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Artificial Intelligence in Education: Perspectives of Secondary Teachers

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Abstract

This descriptive and correlational study investigated the adoption of generative artificial intelligence (AI) by agricultural educators in Alabama, focusing on their perceptions, attitudes, and experiences (N = 80). Grounded by Rogers' diffusion of innovation theory and Davis's technology acceptance model, a mixed-mode survey design was used to assess educators' awareness, perceived benefits, competencies, and barriers to AI adoption. Findings revealed a significant experiential divide across all measured themes, where early-career educators (with ≤5 years of experience) reported significantly higher awareness, perceived benefits, competence, and optimism about overcoming barriers than experienced educators (with ≥ 15 years of experience). The primary barrier to adoption was a shared and uniform high level of concern regarding the pedagogical and ethical implications of AI. This contrast suggests that the central challenge is a pedagogical adoption gap between educators' operational skills and their deeper apprehension of reconciling AI with their professional identity. This study confirms prior research on technology adoption while identifying a novel ethical barrier associated with the use of generative AI in agricultural education. The findings support the recommendation of differentiated approaches to enhance the confidence of experienced educators and reinforce the ethical best practices for early-career educators.

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Introduction and Problem Statement

The rapid diffusion of generative Artificial Intelligence (AI) presents a significant inflection point for the adoption of technology in agricultural education. Unlike the introduction of the World Wide Web, when early adopters had little experiential knowledge to frame their decisions (Nambisan & Wang, 2000; Tan & Teo, 1998), the integration of modern AI is occurring within a landscape already shaped by ubiquitous internet-based systems. While this preconditioning may accelerate diffusion (Hoffman & Beato, 2025; Kelly et al., 2023; Lai, 2013), it does not guarantee straightforward adoption, creating a critical need to investigate the perceptions and attitudes shaping this technological shift.

This study is situated within a well-established tradition of technology adoption research in agricultural education. For decades, scholars have examined the adoption of various digital tools, including personal computers to tablets, smart devices, digital communications, and interactive instructional displays (King & Rollins, 1995; Murphrey & Dooley, 2000; Murphrey et al., 2009; Sevnarayan & Potter, 2024; Smith et al., 2018; Verčič et al., 2024; Williams et al., 2014). This body of research establishes a strong historical foundation by demonstrating that historical barriers, often framed as a skills deficit, manifested in educator anxiety and a need for training, are crucial for successful technology integration (Kotrlik & Redmann, 2009). However, the arrival of generative AI represents a paradigm shift that previous models cannot fully address. The unique abilities of AI (Google, 2025) manifest from a combination of rapid diffusion, advanced user-based content creation capabilities, and the potential for novel professional and ethical complications that will be amplified by future advancements (Grace et al., 2024; Malik, 2024; Zhu et al., 2025). Previous studies have addressed technologies with slower, less complex architectures (Afzal et al., 2023; Card et al., 1983; Ross et al., 2010; Selwyn, 2021; Willis et al., 1999). The confluence of these new factors creates a powerful adoption landscape, leaving a distinct gap in the current literature that necessitates a new investigation explicitly focusing on generative AI. This dynamic reframes the central problem from a skills deficit to a more profound pedagogical adoption gap, which this study investigates.

This study focuses on agricultural educators in Alabama to provide empirically based insights into this phenomenon. While the context is localized, the challenges of AI adoption are not. Disparities in technological resources exist within agricultural education systems, which may hinder the adoption and application of AI technology (Hill & Reimer, 2024). Therefore, the findings from this study provide a foundational model for future research on technology adoption and offer insights that may be generalizable to other career and technical education programs in the United States.

Theoretical Framework

Public considerations of technology adoption are well known (Liehner et al., 2023; Pilisuk et al., 1987). Each iteration of technological advancement presents known and unknown variables for understanding the adoption and diffusion of technology. This study was grounded in Rogers'

(1962) diffusion of innovation theory and the technology acceptance model (TAM) by Davis (1985) to address agriculturalists' perceptions of AI adoption. This dual framework strengthens the critical lens of how an innovation spreads through a social system and how TAM provides a focused lens on the cognitive processes influencing an individual's decision to adopt the technology. By combining these perspectives, the research can examine both external factors and internal beliefs that influence the adoption of technology among agricultural educators. While other frameworks, such as the unified theory of acceptance and use of technology (UTAUT), exist (Williams et al., 2015), the combination of Rogers' and Davis's models was ultimately selected for application. The choice addresses both the external factors of technology adoption within a social system and the internal beliefs of the individual.

The decision to adopt an innovation is influenced by five key characteristics: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1962). As TAM describes, this framework provides the external context that directly shapes an individual's internal beliefs. An Agricultural Educator's assessment of AI's relative advantage and compatibility with their teaching philosophy directly informs them of their perceived usefulness and belief that the technology will enhance their job performance. The complexity of an AI tool is a primary determinant of its perceived ease of use when the user believes the system will require minimal effort. The ability to experiment with AI (trialability) and observe its use by peers (observability) further reduces uncertainty and strengthens these perceptions.

Rogers' theory diverges between categorical frameworks. Innovation addresses a population's relative advantage, compatibility, complexity, trialability, and observability of the innovation. Rogers countered innovation by describing the characteristics of the population, those that ultimately lead to acceptance or rejection, including innovators, early adopters, early majority, late majority, and laggards. Rogers identified five categories to describe the population's stages of adoption: Awareness (knowledge), Persuasion (attitude formation), Decision (adoption or rejection), Implementation (using the innovation), and Confirmation (reinforcing the decision). Harder (2009) noted that identifying and overcoming barriers is critical to adopting an innovation. Rogers' (1962) theory can help us understand the adoption of AI in agricultural education. The diffusion of innovation primarily operates as a linear model, suggesting that individuals progress through well-established stages of adoption. Investigating technology adoption is often more complex, influenced by interacting factors involving non-linear pathways, placing less emphasis on individual beliefs, attitudes, and perceptions, which are critical determinants of technology acceptance. These limitations highlight the need for a complementary theoretical framework to help us better understand individual adoption behavior of AI.

Incorporating Davis's (1985) technology acceptance model may provide a deeper understanding of the participants' choices and rationale, thereby offering a more comprehensive understanding of AI adoption among agricultural educators. Davis posits that an individual's acceptance and use of technology are primarily determined by two key constructs: Perceived usefulness, defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1985, p. 3). In the context of this study, it refers to the extent to which educators believe that using AI would enhance their effectiveness in the classroom. Perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1985, p. 4). Perceived ease of use refers to the extent to which educators anticipate that using AI tools will be effortless. While powerful for assessing individual beliefs, TAM places less emphasis on social influence and other external variables. This potential limitation is addressed through a complementary use of Rogers' diffusion of innovation to mitigate these concerns within this study.

The well-documented challenges of current generative AI models present significant hurdles to the core constructs of the adoption framework. Specifically, the potential for hallucinations in AI-generated responses directly threatens the technology's perceived usefulness; if a tool provides inaccurate information, its ability to enhance job performance is fundamentally flawed. Issues of inherent bias and a general lack of explainability challenge the perceived ease of use. A system that produces biased content or reasoning that is not accurate requires significant mental effort from educators to supervise, verify, and correct, thus making it feel less effortless to use. These technological limitations can decrease user trust, a critical factor in shaping the attitudes that precede the final decision to adopt or reject the technology.

Focused distinctions exist between perceived usefulness and perceived ease of use, as well as their applications in the adoption of technology. Usefulness refers to how the individual perceives the technology will improve their professional work experience and performance. Davis (1989) further explained that the perceived ease of use of the technology under consideration is directly related to the individuals' perceptions of physical and mental freedom. Ideally, the acceptance rate would be correlated (Fuerst & Cheney, 1982) with the practical application of the technology, usability, and effectiveness when measured against the degree of energy expenditure required by the user to learn and apply the technology. The combination of theoretical frameworks provides a clearer understanding of how agriculturalists approach the adaptability, adoption, implementation, and application of technology in their professional careers.

Purpose

The purpose of this study was to investigate the perceptions, attitudes, and experiences of Alabama agricultural educators who are integrating AI into their classrooms. To achieve this purpose, the following research questions guided the investigation:

1. What are the demographic and professional characteristics (years of experience, age, gender, and education level) of agricultural educators in Alabama?
2. What are the current levels of awareness, perceived benefits, self-reported competencies, and barriers to AI adoption among Alabama agricultural educators?
3. Do educators' perceptions of AI (awareness, benefits, competencies, barriers) change based on their teaching experience?

Methods

This descriptive and correlational study employed a mixed-mode survey design utilizing both web-based and mail surveys (Dillman et al., 2014). This research is part of a larger study examining the role of AI in agricultural education. As such, the methods and procedures used to define this study may be similar to future manuscript publications. A review of existing instruments addressing technology adoption in Agricultural Education revealed none were suitable for this study. Specifically, prior instruments focused on adopting hardware or software with defined uses. Therefore, a new instrument was developed to address the unique pedagogical and ethical considerations of generative AI adequately. Following established methodologies for instrument creation (Croom et al., 2023; Dillman et al., 2014), the instrument was designed specifically to investigate the adoption and dissemination of artificial intelligence models among agriculturalists in Alabama. The complete survey instrument is available from the corresponding author.

Developing new and often untested research instruments is crucial for iterative improvement in instrumentation in the social sciences (Dillman et al., 2014). Ten (n = 10) pilot study participants were randomly selected using a stratified random sampling method. The potential participants for this field test comprised all agricultural educators in Alabama (N = 320) with over one year of active service, as well as the Alabama Association of Agricultural Educators (AAAE). While relatively small compared to the population, this sample size is suitable for pilot study analysis (Hancock et al., 2024). The reliability data were examined to assess the internal consistency of the scale-based measures (Lindner & Lindner, 2024; Vaske et al., 2017). Participant responses were captured using Likert-type interval measurement scales: 5 = strongly agree, 4 = agree, 3 = neither agree/disagree, 2 = disagree, and 1 = strongly disagree (Lindner & Lindner, 2024; McKibben et al., 2023). Effect sizes were interpreted using Lindner's non-standardized effect size estimates (ES_L). Thematic and instrument reliability coefficients were conducted using SPSS (Field, 2024), producing a Cronbach's alpha for internal consistency of α = .81. Established researchers (Field, 2024; Kline, 1999) often consider α = .70 the minimum acceptable threshold for exploratory research, they suggest good or adequate reliability for more established instruments at the $\alpha \geq .80$. The final research instrument was revised based on the findings obtained during the pilot study, with slight modifications made to enhance readability, directionality, syntax, and writing clarity.

Instrument Design and Alignment with the Research Context

The research instrument was intentionally designed to operationalize the theoretical frameworks and directly address the study's research questions. The questionnaire was structured in two main sections. Section one of the questionnaire collected characteristic and professional data to answer research question one. Section two contained a series of Likert-type interval measurement scales to assess the core themes of research questions two and three. To bridge the context of AI's emergence with the theoretical frameworks, these themes were designed to capture the unique tensions present for agricultural educators.

Awareness, understanding, and barriers were assessed to evaluate educators' immediate cognitive and affective responses to the rapid integration of AI into everyday life. The awareness theme aligns with Rogers' (1962) initial stages of adoption, while the Barriers theme is a critical factor in diffusion theory. Acknowledging that prior technologies have preconditioned educators, the AI competencies gauged the transferability of existing skills and inherent expectations of usefulness by asking educators to rate their confidence in performing specific AI-related tasks (e.g., generating lesson plans, creating assessments).

To further ground the instrument's design in the cognitive realities of technology adoption, human-computer interaction (HCI) principles (Card et al., 1983) were used as a supporting lens. Although this study did not employ behavioral HCI metrics, the conceptual model acknowledges that tenets such as perceived ease of use and an innovation's complexity are direct outcomes of a user's cognitive experience. The instrument themes, including AI competencies and barriers, were developed to represent the cognitive load a user might experience when deciding whether to adopt or deny the technology.

Selection of the Investigative Sample Group

To better investigate the research questions guiding this study, 320 potential participants were framed from the Alabama Association of Agricultural Education (AAAE) membership list. To reduce the potential for frame error, two Alabama State Department of Agricultural Education (ALSDE) state directors were consulted to ensure the membership list was accurate at the time of the instrument distribution. Using Cochran's theorem (Bartlett et al., 2001) for survey sample representation, 280 potential participants were randomly selected from established strata based on years of education experience and school district size, with an oversampling of 20%. After multiple follow-up reminders, a response rate of 28.37% (n = 80) was achieved. While the response rate presents a potential limitation to the study's external validity, it is consistent with similar survey-based research in agricultural education (Emerson et al., 2024; McKibben et al., 2025). Early versus late comparisons were also calculated to estimate the potential threat to the study's external validity, as suggested by Lindner (2002). There were no differences between the variables of interest, supporting the notion that the sample was representative.

Findings

This exploratory study investigated the experiences, perceptions, and attitudes of agricultural educators regarding the current and future use of generative artificial intelligence in agricultural education. This section presents the results of the quantitative analysis of collected data, organized by the study's research questions: (a) What are the demographic and professional characteristics (years of experience, age, gender, and education level) of secondary agricultural educators in Alabama? (b) What are the Alabama agricultural educators' current levels of awareness, perceived benefits, self-reported competencies, and barriers to AI adoption? (c) Do educators' perceptions of AI (awareness, benefits, competencies, barriers) change based on their teaching experience?

Research Question 1: What are the demographic and professional characteristics (years of experience, age, gender, and education level) of agricultural educators in Alabama?

To better understand the personal characteristics of the respondents, personal and professional characteristics (N = 80) were collected from the participants (see Table 1). Of this group, 78 participants responded to the question of gender, with 44 (56.40%) identifying as male and 34 (43.60%) identifying as female; two participants chose not to respond to this item. The mean age for participants (N = 77) responding to this question was M = 39.30 years (SD = 10.83), with the distribution being nearly equal in all four age brackets (see Table 1). All 80 participants reported a varied teaching experience (M = 11.18, SD = 9.06). A disaggregated analysis showed that male participants (n = 44) had more years of teaching experience (M = 12.75, SD = 10.18) than female participants (n = 34; M = 7.57, SD = 4.35).

Table 1

Participant Characteristics by Gender, Age, and Years of Experience (N = 80)

Characteristic Type	Indicator	*N*	*f*	%	*M*	*SD*
[1]Gender		78		100		
	Male		44	56.40		
	Female		34	43.60		
[2]Age		77			39.30	10.83
	30 or younger		19			
	30 - 39		20			
	40 – 49		19			
	50 and over		19			
Experience		80			11.18	9.06
	<5 years		24			
	5 – 14 years		34			
	>15 years		21			
Experience by Gender		78				
	Male		44		12.75	10.18
	Female		34		7.57	4.35

Note: [1]Two participants did not respond to the question about their gender. [2]Three participants did not report their age. All gender percentages are based on the n = 78 participants who responded to the item.

Of the 79 participants who reported their highest earned degree (see Table 2), a majority held a master's degree (n = 38, 48.10%), followed by a bachelor's degree (n = 26, 32.90%), and a degree earned above a master's (n = 15, 19.00%).

Table 2
Highest Degree Earned (n = 79)

Highest Degree Earned	*f*	%
Master's	38	48.10
Bachelor's	26	32.90
Degree Earned Above Master's (Ph.D., etc.)	15	19.00

Research Question 2. Determine the current levels of awareness, perceived benefits, self-reported competencies, and perceived barriers regarding AI adoption among Alabama agricultural educators.

The second research question assessed educators' perceptions regarding AI adoption across four themes. To provide context, the awareness of the AI theme measured familiarity with AI tools, while the benefits of the AI theme assessed their belief that AI could enhance job performance. The competencies of AI use theme gauged participants' confidence in using AI for specific pedagogical tasks. In contrast, the barriers to the use of AI theme measured their concern about its pedagogical and ethical implications. Central tendencies for each theme are presented in Table 3.

Table 3
Instrument Theme, Central Tendency, and Vague Quantifier

Instrument Theme	*M*	*SD*	Quantifier
Awareness of AI	3.18	1.03	NADA*
Benefits of AI	3.34	1.04	NADA
Competencies of AI Usage	3.08	1.07	NADA
Barriers to the Use of AI	3.82	1.07	Agree

Note. *Neither Agree Nor Disagree.

Research Question 3: Do educators' perceptions of AI (awareness, benefits, competencies, barriers) change based on their teaching experience?

To address the third research question, analyses were conducted to determine if educators' perceptions of AI differed based on their personal and professional characteristics. Independent samples t-tests and one-way analysis of variance (ANOVAs) found no statistically significant differences in perceptions based on gender, age group, or highest level of education across any of the four instrument themes. Statistical significance for all tests was set a priori at $\alpha = 0.05$.

In contrast, educators' years of professional service were the only characteristic that significantly affected their perceptions of AI. This effect was consistent between all four themes, indicating a distinct experiential divide. As reported in Table 4, educators with five years or fewer of experience reported significantly higher awareness of AI, perceived benefits, and competence with AI than their more experienced peers.

A significant main effect was found for awareness of AI (*F*(2, 76) = 4.85, *p* = .01), where early-career educators reported higher awareness (*M* = 3.60) than their peers with 15 or more years of experience (*M* = 2.73). This difference represented a large effect size (ES_L = 0.87). Similarly, the barriers to AI theme found a significant main effect for the benefits of AI (*F*(2, 76) = 9.37, *p* < .01). A Tukey's HSD post hoc analysis revealed that early career educators had significantly higher perceptions of AI's benefits than other groups, a difference representing a large effect size (ES_L = 1.07).

Table 4

Comparison of AI Perceptions by Years of Teaching Experience

Instrument Theme	Experience Group	*M*	*F*	*P*	ES_L
Awareness of AI	< 5 years	3.60	4.85	0.01*	0.87
	5 - 14 years	3.23			
	> 15 Years	2.73			
Benefits of AI	< 5 years	3.98	9.37	<.01*	1.07
	5 - 14 years	2.91			
	> 15 Years	3.21			
Competencies of AI	< 5 years	3.53	4.37	.02*	0.84
	5 - 14 years	3.01			
	> 15 Years	2.69			
Barriers to AI	< 5 years	4.28	4.30	.02*	0.54
	5 - 14 years	3.74			
	> 15 Years	3.74			

Note. *p < 0.05 indicates statistical significance. ES_L = Lindner's non-standard effect size for the largest mean difference identified in post-hoc analysis.

Findings related to competencies of AI usage (*F*(2, 76) = 4.37, *p* = .02) identified that early career educators (*M* = 3.53) reported significantly higher competence than those with 15 or more years (*M* = 2.69) of service (ES_L = 0.84). Participant data analysis also revealed that a significant main effect was also found for the barriers to AI theme (*F*(2, 76) = 4.30, p = .02). Post-hoc analysis showed that educators with five years of service or less (*M* = 4.28) had significantly more positive perceptions about the potential to reduce barriers than educators with 15 or more years of service (*M* = 3.74), a difference representing a large effect size (ES_L = 0.54).

Conclusions, Discussion, and Recommendations

This exploratory study investigated the factors influencing the adoption of generative AI by agricultural educators in Alabama. The findings reveal a complex adoption environment characterized by two primary conclusions: the emergence of a distinct experiential divide based on years of professional service and the pervasive nature of pedagogical and ethical concerns among the participants.

The primary finding of this study is an experiential divide that predicts educators' perceptions of AI more significantly than the other investigated characteristics. Early-career educators (with ≤5 years of experience) reported substantially higher awareness, perceived benefits, and competence with AI than experienced educators (with≥15 years of experience). Confirmation of a long-standing theme in agricultural education research, which has consistently identified professional experience as a critical variable influencing the adoption of new technology and tools for instructional use. The divide observed in this study echoes the barriers related to training and educator anxiety that Kotrlik and Redmann (2009) identified, reinforcing their conclusion that professional experience is crucial to technology integration.

However, the second key finding introduces a deeper layer of apprehension centered on student misuse and AI's capacity to automate complex cognitive and creative tasks central to the learning process. This distinguishes AI from historical technological tools, such as the Internet or the calculator. While experience divided educators on the skills and optimism surrounding AI, a high level of pedagogical and ethical concern was a universal barrier. The identification of a universal ethical barrier that transcends technical skill, these results extend the work of earlier studies by King and Rollins (1995) and Williams et al. (2014). The rapid and ubiquitous diffusion of generative AI introduces a deeper layer of concern about its appropriate instructional use that extends beyond the operational competence of agricultural educators. This creates a fundamental disconnect between operational skills and ethical apprehension, a key investigative concern.

These findings hold significant implications for the theoretical frameworks that guided this study. The experiential divide aligns directly with Rogers' (1962) diffusion of innovation theory, where early-career educators function as innovators or early adopters. Their digital nativity and higher competence reduce the perceived complexity of AI, while their optimistic view of its benefits enhances its relative advantage. This finding may help explain their accelerated willingness to adopt AI technology as a contemporary component of their pedagogical preparation and internal constructs that frame their approach to the future of agricultural education instruction. In contrast, experienced educators more closely align with the late majority, perceiving AI as less compatible with their established pedagogical identities. This contrast suggests that experienced educators rely on established pedagogical frameworks, which allow them to perform their duties consistently and predictably.

From the perspective of Davis's (1985) technology acceptance model, the higher self-reported competence and perceived benefits among early-career educators directly translate to higher perceived ease of use and perceived usefulness. This critical insight, however, is that the universal ethical concern acts as a powerful external variable that negatively impacts these beliefs for all participants. This suggests that for ethically complex technologies like AI, user trust and pedagogical alignment are critical factors that can moderate or even override the core constructs of TAM, a potential nuance not fully explored in Davis's (1985) original model.

The pragmatic approach to interpreting these results suggests that the digital divide in education is evolving into a more complex pedagogical adoption gap. For experienced educators, the challenge transcends learning a new skill; it involves reconciling a disruptive technology with an established professional identity developed over many years of professional experience. A uniform approach to professional development is likely to be ineffective and could reinforce the cognitive dissonance that educators have experienced.

State education departments, university agricultural educators, and extension specialists should address this gap by developing differentiated training pathways tailored to the needs of diverse learners. These should include foundational support for experienced educators that focuses on building confidence and reducing cognitive demand. In contrast, programming for early-career educators should reinforce the ethical best practices of AI integration. Furthermore, implementing peer-mentorship programs, which leverage the expertise of technologically aware early-career educators to support their more experienced peers, should be considered. This potential for experiential collaboration could foster a collaborative adoption format; however, the potential implications of this recommendation warrant further investigation, as historically, formal mentoring programs have been received with mixed results. The nature of this mentorship should be informal and collaborative rather than a top-down mandate, which could help mitigate the historical issues with traditional mentoring frameworks.

The conclusions of this exploratory study should be interpreted with consideration for its potential limitations. The sample size (N = 80) and focus on a single state limit the generalizability of the findings. As such, this paper should be viewed as a foundational, empirically based study that established a baseline and a model for future inquiry into this critical new area of research, as intended by its design. Additionally, this study relies on self-reported data, which measures educators' perceptions of their competence rather than their objectively demonstrated skills. Furthermore, while this study found years of service to be a significant predictor of professional experience and the formation of a pedagogical identity, it is important to acknowledge the inherent correlation between experience and age. Future research should investigate these variables by examining alternatively certified educators who enter the profession later, with varying levels of prior technological exposure. Future studies addressing observational or performance-based metrics could further validate these findings.

These limitations directly inform the need for future investigations to build upon these nuanced findings. The rapid development of AI and the corresponding increase in public exposure, particularly among agricultural educators, suggest that the instrument used in this study has a finite timeframe of validity. Any subsequent quantitative studies would require the instrument to be amended, reflecting the perceptions and technological advancements of generative AI. A revised instrument, built upon the original, would need to test if participants' attitudes towards AI and their adoption or rejection have changed from the original data collection. Without modification, the potential for threats to validity should be considered credible, as the primary research questions may not adequately address the current technological and social landscape.

Future research should first include a qualitative study to explore the specific reasons for the experiential divide and the nature of the ethical concerns shared by the participants. A replication study in other states and career and technical education disciplines is also necessary to determine if the pedagogical adoption gap is a broader, more representative trend. Finally, a longitudinal study that tracks educators over several years would provide valuable insights into how their perceptions and adoption behaviors evolve as AI technology becomes more advanced and integrated into the educational frameworks.

New AI models will undoubtedly become immensely more powerful, nuanced, and insightful, for example, Gemini 3.0 (Google, 2025), offering educators opportunities that have not yet been considered. As these tools evolve, so too will educators' perceived usefulness (Davis, 1989) and their assessment of AI's relative advantage (Rogers, 1962). This rapid evolution must be a continuous endeavor, reevaluating these theoretical constructs as the technology itself evolves.

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Author Contribution Statement: **James Lindner** — methodology, reviewing, editing; **Christopher Clemon** — conceptualization, methodology, writing original draft, data analysis, reviewing and editing; **Jason McKibben** — data analysis, writing original draft, reviewing and editing.

References

Afzal, A., Khan, S., Daud, S., Ahmad, Z., & Butt, A. (2023). Addressing the digital divide: Access and use of technology in education. *Journal of Social Sciences Review*, *3*(2), 883–895. https://doi.org/10.54183/jssr.v3i2.326

Bartlett, J. E., II, Kotrlik, J. W., & Higgins, C. C. (2001). Organizational research: Determining appropriate sample size in survey research. *Information Technology, Learning, and Performance, 19*(1). 43. https://www.opalco.com/wp-content/uploads/2014/10/Reading-Sample-Size1.pdf

Card, S. K., Moran, T. P., & Newell, A. (1983). *The Psychology of Human-Computer Interaction*. Lawrence Erlbaum Associates.

Croom, D. B., Yopp, A. M., Edgar, D., Roberts, R., Jagger, C., Clemons, C., McKibbon, J., McCubbins, O. P., & Wagner, J. (2023). Technical professional development needs of agricultural education teachers in the southeastern United States by career pathway. *Journal of Southern Agricultural Education Research*, *73*, 1–15. http://jsaer.org/2023/04/10/technical-professional-development-needs-of-agricultural-education-teachers-in-the-southeastern-united-states-by-career-pathway/

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* [Doctoral dissertation, Massachusetts Institute of Technology].

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed mode surveys: The tailored design method (4th ed.).* John Wiley & Sons.

Emerson, C., Myers, B. E., Bunch, J. C., & Dossett, J. (2024). Determining collaboration between University of Florida Institute of Food and Agricultural Sciences Extension agents and secondary school-based agricultural educators. *Advancements in Agricultural Development*, *5*(4), 1–13. https://doi.org/10.37433/aad.v5i4.469

Field, A. (2024). *Discovering statistics using IBM SPSS statistics, North American Edition* (6th ed.). Sage.

Fuerst, W. L., & Cheney, P. H. (1982). Concepts, theory, and techniques: Factors affecting the perceived utilization of computer-based decision support systems in the oil industry. *Decision Sciences*, *13*(4), 554–569. https://doi.org/10.1111/j.1540-5915.1982.tb01182.x

Google. (2025, October 15). *Gemini API release notes.* Google for AI Developers. https://ai.google.dev/gemini-api/docs/changelog

Grace, K., Stewart, H., Sandkühler, J. F., Thomas, S., Weinstein-Raun, B., & Brauner, J. (2024). *Thousands of AI authors on the future of AI*. arXiv. https://doi.org/10.48550/arXiv.2401.02843

Hancock, G., Hancock, C., & McKibben, J. (2024). The teaching techniques of Alabama's traditionally and alternatively certified school-based agricultural education instructors. *Journal of Agricultural Education*, *65*(3), 18–34. https://doi.org/10.5032/jae.v65i3.166

Harder, A. M. (2009). *Characteristics and barriers impacting the diffusion of e-extension among Texas Cooperative Extension County Extension agents* [Doctoral dissertation, Texas A&M University]. https://hdl.handle.net/1969.1/ETD-TAMU-1408

Hill, J., & Reimer, T. (2024). Technology as a tool to address educational inequities: Practices implemented during the COVID-19 pandemic that have been sustained. *Education and Information Technologies*, *29*(9), 10879–10898. https://doi.org/10.1007/s10639-023-12236-z

Hoffman, R., & Beato, G. (2025). *Superagency: What could possibly go right with our AI future?* Authors Equity.

Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Information,* (*77*), 101925. https://doi.org/10.1016/j.tele.2022.101925

King, R. N., & Rollins, T. (1995). Factors influencing the adopters and nonadopters. *Journal of Agricultural Education*, *36*(4), 39–48. https://doi.org/10.5032/jae.1995.04039

Kline, P. (1999). *The handbook of psychological testing* (2nd ed.). Routledge.

Kotrlik, J. W., & Redmann, D. H. (2009). A trend study: Technology adoption in the teaching-learning process by secondary agriscience teachers-2002 and 2007. *Journal of Agricultural Education*, *50*(2), 62–74. https://doi.org/10.5032/jae.2009.02062

Lai, P. P. (2013, May). Efficient and effective information finding on small screen devices. In *Proceedings of the 10th International Cross-Disciplinary Conference on Web Accessibility* (pp. 1–10). https://doi.org/10.1145/2461121.2461127

Liehner, G. L., Biermann, H., Hick, A., Brauner, P., & Ziefle, M. (2023). Perceptions, attitudes and trust towards artificial intelligence—An assessment of the public opinion. *Artificial Intelligence and Social Computing*, *72*(72), 32–41. https://doi.org/10.54941/ahfe1003271

Lindner, J. R. (2002). Handling of nonresponse error in the Journal of International Agricultural and Extension Education. *Journal of International Agricultural and Extension Education*, *9*(3), 55–60. https://www.researchgate.net/profile/Ismet-Boz-3/publication/271247374_Does_Early_Adoption_Affect_Farmers'_Use_of_the_Extension_Service/links/5b44ae1da6fdcc661914822c/Does-Early-Adoption-Affect-Farmers-Use-of-the-Extension-Service.pdf#page=57

Lindner, J. R., & Lindner, N. (2024). Interpreting Likert-type, summated, unidimensional, and attitudinal scales: I neither agree nor disagree, Likert or not. *Advancements in Agricultural Development*, *5*(2), 152–163. https://doi.org/10.37433/aad.v5i2.351

Malik, A. (2024). The future of AI: Predicting technological advancements and their societal impact. *Frontiers in Artificial Intelligence Research, 1*(3), 467–493. https://sprcopen.org/index.php/FAIR/article/view/49/47

McKibben, J. D., Clemons, C. A., & Blythe, J. M. (2025). Survey response rates by requestor's characteristics. *Advancements in Agricultural Development, 6*(1), 43–54. https://doi.org/10.37433/aad.v6i1.525

McKibben, J. D., Holler, K., Clemons, C., & Lindner, J. (2023). Locus of control and pedagogy in skill-based agricultural mechanics. *NACTA Journal*, *67*, 257–261. https://doi.org/10.56103/nactaj.v67i1.88

Murphrey, T. P., & Dooley, K. E. (2000). Perceived strengths, weaknesses, opportunities, and threats impacting the diffusion of distance education technologies in a college of agriculture and life science. *Journal of Agricultural Education*, *41*(4), 39–50. https://doi.org/10.5032/jae.2000.04039

Murphrey, T. P., Miller, K. A., & Roberts, T. G. (2009). Agricultural science and technology teachers' perceptions of iPod and MP3 technology integration into curricular and cocurricular Activities. *Journal of Agricultural Education*, *50*(4), 110–119. https://doi.org/10.5032/jae.2009.04110

Nambisan, S., & Wang, Y. M. (2000). Web technology adoption and knowledge barriers. *Journal of Organizational Computing and Electronic Commerce, 10*(2), 129–147. https://doi.org/10.1207/S15327744JOCE1002_4

Pilisuk, M., Parks, S. H., & Hawkes, G. (1987). Public perception of technological risk. *The Social Science Journal*, *24*(4), 403–413. https://doi.org/10.1016/0362-3319(87)90056-5

Rogers, E. M. (1962). *Diffusion of innovations*. Free Press.

Ross, S. M., Morrison, G. R., & Lowther, D. L. (2010). Educational technology research past and present: Balancing rigor and relevance to impact school learning. *Contemporary Educational Technology*, *1*(1), 17–35. https://dergipark.org.tr/en/pub/cet/issue/25719/271396

Selwyn, N. (2021). *Education and technology: Key issues and debates.* Bloomsbury Publishing.

Sevnarayan, K., & Potter, M. A. (2024). Generative artificial intelligence in distance education: Transformations, challenges, and impact on academic integrity and student voice. *Journal of Applied Learning and Teaching*, *7*(1), 104–114. https://doi.org/10.37074/jalt.2024.7.1.41

Smith, H. E., Stair, K. S., Blackburn, J. J., & Easley, M. (2018). Is there an app for that? Describing smartphone availability and educational technology adoption level of Louisiana school-based agricultural educators. *Journal of Agricultural Education, 59*(1), 238–254. https://doi.org/10.5032/jae.2018.01238

Tan, M., & Teo, T. S. H. (1998). Factors influencing the adoption of the Internet. *International Journal of Electronic Commerce, 2*(3), 5–18. https://doi.org/10.1080/10864415.1998.11518312

Vaske, J. J., Beaman, J., & Sponarski, C. (2017). Rethinking internal consistency in Cronbach's alpha. *Leisure Sciences, 39*(2), 163–173. https://doi.org/10.1080/01490400.2015.1127189

Verčič, A. T., Verčič, D., Čož, S., & Špoljarić, A. (2024). A systematic review of digital internal communication. *Public Relations Review*, *50*(1), 102400. https://doi.org/10.1016/j.pubrev.2023.102400

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, *28*(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088

Williams, M. R., Warner, W. J., Flowers, J. L., & Croom, D. B. (2014). Teaching with technology: North Carolina agriculture teachers' knowledge acquisition, attitudes, and identified barriers. *Journal of Agricultural Education*, *55*(5), 1–15. https://doi.org/10.5032/jae.2014.05001

Willis, J., Thompson, A., & Sadera, W. (1999). Research on technology and teacher education: Current status and future directions. *Educational Technology Research and Development*, *47*(4), 29–45. https://doi.org/10.1007/BF02299596

Zhu, Y., Huang, Z., Dou, Z., & Wen, J. R. (2025). One token can help! Learning scalable and pluggable virtual tokens for retrieval-augmented large language models. In *Proceedings of the AAAI Conference on Artificial Intelligence, 39*(24), 26166–26174. https://doi.org/10.1609/aaai.v39i24.34813