Practices, perceptions, and adoption intentions of generative AI among agriculture teachers: perspectives from the technology acceptance model

Introduction

Paralleling the recent application of generative artificial intelligence (Gen AI) in education, Gen AI is becoming an increasingly integral component of agriculture teachers' daily teaching practice (Pehrson et al., 2025). In a recent U.S. national survey, 60% of K-12 public school teachers report they have used Gen AI tools during the 2024–2025 school year, with great time savings and quality gains in their work (Gallup & the Walton Family Foundation, 2025; Hernholm, 2025; Pehrson et al., 2025). Advances in technology have a dramatic impact on the approach agriculture teachers take in delivering the school-based agricultural education (SBAE) and student achievement (Talbert et al., 2022). The emergence of Gen AI tools, marked by the release of ChatGPT-4, has made their educational affordances equally accessible to all teachers (van den Berg & du Plessis, 2023), while the pedagogical contributions of AI have been recognized by agriculture teachers (Pehrson et al., 2025). In vocational or laboratory settings, AI has the potential to offer personalized and effective learning experiences by providing students with customized feedback and explanations, as well as creating realistic virtual simulations for hands-on learning (Ghosh & Ravichandran, 2024; Qadir, 2023).

To efficiently exploit the merits of Gen AI in agricultural education, it is crucial to investigate factors influencing agriculture teachers' adoption intention of Gen AI, which also meet their professional teaching development needs (Mathew & Stefaniak, 2024). Empirical evidence showed that the Technology Acceptance Model (TAM) explains teachers' technology adoption of Gen AI well in diverse cultural and disciplinary contexts (Choi et al., 2023; Hazzan-Bishara et al., 2025). A body of research has examined teachers' intention to adopt Gen AI in elementary, secondary, and higher education (Celik, 2023; Hazzan-Bishara et al., 2025; Lyu et al., 2025). However, limited research focuses on the application of AI in courses emphasizing application and practicality (Zafari et al., 2022). As the SBAE operates in highly interdisciplinary, hands-on, and practice-driven environments, agriculture teachers represent a critical yet understudied group in the discourse of AI-supported teaching.

Purpose and objectives

This study aims to map the landscape of current applications of Gen AI in agricultural education by investigating agriculture teachers' current practices, perceptions, and examining factors influencing their intention to adopt Gen AI in teaching practice. To construct a better understanding of the facilitators and barriers of AI adoption among agricultural educators, the TAM theory provides a robust framework. To guide these inquiries, the following research questions are proposed:

RQ1: What is the current practice of agriculture teachers using Gen AI?

RQ2: How do agriculture teachers perceive the integration of Gen AI in agricultural education?

RQ3: Does the Technology Acceptance Model well explain the mechanism of AI adoption in agricultural teaching practice? What other external factors are also effective?

Theoretical framework

Gen AI adoption and Technology Acceptance Model

According to the TAM framework (Davis, 1987), two crucial factors play a role in shaping an individual's willingness to adopt a technology. The first factor is perceived usefulness, which reflects an individual's belief that the technology will help them achieve their goals. The second factor is perceived ease of use, which involves individual confidence that the technology is friendly and easy to understand and use. Researchers have used this framework to predict or explain the level of technology acceptance by agriculture teachers at the secondary levels (Ganpat et al., 2013; Pehrson et al., 2025; Zarafshani et al., 2020). In the context of Gen AI adoption in education, perceived usefulness and perceived ease of use are found to have a great significantly positive impact (Choi et al., 2023; Hazzan-Bishara et al., 2025). Thus, the following hypotheses are proposed:

> Hypothesis 1. Perceived usefulness positively influences agriculture teachers' intention to adopt Gen AI.
> Hypothesis 2. Perceived ease of use positively influences agriculture teachers' intention to adopt Gen AI.

Self-efficacy

Self-efficacy refers to an individual's judgment or belief in oneself ability to organize and perform tasks successfully, serving as an internal factor that determines individuals' behavior changes (Bandura,1977). In education, studies show that teachers with a higher confidence in their ability to integrate AI technology tend to perceive a higher level of usefulness and ease of use of AI technology (Hazzan-Bishara et al., 2025). Thus, increasing the self-efficacy of agricultural teachers is a key strategy for promoting the perceived usefulness and ease of use of Gen AI. Thus, the following hypotheses are proposed:

> Hypothesis 3. Self-efficacy positively influences agriculture teachers' perceived ease of use of Gen AI.
> Hypothesis 4. Self-efficacy positively influences agriculture teachers' perceived usefulness of Gen AI.

Institutional support

Institutional support refers to diverse supports provided by educational institutions for teachers in terms of policy, infrastructure, general guidelines, or training programs (Hazzan-Bishara et al., 2025). This external factor highlights the need to equip teachers with essential knowledge, skills, and sufficient access to technology (Mathew & Stefaniak, 2024; Ganpat et al., 2013). Research revealed that a supportive environment established by schools facilitates teachers' AI adoption (Hazzan-Bishara et al., 2025). Thus, the following hypotheses are proposed:

> Hypothesis 5. Institutional support positively influences agriculture teachers' perceived ease of use of Gen AI.
> Hypothesis 6. Institutional support positively influences agriculture teachers' perceived usefulness of Gen AI.

Methods

Date collection and sample

Data was collected using a questionnaire conducted on Qualtrics, approved by the University of Georgia Institutional Review Board. Using the convenience sampling method, participants were recruited at state-level education conferences in July 2025. A total of 52 participants completed the quantitative section of the TAM measures. Of these, 32 participants completed all sections of the survey, including the qualitative open-ended questions. Most participants were from North Carolina (n = 22), followed by Georgia (n = 14) and Maryland (n = 1). Age ranged from 22 to 66, with 22-30 (n = 7), 31-40 (n = 12), 41-50 (n = 6), and 51 and above (n = 7). The sample included 16 males and 22 females. The majority were high school agriculture teachers (n = 32), with 8 taught at the middle school level. Teaching experience varied: 0-5 years (n = 9), 6-10 years (n = 10), 11-20 years (n = 13), and 21 years or more (n = 8).

Measures

To address RQ1, the following variables were assessed on a five-point Likert scale. **Familiarity** was measured by asking "How familiar are you with Generative Artificial Intelligence (Gen AI)?" (M = 2.46, SD = 0.70). **Perceived Knowledge** was measured by asking "How would you rate your current knowledge of artificial intelligence (AI) in the context of education?" (M = 2.40, SD = 0.98). **Usage Frequency** was measured on a 6-point scale: "How frequently do you use Gen AI tools (e.g., ChatGPT, Copilot) in your teaching practice?" (M = 3.87, SD = 1.14).

To address RQ2, we included open-ended questions asking participants about perceived benefits and concerns, as well as specific positive or negative examples from their experiences, to capture agriculture teachers' perceptions of integrating Gen AI tools in agricultural education settings.

To address RQ3, participants rated their agreement with statements measuring constructs in the Technology Acceptance Model on a five-point Likert scale, unless otherwise specified. **Self-efficacy** was measured via a three-item scale (Hazzan-Bishara et al., 2025; e.g., "I feel confident in my ability to use AI tools to support my teaching activities; M = 3.56, SD = 0.84, Cronbach's α = .91). **Institutional Support** was measured via a five-item scale (Hazzan-Bishara et al., 2025; e.g., "The availability and accessibility of technological tools and equipment at my school meet my needs"; M = 3.39, SD = 0.74, Cronbach's α = .84). **Perceived Usefulness** was measured via a four-item scale (Choi et al, 2023; e.g., "The usage of Gen AI tools will improve my work"; M = 4.10, SD = 0.65, Cronbach's α = .95). **Perceived Ease of Use** was measured via a six-item scale (Hazzan-Bishara et al., 2025; e.g., "Learning to operate Gen AI tools is easy for me"; M = 3.62, SD = 0.60, Cronbach's α = .85). **Intention to adopt AI** was measured via a five-item scale (Hazzan-Bishara et al.,2025;e.g., "I intend to actively learn practical applications of AI to implement them in teaching"; M = 4.03, SD = 0.72, Cronbach's α = .95).

Data analysis

The open-ended responses were examined using an inductive thematic approach by the author. Codes were identified from the data and then organized into overarching themes. Path analysis was conducted via structural equation modeling (SEM) to test the proposed hypotheses, using maximum likelihood estimation with the Mplus (Version 8.10) software.

Results

Descriptive statistics

To answer RQ1, Table 1 showed a comprehensive overview of the current practices of agriculture teachers using Gen AI in the educational context. Those who have used Gen AI tools reported that they primarily used Chatbots (e.g., ChatGPT, Google Gemini; *n* = 89), AI writing assistants (e.g., GrammarlyGO, Quillbot; *n* = 47), Voice assistants (e.g., Alexa, Siri, Copilot; *n* = 39), and Image generators (e.g., DALL·E, Canva AI; *n* = 38), while a few utilized AI presentation tools (e.g., Gamma, Tome; *n* = 12), AI-powered grading or feedback tools (*n* = 10).

Table 1
Familiarity, Perceived Knowledge, and Usage Frequency of Generative AI among Participants

Variable	Responses	*n*	%
Familiarity	Not at all familiar	6	5.9
	Slightly familiar	36	35.6
	Moderately familiar	47	46.5
	Very familiar	11	10.9
	Extremely familiar	1	1.0
Perceived Knowledge	I know very little about it	15	14.9
	I have a basic understanding of AI in education	36	35.6
	I have some knowledge of AI tools in education	30	29.7
	I have a good understanding and feel fairly confident using AI in education	15	14.9
	I have a strong, expert-level knowledge of AI and its educational applications	0	0.0
Usage Frequency	I have never used them and do not plan to start	1	1.0
	I have never used them but do plan to start in the future	9	9.4
	I've experimented with AI tools a few times	21	21.9
	I use them occasionally	30	31.3
	I use them weekly	23	24.0
	I use them every workday	12	12.5

The top five task types frequently used with Gen AI tools were the same ones participants were highly interested in learning: creating instructional materials (*n* = 27 for use, *n* = 38 for interest), generating lesson plans (26, 35), creating quizzes and assessments (21, 28), developing assignments (16, 23), and differentiating instruction based on student needs (12, 24).

Qualitative findings

To answer RQ2, open-ended responses were coded thematically. Among positive perceptions, work assistance (*n* = 24) and time-saving/efficiency (*n* = 23) were primary, with improved quality/creativity (*n* = 16), student learning (*n* = 5), none (*n* = 7) and not yet experienced (*n* = 9). In the themes of negative perceptions, most concerns are related to students (e.g., academic dishonesty, overreliance, surface learning, slack; *n* = 33), skill atrophy (*n* = 11), accuracy/quality of AI output (*n* = 5), ethical concern (*n* = 5), none (*n* = 34) and not yet experienced (*n* = 2).

Correlation and Structural equation modelling results

Initially, a preliminary correlation analysis was conducted to examine the relationships among the main variables (Table 2) and to inform the subsequent SEM analysis described below.

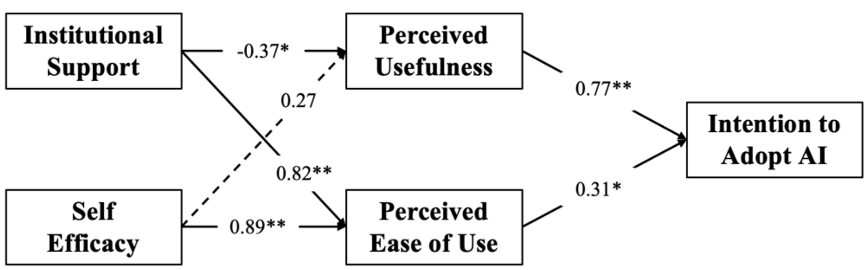
Table 2
Correlations Among Main Variables

	1	2	3	4	5
Self-efficacy (1)	1				
Institutional Support (2)	.395**	1			
Perceived Usefulness (3)	.398**	-.084	1		
Perceived Ease of Use (4)	.604**	.460**	.269	1	
Intention to Adopt AI (5)	.271	-.123	.774**	.337*	1

Note. ** $p < .001$; * $p < .05$.

A total of 52 participants completed the TAM measurement section. The SEM path analysis indicated a moderate model fit ($\chi^2/df = 1.61$, $p < 0.001$; the comparative fit index (CFI) = 0.867; Tucker Lewis index (TLI) = 0.849; the root mean square error of approximation (RMSEA) = 0.108; and the standardized root mean square residual (SRMR) = 0.091). Although some indices fall below the threshold for excellent fit, this may be a consequence of the relatively small sample size and the complexity of the model (Dash & Paul, 2021). Importantly, the estimated path coefficients mostly align with theoretical expectations (Figure 1).

Figure 1
Model Estimation Results



Note. ** $p < .001$; * $p < .05$.

The results showed that intention to adopt AI was positively influenced by perceived usefulness ($\beta = 0.77$, $p < .001$) and perceived ease of use ($\beta = 0.31$, $p = .02$), supporting Hypothesis 1 and Hypothesis 2, respectively. Additionally, self-efficacy was found to have a positive impact on perceived ease of use ($\beta = 0.89$, $p < .001$), supporting Hypothesis 3. Hypothesis 4 was rejected due to the non-significant effect of self-efficacy on perceived usefulness ($\beta = 0.27$, $p = .10$). Institutional support significantly predicted perceived ease of use ($\beta = 0.82$, $p < .001$). Hypothesis 5 was supported. In contrast, institutional support negatively influenced perceived usefulness ($\beta = -0.37$, $p = .03$), which was contrary to expectation. Hypothesis 6 was rejected.

Conclusions/Discussion/Implications/Recommendations

Based on the TAM, the present study provides new empirical insights into factors motivating teachers to adopt advanced technologies of Gen AI within the agricultural education context.

First, this study shows that the majority of agriculture teachers demonstrated slight to moderate levels of familiarity, knowledge, and use frequency with Gen AI tools, suggesting that they are in the exploratory or developing stages of engagement with AI tools in current practice. According to Celik (2023), technological knowledge equips teachers to judge AI outputs more astutely, but technological pedagogical knowledge is what enables them to harness AI tools pedagogically and deploy them in educational settings. To promote the utilization of AI technologies in agricultural education, practitioners and policymakers should emphasize the practical, real-world applications of AI for agricultural pedagogical approaches.

Second, the qualitative results reveal that agriculture teachers hold ambivalent perceptions toward the integration of Gen AI in teaching, consistent with previous findings of mixed feelings among SBAE teachers (Pehrson et al., 2025). AI can substantially reduce the cognitive effort of knowledge workers (Lee et al., 2025). This effect is also evident among agriculture teachers, who carry multiple roles and responsibilities beyond classroom instruction (Talbert et al., 2022). However, these benefits are constrained by values and ethical considerations over students' misuse of AI, which likely slows and tempers AI adoption in agricultural education.

Third, the findings correspond with previous research (Choi et al., 2023; Hazzan-Bishara et al., 2025), indicating the applicability of the TAM's core principles in explaining adoption intentions of Gen AI among agriculture teachers. These results highlight that when agriculture teachers perceive using AI is easy and useful, they are more likely to integrate it into teaching practices.

Furthermore, the results showed that self-efficacy, the internal factor, is found to positively predict ease of use. Contrary to previous research (Hong, 2022; Shao et al., 2025), the relationship between self-efficacy and usefulness was not significant. One possible explanation is that while conversational AI may be easy to use, perceived usefulness may be limited by the overly generic outputs when tasks in agricultural teaching require contextualized reasoning, originality, or domain-specific judgment. A research review on the application of self-efficacy theory in agricultural education indicated a shift from mastery experiences to vicarious experiences in the teacher development process of self-efficacy (McKim & Velez, 2016), a key environmental source in Bandura's self-efficacy framework. Therefore, to boost agriculture teachers' confidence in using Gen AI, peer-shared success stories and case studies, serving as a form of vicarious experience, can allow teachers to observe how comparable peers effectively integrate AI into instructional tasks and thereby strengthen their self-efficacy.

With regard to institutional support, this external factor positively affected perceived ease of use but negatively affected perceived usefulness. This finding demonstrates that while institutional support may help teachers build technological knowledge, many secondary agriculture teachers remain skeptical about the performance and ethical implications of Gen AI. Consistent with this interpretation, Pehrson et al. (2025) found that teachers often lack strategies to address and manage the negative aspects of AI in SBAE. Therefore, school leaders should prioritize providing clear ethical guidance and professional support to foster teachers informed and balanced engagement with AI technologies.

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