer mental health. They evaluated the feasibility and appropriateness of a quasi-randomized multiple-baseline single-case experimental design to examine agricultural advisors' experiences with training in a digital Acceptance and Commitment Therapy (ACT) intervention. Eighteen advisors participated, completing a three-item daily measure for 55 days, attending two 2.5-hour Zoom training sessions, and completing three comprehensive surveys at pre-intervention (Time 1), post-intervention (Time 2), and three months later (Time 3). Their findings indicated acceptable participant retention, minimal missing data, and low error rates, supporting the feasibility of this design. Outcomes aligned with expectations at the nomothetic level for Times 2 and 3, suggesting preliminary effectiveness. The study advocates for future research employing single-case experimental designs and addressing multiple levels of analysis, psychological, sociocultural, and biophysiological, to strengthen the evidence base for digital mental health interventions in agricultural contexts.

Teaching and Workforce Development

Rose (2026) examined the role of creative teaching methodologies in preparing university students, particularly those studying agri-food systems, to critically engage with emerging "Agriculture 4.0" technologies such as robotics, artificial intelligence (AI), and drones. While these technologies are often portrayed as transformative solutions for producing more with fewer resources, social science research, including Science and Technology Studies (STS), Sociology, and Transition Studies, highlights that technological adoption carries both benefits and risks. To ensure a responsible future for farming, it is essential to anticipate these consequences and foster critical thinking among future professionals. The study introduced pedagogical approaches designed to expose students to STS literature, with a focus on the concept of "responsible innovation," which is often absent from agri-food curricula. Responsible innovation equips students to evaluate opportunities and risks associated with agricultural technologies, making trade-offs more tangible. The primary learning objective was to enable students to explore these complexities through student-led narratives that depicted agricultural utopias and dystopias. These stories served as tools for critical discussion, encouraging reflection on the social, ethical, and environmental implications of technological change. Ultimately, the paper underscored the importance of integrating interdisciplinary perspectives into agricultural education to prepare students for informed decision-making in future farming systems.

Lindner et al. (2026) conducted a descriptive and correlational study examining the adoption of generative artificial intelligence (AI) among agricultural educators in Alabama, focusing on their perceptions, attitudes, and experiences (N = 80). Guided by Rogers' diffusion of innovation theory and Davis's technology acceptance model, the research employed a mixed-mode survey to evaluate educators' awareness, perceived benefits, competencies, and barriers to AI integration. Results revealed a pronounced experiential divide across all measured dimensions. Early-career educators (≤ 5 years of experience) demonstrated significantly higher levels of awareness, perceived benefits, competence, and optimism regarding overcoming barriers compared to their more experienced counterparts (≥ 15 years of experience). Despite these differences, a shared and uniform concern emerged as the primary barrier: the pedagogical and ethical implications of AI use in education. This finding suggests that the central challenge lies in reconciling operational adoption with educators' professional identity and ethical considerations. The study corroborates prior research on technology adoption while introducing a novel ethical dimension specific to generative AI in agricultural education. Recommendations include implementing differentiated strategies to build confidence among experienced educators and reinforcing ethical best practices for early-career educators, ensuring responsible and effective integration of AI into agricultural education.

Stedman (2026) presented a conceptual paper that linked the application of AI tools to emotional intelligence. She asserted that agricultural leaders must cultivate emotional intelligence and critical thinking skills. These competencies enable leaders to anticipate and mitigate concerns related to the perceived impacts of AI on work practices and professional identity. By employing emotionally engaged thinking, leaders can foster trust, address resistance, and create inclusive dialogues that prioritize human-centered perspectives in the adoption of technology. This approach ensures that implementation strategies are not solely driven by efficiency or innovation but also by sensitivity to social and organizational implications. Ultimately, preparing agricultural leaders to combine technical expertise with emotional and cognitive adaptability is crucial for guiding the responsible integration of AI. Such preparation supports both technological progress and the well-being of individuals within agricultural systems, reinforcing the importance of holistic leadership in an era of rapid digital transformation.

Conclusions

This symposium brought together a diverse group of experts from around the world for two days to examine how artificial intelligence and other agriculture 4.0 technologies are impacting agricultural development. Participants brought a wealth of experience as researchers and practitioners, which facilitated robust discussions about the topics of each paper. In her closing remarks, Harder (2026) used storytelling as a way of synthesizing how the papers connected to each other. We are proud of this special issue and hope the agricultural development community finds it useful. We also recognize that the outcomes of events like this symposium go far beyond the papers published in this special issue. Expanded professional networks will facilitate future collaborations and provide opportunities to address emerging issues in the field.

Acknowledgments

Artificial Intelligence: Microsoft CoPilot was used to help draft summaries of each paper.

References

Ahn, J., Myers, B. E., Warner, L. A., Diaz, J. M., & Lamino, P. (2026). Revisiting Everett M. Rogers: A systematic review and random forest analysis of technology adoption in modern agriculture. *Advancements in Agricultural Development*, *7*(2), 8–22. https://doi.org/10.37433/aad.v7i2.629

Harder, A. (2026). Responsible use of artificial intelligence and digital technologies in agricultural development. *Advancements in Agricultural Development*, *7*(2), 136–139. https://doi.org/10.37433/aad.v7i2.697

Hill, P. A., & Narine, L. K. (2026). Large language models for agricultural and rural development: An application of foundational models in extension. *Advancements in Agricultural Development*, *7*(2), 23–34. https://doi.org/10.37433/aad.v7i2.603

Jones-Garcia, E., Singaraju, N., Davis, K., & Koo, J. (2026). Asking the right question: Toward a research agenda for responsible GAI in agricultural extension. *Advancements in Agricultural Development*, *7*(2), 35–49. https://doi.org/10.37433/aad.v7i2.633

Lindner, J. R., Clemons, C. A., & McKibben, J. D. (2026). Artificial intelligence in education: Perspectives of secondary teachers. *Advancements in Agricultural Development*, *7*(2), 109–124. https://doi.org/10.37433/aad.v7i2.637

McGrath, K., Kinsella, J., Regan, A., & Russell, T. (2026). Insights and learnings from the use of design thinking for agricultural innovation design. *Advancements in Agricultural Development*, *7*(2), 60–74. https://doi.org/10.37433/aad.v7i2.621

Rose, D. C. (2026). Creative teaching methods for imagining the future of technology in farming: storytelling for responsible transitions. *Advancements in Agricultural Development*, *7*(2), 91–108. https://doi.org/10.37433/aad.v7i2.623

Singh, V., Singh, S., Pedapudi, L., Pasha, W., Kumari, E., Gandhi, R., Miller, A., Repishti, J., Karanam, A., & Firnhaber, E. (2026). Application of reinforcement learning from human feedback for localizing quality agricultural advice using generative AI. *Advancements in Agricultural Development*, *7*(2), 50–59. https://doi.org/10.37433/aad.v7i2.625

Stapleton, A., Moore, B., Stynes, G., Richardson, N., Russell, T., & McHugh, L. (2026). Single case experimental designs in agricultural advisor training: A novel method for evaluating capacity building in farmer mental health interventions. *Advancements in Agricultural Development*, *7*(2), 75–90. https://doi.org/10.37433/aad.v7i2.657

Stedman, N. L. P. (2026). Maintaining connection: Using emotionally engaged thinking to enhance artificial intelligence initiatives in agricultural domains. *Advancements in Agricultural Development*, *7*(2), 125–135. https://doi.org/10.37433/aad.v7i2.639