Examining the Impact of Integrating AI in a Public Speaking Course on Students' Confidence in Public Speaking and Perceptions of AI

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Abstract

Artificial intelligence (AI) is a rapidly developing technology, particularly in the workforce and educational settings. This study sought to examine the impact of integrating AI tools into an oral communications course within a college of agriculture. We utilized a quasi-experimental design to divide six course sections into a treatment (n = 40) and a control group (n = 40) for comparison. The treatment group engaged in learning activities that involved the use of generative AI and AI tools for feedback on public speaking assignments. We measured participants' confidence in public speaking and perceptions of AI in a pretest-posttest design. Findings indicated that students' confidence in public speaking was higher after the course in both groups, with slightly higher confidence in the treatment group. Additionally, students in the control group demonstrated an improvement in AI efficacy not seen in the control group. Trust in AI and attitudes toward AI remained relatively unchanged; however, female students in the treatment group were more likely to have lower attitudes toward and less trust in AI. Our findings indicate that the integration of AI tools was impactful and has potential implications for the future preparation of students as they prepare to enter the agricultural workforce.

Introduction

The emergence of Artificial Intelligence (AI) in the teaching and learning environment has caused considerable disruption and debate in higher education (Bozkurt et al., 2023). As AI becomes more mainstream, teachers and students are learning how to navigate the social, ethical, and practical implications of using AI in academia. While some educators forewarn that students' use of AI will loosen academic integrity (Chen et al., 2024) and hamper the development of critical thinking (Özer et al., 2025), others see merit in the appropriate use of AI as a tool to support and empower student learning (Almusaed et al., 2023; Nagaraj et al., 2023; Walter, 2024). In fact, many higher education institutions have sought to embrace AI and have developed strategies to integrate it into their educational landscape (Jin et al., 2025). This endeavor has largely been influenced by the rapid adoption of AI technologies in the workforce (Leal et al., 2025). A report by the International Monetary Fund illustrated that 40 percent of global employment is exposed to AI, rising to 60 percent in advanced economies (Georgieva, 2024). Therefore, due to the current and predicted prevalence of AI in the workforce, educators should familiarize students with the capabilities of AI and develop their abilities to effectively use AI tools, thereby preparing them for the job market (Chiu, 2024; Hashmi & Bal, 2024).

Approaches to integrating AI in teaching and learning vary widely. Some AI tools are designed specifically for education and can optimize support for individual students. For example, many AI tools have been developed to serve as virtual tutors and provide real-time student feedback to improve students' writing performance (Colclasure et al., 2025; Merin-

Campos, 2025; Shum et al., 2017). Other tools have been developed to be teacher-facing and can be used to identify discrepancies and learning difficulties at early stages of student learning (Babu et al., 2024). Furthermore, AI platforms that have emerged in everyday life, such as generative AI chatbots (ChatGPT, Gemini, Dali, etc.), can have many applications in education (Campbell & Cox, 2024). Prior scholarship of teaching and learning in the agricultural sciences has explored the impact of ChatGPT as a teaching tool in biology education (Faldi et al., 2023), veterinary education (Martín-Alguacil et al., 2025), and teacher education (Kwack & Im, 2023).

In addition to the emerging industry demand for students to be proficient at using AI technologies (Leal et al., 2025), employers have long sought graduates with strong communication skills (Carnevale & Smith, 2013; Wahab et al., 2024). Oral communication competence has been found to lead to an increase in an individual's creditability, success in the workplace, and positive reputation (Crosling & Ward, 2002). Yet, public speaking has been one of the leading fears among individuals in the United States (Furmark, 2002) and has been found to be a significant cause of anxiety to college students (Grieve et al., 2021). Each year, millions of college students take communication courses to improve their communication skills. In fact, most colleges require a public speaking or oral communication course for undergraduate degree completion. Therefore, the teaching methods and curricular design of such communication courses should be consistently evaluated to best meet learners' needs and empower students to become effective communicators. An opportunity to improve teaching and learning in oral communications could be through the integration of AI tools in these courses. As such, in this study, we explored the impact of integrating AI tools in an undergraduate oral communications course in a college of agriculture.

Course Context

The course that served as the context for this study was *Effective Oral Communications*, an undergraduate course in the Herbert College of Agriculture at the University of Tennessee. Each fall and spring semester, approximately 100 students enroll in this course. Most students have majors within the Herbert College of Agriculture and take the course to earn the required education credits for public speaking/oral communication for degree completion. There are typically six sections of the course offered each semester. Each course section covers the same content and aligns to a similar timeline, but sections differ in meeting times. The course is taught in these sections to provide small class sizes (e.g., 18 students), which encourages more student interaction and allows time for each student to deliver several graded speeches to their peers throughout the semester.

The 16-week course is broken down into five learning modules: (a) telling your story, (b) demonstrating your skills, (c) communicating to inform, (d) communicating to persuade, and (e) communicating in groups. Throughout the course, students are taught strategies for creating and delivering impactful speeches, such as speech development and organization, verbal and non-verbal delivery, audience engagement, and visual aid design. Students create speaking outlines and deliver speeches that serve as summative assessments for each module. These include personal narrative, informative, demonstrative, persuasive, and team-based speeches. The contexts of speech topics are required to be on agriculture, food, natural resources, and environmental sciences, broadly defined. Each speech is graded by the instructor, and peers provide each other feedback on each speech.

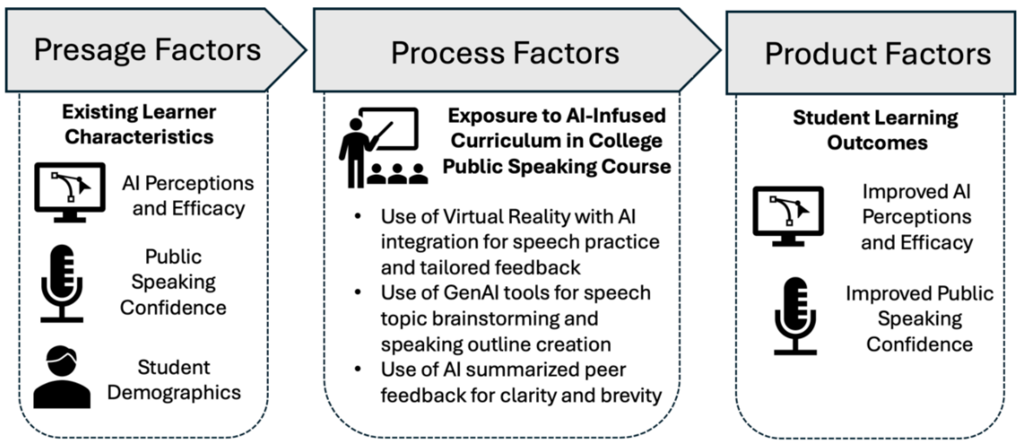
In the Fall 2025 semester, we obtained a university-sponsored grant to integrate GenAI into the curriculum of *Effective Oral Communications* with the goal of improving student learning outcomes and AI literacy. We incorporated GenAI into three sections of the course as a required course component. A three-pronged approach was used to achieve this endeavor. First, we implemented a lesson early in the semester on how to use appropriate prompting within GenAI tools (i.e., ChatGPT, Gemini, UT Verse) to brainstorm speech topics, speech components (e.g., interest approaches, arguments, transitions), and speaking outlines. We required students to use these tools and submit GenAI chat logs for their speeches throughout the semester. Secondly, we used the Ovation platform, an app for virtual reality headsets, to practice oral communication. The app allows students to be placed in a realistic, 360-degree virtual environment (e.g., classroom, conference room, etc.) with audience avatars. In the app, students practice delivering their speeches, receive tailored, AI-generated questions from avatars in the audience, and receive feedback on their speech performance (e.g., content, clarity, persuasiveness, speed, presence of filler words, etc.). We organized breakout rooms during course meeting times and required students to use Ovation for speech practice. Reports on students' practice sessions were generated from Ovation and could be seen by the instructor to examine student progress. Lastly, GenAI was used to summarize each student's peer feedback for each speech. During student speeches, peers filled out a brief open-ended form that requested comments on their peers' speaking performance, including strategies that were effective and areas for future growth. These comments were then summarized for each student using AI, and a single paragraph summarizing audience comments was shared as feedback.

By implementing these three AI-based components in the course, we hoped to improve students' speaking confidence and increase their trust, attitudes, and efficacy regarding the effective and ethical use of AI in teaching and learning. The purpose of this study was to examine the impact of our AI integration in *Effective Oral Communications* using a quasi-experimental, pretest-posttest control group research design.

Conceptual Framework

We used the Presage-Process-Product (3P) Model by Biggs (2003) to guide the development of our study. The 3P Model illustrates the connection between presage, process, and product factors in teaching and learning. Presage factors are described as inputs in the learning environment. One of the most significant presage factors is preexisting learner characteristics. These can include students' demographic characteristics (e.g., age, year in school, gender, race, and ethnicity) and prior knowledge, perceptions, and skills. Process factors are described as the structures and systems teachers use to facilitate teaching and learning, such as curricular design, instructional strategies, and delivery methods (Han, 2014). Lastly, product factors are students' learning outcomes from exposure to the learning experience (Biggs, 2003). Although knowledge is often the most frequently measured learning outcome, changes in students' perceptions and skills are also foundational learning outcomes. The presage, process, and product factors of interest in the present study are illustrated in our adapted 3P model below.

Figure 1. *The Presage-Process-Product (3P) Model adapted to examine the impact of students' exposure to an AI-infused curriculum in a college public speaking course.*



To further conceptualize our study, we explored existing AI and communication research that examined the presage, process, and product factors under our investigation.

AI Perceptions

Students' perceptions toward AI have been shown to be influenced by gender. For example, in a study examining 380 students in higher education, Cachero et al. (2025) found significant gender disparities in AI perceptions, such that females exhibited significantly lower levels of perceived knowledge and exposure to AI. Furthermore, the researchers found that females held less favorable attitudes toward AI and held lower positive expectations toward AI technology use. Similarly, in a survey involving nearly 6,000 Swedish university students on use and perceptions of ChatGPT in education, Stöhr et al. (2024) found that female students reported lower usage of the platform and held less favorable attitudes toward AI Chatbots. Additional findings indicated that students' familiarity and perceptions toward the technology varied by major, where students majoring in engineering were more engaged with and held more favorable perceptions. Based on their study, Stöhr concluded that students' background characteristics (i.e., gender, year in school, and field of study) are determinants of technology adoption; therefore, they should be considered when implementing AI in higher education.

Public Speaking

Prior research illustrates that public speaking is a major source of anxiety among college students (Grieve et al., 2021). In fact, in a large survey of over 1,000 undergraduate students, Marinho et al. (2017) found that nearly 64% of students reported a fear of public speaking, with female students reporting more fear compared to males. However, the authors also identified that nearly 90% of students desired a public communication course within their undergraduate degree to improve public speaking. Improving students' self-efficacy in communication is an important outcome of public speaking courses, as a correlation between self-confidence and achievement has been well established (Bandura, 1977). Novel educational technologies have been successfully integrated into public speaking courses to accomplish this task. For example, Sandoval et al. (2025) measured the effectiveness of a Virtual Reality platform on students' self-perceptions and performance. The authors found that the VR platform improved students' public speaking confidence and presentation skills. In a small study employing a quasi-experimental design using English language learners, Huang et al. (2026) tested the impact of an AI-integrated VR training application on students' public speaking anxiety. Findings indicated that students using the VR technology had reduced anxiety levels and improved self-efficacy.

Purpose and Objectives

The purpose of this study was to examine the impact of AI tool integration in an introductory oral communications course in the Herbert College of Agriculture at the University of Tennessee. Three primary objectives guided our investigation:

1. Determine students' confidence in public speaking and perceptions of AI before and after exposure to the treatment or the control.
2. Determine if the treatment can account for changes to students' confidence in public speaking and perceptions of AI when compared to the control.
3. Examine relationships between student characteristics and students' confidence in public speaking and perceptions of AI after being exposed to the treatment or the control.

Methods

Study Design

We used a pretest-posttest control group design (Cook & Wong, 2008) for this study. In our situation, the most ecologically valid setting for us to conduct this research was the use of intact classes (Plonksy, 2017), thus limiting us to quasi-experimental research. In the fall semester of 2025, six intact sections of *Effective Oral Communications* in the Herbert College of Agriculture served as the courses of our study. Three classes were assigned to the treatment group, which received strategic AI integration, and three to the control group, which received normal classroom instruction. Although students were not randomly assigned to the treatment or control group, they were not made aware that there would be differences in how the classes were taught. Therefore, students' self-selection into treatment or control groups was not a concern.

A survey was designed and administered as a pretest and posttest for this study. Prior to the administration of the survey, a panel of experts consisting of three faculty in agricultural education and communication reviewed it for content validity (Kerlinger, 1986). The pretest was administered during the second week of classes after the add/drop date, and the posttest was administered on the last full week, week 14, before the final exam period. Paper copies were used for both the pretest and posttest, and a faculty member external to the course administered the surveys while the faculty instructor left the room. To provide an additional layer of student protection, the external faculty member distributed and collected informed consent forms and retained the surveys and forms until final grades were entered. This study was approved by the University of Tennessee IRB (#25-09226-XP).

Instrumentation

The crux of the survey included scales to measure students' public speaking confidence and perceptions of AI. Student self-efficacy or confidence of communication ability was measured by a modification of the Personal Report of Confidence as a Speaker (PRCS) scale (Paul, 1966), which has previously been reported in a variety of studies (Kroczek & Mühlberger, 2023; Lintner & Belovecová, 2024; Monteiro et al., 2023). Five items on the scale were positively framed, including "I feel comfortable and relaxed while speaking before an audience" and "I have no fear of facing an audience". Five items were negatively framed and included items such as "My thoughts become confused and jumbled when I speak before an audience" and "When I prepare for a speech, I am in a constant state of anxiety". For each item, respondents were asked to indicate their level of agreement on a scale from *1 = strongly disagree* to *5 = strongly agree*. Items that were negatively framed were reverse-coded. Post hoc internal scale reliability was calculated, and Cronbach's alpha was found to be .837, which is above the .70 threshold for internal scale reliability (Field, 2013).

Students' perceptions toward AI in teaching and learning were measured through the constructs of AI Trust, AI Efficacy, and AI Attitude. Each construct was measured through a scale used in prior literature. A 5-item scale to measure AI Trust was borrowed from Yan et al. (2025). Each item was negatively framed and used a 5-point, Likert-type scale from *1 = strongly disagree* to *5 = strongly agree*. Example items included "I believe the content generated by AI in learning may lack accuracy and reliability", "I believe using AI in learning may lead to plagiarism and academic fraud", and "I believe using AI in learning may have data privacy and security issues". Items were later reverse-coded so that a lower scale mean would indicate lower trust in AI. A similar scale, also borrowed from Yan et al. (2025), was used to measure students' AI Efficacy. The scale included four items and used a 5-point Likert-type scale from *1 = strongly disagree* to *5 = strongly agree*. Example items included "I believe it is easy to accomplish what I want to do with AI", "I believe using AI in learning is simple and clear", and "I believe learning how to use AI in learning is simple and clear." Post hoc internal scale reliability was found for both AI Trust ($\alpha = .780$) and AI Efficacy ($\alpha = .897$). AI Attitude was measured through an 8-item, 5-point, bipolar semantic differential scale. The scale included eight sets of adjective pairs (e.g., Good/Bad; Beneficial/Not Beneficial, etc.) where students were asked to select the point between each adjective pair that represented their perspective on AI in teaching and learning. Several adjective pairs were reverse-framed and recoded to improve scale reliability. The same scale has been used in prior studies to measure attitudes toward a topic (Ruth et al., 2019). Post hoc internal scale reliability was found ($\alpha = .889$).

The same scales used to measure Public Speaking Confidence, AI Trust, AI Efficacy, and AI Attitude were used for both the pretest and posttest. Additionally, respondents were asked to provide four unique digits (e.g., the last four digits of a telephone number) to match each respondent's pretest and posttest while maintaining anonymity. On the posttest, several questions were asked to collect student demographics, including gender (male, female, non-binary), year in school (freshman, sophomore, junior, senior), and the home of their academic major (within the College of Agriculture, outside the College of Agriculture).

Data Analysis

Each paper survey was entered into a replicated digital survey on Qualtrics. Data were then exported from Qualtrics to SPSS for data analysis. Each student's pretest and posttest data were matched, and data from unmatched surveys were removed. Descriptive statistics in the form of means, standard deviations, and boxplots were used to address Objective 1. True limits were used to interpret grand means for Likert-type scales (Lindner & Linder, 2024). Paired samples t-tests were used for Objective 2. At the 0.05 alpha level, these tests yield a statistical power of .92 for a medium effect (*Cohen's d* = 0.50; Cohen, 1988). Additionally, variables that demonstrated significant change from pretest to posttest in the treatment group were further analyzed and compared with the control group using one-way ANCOVAs. Pretest scores for each construct were used as a covariate to adjust posttest means for that construct to determine the effect of the treatment when accounting for the control. Assumptions for all statistical procedures were tested and met. Lastly, point-biserial correlations were used to address Objective 3.

Limitations

Prior to presenting our findings, we must address the limitations of this study. First, this study was quasi-experimental in nature; therefore, we acknowledge that threats to internal validity, such as selection bias, are greater than with an experimental design. Additionally, this study focused on confidence in public speaking, perceptions of AI, and student characteristics as variables, which only partially address the factors of the 3P model. Additional factors, including instructor characteristics, learning environment, and other potentially influential factors related to variations between the treatment and control groups, were not explored.

Results

In the fall 2025 semester, 101 students were enrolled across six sections of the public speaking course. Three sections of the course, comprising 52 students, served as the treatment group for AI integration. The remaining three sections, with 49 students enrolled, were taught in a traditional format and served as the control group for this study. All students enrolled across the six sections were invited to participate in this research study. A total of 41 students in the treatment agreed to participate and completed surveys, indicating a 77% response rate. A total of 45 students in the control group agreed to participate, representing a 92% response rate. Pretest and posttests were matched by unique identifiers, and only data from students completing both the pretest and posttest surveys were used. Matched pairs, which comprised the data for this study, were found for a total of 80 students (40 students in the treatment group; 40 students in the control group), yielding a usable response rate of 79%. There was an even distribution of male and female students, and most students had a major within the College of Agriculture. Sophomores represented the largest class standing of the participants. Characteristics of the students completing our study are shown in Table 1.

Table 1

Characteristics of Students Completing the Study

Student Characteristic	Treatment (n = 40)		Control (n = 40)		Total (n = 80)	
	f	%	*f*	%	*f*	%
Gender						
Male	20	50.0	20	50.0	40	50.0
Female	20	50.0	20	50.0	40	50.0
Year in School						
Freshman	7	17.5	5	12.5	12	15.0
Sophomore	15	37.5	22	55.0	37	46.3
Junior	10	25.0	8	20.0	18	22.5
Senior	8	20.0	5	12.5	13	16.3
Major						
Inside College of Agriculture	33	82.5	32	80.0	65	81.3
Outside College of Agriculture	7	17.5	8	20.0	15	18.8

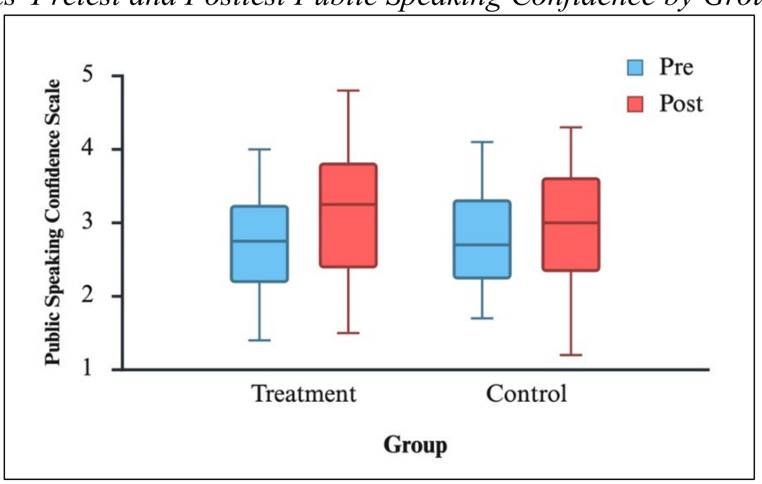
Objective 1: Determine Students' Confidence in Public Speaking and Perceptions of AI Before and After Exposure to the Treatment or the Control.

Public Speaking Confidence

Public speaking confidence was measured using a 10-item, 5-point, Likert-type scale. Students in the treatment group reported a mean confidence of 2.77 (SD = 0.60) on the pretest, which can be interpreted as neither agreeing nor disagreeing that they were confident in public speaking. Students reported having higher confidence in public speaking (M = 3.12; SD = 0.74) on the posttest. Students in the control group reported a mean initial confidence of 2.76 (SD = 0.70), which can also be interpreted as neither agreeing nor disagreeing that they were confident in public speaking. After the course, an increase in students' confidence in public speaking was also noted in the control group (M = 2.91; SD = 0.80). Boxplots of pretest and posttest public speaking confidence scores by treatment and control groups are shown in Figure 2.

Figure 2

Boxplots of Students' Pretest and Posttest Public Speaking Confidence by Group



Perceptions of AI

Students' perceptions of AI were observed through three constructs in the context of teaching and learning: (a) AI Trust, (b) AI Efficacy, and (c) AI Attitude.

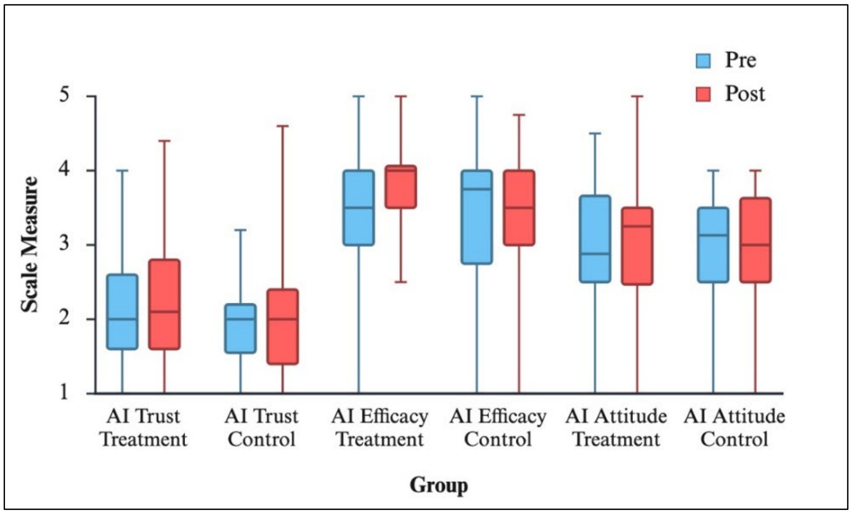
AI Trust. Students' trust in AI in the context of teaching and learning was assessed through a 5-item, 5-point, Likert-type scale. The measure of the scale was reverse-coded so that a higher score indicated greater trust in AI. In the pretest, students in the treatment group reported a mean score of 2.09 (SD = 0.71), which can be interpreted as disagreeing that they trusted AI. At the conclusion of the course, students in the treatment reported slightly more trust in AI, yet the level of trust remained low (M = 2.20; SD = 0.89). Students in the control group had an initial mean score of 1.94 (SD = 0.58), which can also be interpreted as disagreeing that they trusted AI. Students reported a marginal decrease for AI Trust at the conclusion of the course (M = 1.92; SD = 0.70).

AI Efficacy. Students' AI Efficacy within the context of teaching and learning was measured through a 4-item, 5-point Likert-type scale. Higher measures on the scale indicate higher self-efficacy in using AI to support learning. Students in the treatment group reported a mean AI Efficacy of 3.39 (SD = 0.82) on the pretest, which can be interpreted as neither agreeing nor disagreeing that they can effectively use AI to support learning. A mean increase in students' AI Efficacy was observed at the conclusion of the course (M = 3.89; SD = 0.65), indicating that they agreed they could effectively use AI tools to support learning. Students in the control group had a mean AI Efficacy score of 3.38 (SD = 0.93) on the pretest, and no change was observed in their posttest mean AI Efficacy score (M = 3.38; SD = 0.70).

AI Attitude. Students' AI Attitudes were measured using an 8-item, 5-point bipolar semantic differential scale, with higher scores indicating a more positive attitude toward AI. Students in the treatment group reported a scale mean of 2.99 (SD = 0.76) in the pretest, which can be interpreted as neutral. A very slight increase in students' AI Attitudes was found at the conclusion of the course (M = 3.05; SD = 0.83). Students in the control group reported an initial mean score of 2.94 (SD = 0.72) and a posttest mean of 2.96 (SD = 0.72), both representing a neutral AI Attitude, on average. Boxplots of students' pretest and posttest scores for AI Trust, AI Efficacy, and AI Attitude are shown in Figure 3.

Figure 3

Boxplots of Students' Pretest and Posttest Measures for Perceptions of AI by Group



Objective 2: Determine if the Treatment can account for Changes to Students' Confidence in Public Speaking and Perceptions of AI.

Paired-samples t-tests were used to determine if significant changes in students' confidence in public speaking and perceptions of AI existed between the start and conclusion of the treatment and control sections of the course. In the treatment group, no significant changes were observed between students' pretest and posttest scores for AI Attitude or AI Trust. However, a positive and significant change was observed between students' pretest (M = 2.77; SD = 0.60) and posttest scores (M = 3.12; SD = 0.74) for confidence in public speaking, with a medium effect size (*Cohen's d* = .46; Cohen, 1988). Additionally, a positive and significant change was also observed in the treatment group between students' pretest (M = 3.39; SD = 0.82) and posttest (M = 3.89; SD = 0.65) scores for AI Efficacy, with a large effect size observed (*Cohen's d* = .78; Cohen, 1988). For the control group, paired-samples t-tests indicated a significant difference between students' pretest (M = 2.76; SD = 0.70) and posttest scores (M = 2.90; SD = 0.80) for confidence in public speaking. A medium effect size was found (*Cohen's d* = .47; Cohen, 1998). No significant changes were observed in the control group for students' AI Trust, AI Attitude, or AI Efficacy. Paired-samples t-tests for the treatment and control groups are shown in Table 2.

Table 2

Pre- and Posttests Comparisons for Variables of Interest within Treatment and Control Groups

Construct	Treatment			Control		
	df	*t*	*p*	*df*	*t*	*p*
Confidence in Public Speaking	39	4.926	<.001	39	2.157	.037
AI Attitude	39	0.680	.501	39	.293	.771
AI Trust	39	1.065	.293	39	.254	.800
AI Efficacy	39	4.052	<.001	39	0.00	1.00

To further determine if students' increase in public speaking confidence and efficacy in using AI can be attributed to the effect of the treatment, one-way ANCOVAs were used. In doing so, pre-test means were used as covariates to adjust posttest means for students' confidence in public speaking and efficacy in using AI, and treatment and control groups were compared. As could be expected, an increase in students' confidence in public speaking was observed for both the treatment and control sections. However, when controlling for pretest scores, findings indicated that students in the treatment gained significantly more confidence in public speaking compared to students in the control (F [1, 78] = 4.10, p = .046). Post-hoc analysis indicated an adjusted mean difference of 0.21 between posttest means for the treatment group ($M = 3.12$) and control group ($M = 2.91$). However, this difference is minor, and a small effect size was observed ($\eta^2_p = .051$).

A one-way ANCOVA was conducted to determine if a statistically significant difference existed between the treatment and control on students' posttest AI Efficacy while controlling for pretest scores. Findings show that the treatment had a significant effect on students' posttest AI Efficacy, after controlling for pretest scores (F [1, 78] = 13.65, p < .001). Follow-up analysis was used to compare adjusted posttest means. An adjusted posttest mean difference of 0.51 was found between the treatment ($M = 3.89$) and control ($M = 3.38$), and a large effect size from the treatment was observed ($\eta^2_p = .151$).

Objective 3: Examine Relationships between Student Characteristics and Students' Confidence in Public Speaking and Perceptions of AI After Being Exposed to the Treatment or the Control

We analyzed point-biserial correlations between student characteristics and posttest measures for the variables of interest in our study. Separate correlations were run for the students in the treatment and the control. In the control, no significant associations were found between student characteristics and public speaking confidence, AI Attitude, AI Efficacy, and AI Trust. Similarly, in the treatment group, no significant associations were found between year in school and post-test variables, nor between major and post-test variables. However, in the treatment group, a significant, moderate association was found (Davis, 1971) between gender and AI attitude, such that males were found to have more positive AI attitudes ($r = .405$, $p < .01$). Additionally, a significant, moderate association (Davis, 1971) was observed between gender and AI Trust, such that males were found to have higher AI Trust compared to females in the treatment ($r = .334$, $p < .05$). No significant associations were found between gender and public speaking confidence nor AI Efficacy.

Table 3

Point-Biserial Correlations Between Student Characteristics and Posttest Variables in the Treatment and Control Groups

Student Characteristic	Public Speaking Confidence	AI Attitude	AI Efficacy	AI Trust
Treatment				
Gender	.223	$.405^{**}$	.205	$.334^{*}$
Year in School	.048	-.002	.032	.040
Major	-.220	-.022	.078	-.017
Control				
Gender	.298	.184	.172	.122

Student Characteristic	Public Speaking Confidence	AI Attitude	AI Efficacy	AI Trust
Year in School	-.228	-.085	.178	-.115
Major	-.062	.247	-.131	.155

Note. * Correlation is significant at the 0.05 level; ** correlation is significant at the 0.01 level

Discussion, Conclusion, and Implications

Through this study, we sought to determine the impact of integrating AI tools into an oral communications course by examining students' confidence in public speaking, attitudes toward AI, efficacy in using AI, and trust in AI, using a quasi-experimental pretest-posttest design. Our findings indicated that all participants in both the treatment and control groups increased their public speaking confidence over the semester, consistent with the expected course outcome, regardless of AI integration. However, students in the treatment group demonstrated minor improvements in public speaking confidence compared to the control group, which may be attributed to the use of novel tools, such as Ovation, for public speaking practice.

When examining students' perceptions of AI, the participants began this study generally distrustful of AI, which was not significantly impacted by the integration of AI tools into the course. The lack of impact was also reflected in students' attitudes towards AI, which remained neutral throughout the course, regardless of the treatment. AI efficacy, however, was significantly increased by students' interaction with AI tools in the course. Collectively, these results indicate that students' perceptions of the AI tools themselves, in the form of trust and attitudes, were not impacted positively or negatively by interacting with them in the course, unlike their belief in their own abilities to use the tools, which significantly increased with integration. These increases are supported by Bandura's (1977) self-efficacy theory, which holds that mastery experiences, or the opportunity for an individual to perform a skill or task successfully, are the strongest source of self-efficacy judgements.

Although the demographic characteristics of students showed few significant correlations with the variables of interest in this study, the correlations between gender and attitudes and trust toward AI are noteworthy. Our findings indicated that female students in the treatment group were more likely to have negative attitudes and less trust in AI after interacting with AI tools than their male counterparts or students in the control group. Although these findings align with Stöher et al.'s (2024) work, questions remain about how the female students in this class formed their perceptions of AI throughout the semester. Future studies may benefit from an in-depth examination of this process among students who actively engage with AI tools.

Oral communication skills are frequently emphasized in the undergraduate curriculum in agricultural communications across the United States and are among the skills employers desire (Corder & Irlbeck, 2018). Coupled with the recent exposure of global employment to AI across sectors (Georgieva, 2024), the need for further research on AI integration in agricultural communications courses stands to benefit students entering the agricultural workforce. Although public speaking and AI literacy were the primary focuses of the AI integration work in the course at the center of this study, additional investigations into AI efficacy in written communications and visual and technical communication skills are warranted.

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