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AI Literacy in a Basic Communication Course: Insights on Equity, Motivation, and Reducing Uncertainty

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Abstract: As artificial intelligence (AI) technologies become increasingly integrated into professional and civic life, developing AI literacy has emerged as a critical priority for higher education. This study investigated the integration of AI literacy into a basic communication course through a series of scaffolded interventions aligned with core public speaking objectives. Using a pre- and posttest survey design with 133 undergraduate students, we examined changes in intrinsic motivation, perceived competence, and anxiety related to AI tools. Findings suggest that embedding AI literacy increased students' enjoyment and perceived value of AI while reducing anxiety, although perceived competence initially declined, indicating a productive recalibration of skills. Gender and racial/ethnic identity subgroup analyses reveal important differences in confidence and stress reduction, highlighting the need for more inclusive pedagogical approaches. These results offer insights on motivation, uncertainty, and scaffolded learning as essential considerations for developing critical, ethical AI literacy in foundational communication courses.

Keywords: AI literacy, communication education, public speaking, motivation, uncertainty, scaffolded learning, higher education pedagogy

Artificial intelligence (AI) has rapidly emerged as a transformative force in higher education, especially with the public release of generative AI (GenAI) tools such as ChatGPT in late 2022. The past year witnessed a "cataclysmic boom of collective attention" (Petricini, 2024b, p. 93) to AI across disciplines as educators grappled with how to integrate these tools into teaching, learning, and research. Initial reactions in academia were often cautious or defensive: Many institutions rushed to update academic integrity policies, and some even temporarily banned AI tools (Mok, 2023). These reactive measures, however, frequently occurred in the absence of much evidence about how students and faculty actually felt about AI (Zipf et al., 2023).

Broader societal and workforce trends underscore the urgency for higher education to adapt. Surveys of industry leaders have revealed that the large majority of employers seek graduates with GenAI experience, yet only a small fraction of students have received any AI training (Petricini, 2024c). This mismatch between necessity and reality can been characterized as an emerging crisis. It is imperative that higher education provides students with the skills necessary to navigate the workforce and globe, yet AI literacy efforts are still in preliminary phases, and many students are still unprepared.

Educators thus face a dual challenge: addressing widespread uncertainty and mistrust of AI in academic contexts, while proactively equipping students with AI literacy for the future (Petricini et al., 2024). The present literature review situates the current study that embeds AI literacy into a basic communication (public speaking) course.

AI in Higher Education: Perceptions and Preparedness

Research to date has shown that both faculty and students are aware of GenAI's rise, yet many feel unprepared to use such tools effectively. In a recent survey of 286 faculty and 380 students, we found overall use of ChatGPT was infrequent, though most respondents acknowledged its use is inevitable in higher education (Petricini et al., 2024). Both groups were generally familiar with the technology but remained uncertain about it. A substantial concern was academic integrity: Faculty and students widely agreed that using ChatGPT in coursework would violate current institutional policies, even as they also agreed that GenAI holds educational value. This reflects a tension between the perceived benefits of AI and the constraints of existing rules. Building trust appears essential; and an institutional imperative should be building trust, by both facilitating an understanding of the advantages and disadvantages of AI tools and building trust between faculty and students.

Perceptions are shaped by limited direct experience with AI. In the group of faculty and students surveyed, at the time only a minority had actually used ChatGPT, although the majority reported high familiarity. The vast majority expressed a desire for training and education on AI tools (Petricini et al., 2024). While there are numerous factors that contribute to uncertainty and mistrust of AI, including cultural framing and pop culture representations (Petricini, 2024a; Petricini, 2025), one major impact that affects higher education and society at large is a lack of understanding and training on how AI tools operate and function. There is significant desire among all users to learn how to use AI appropriately, but formal preparation is lacking. Without guidance, people often fall back on exaggerated public narratives about AI that swing between utopian and dystopian extremes (Cave et al., 2020). Overall, the research suggests that higher education stakeholders acknowledge AI's importance and inevitability but need support to overcome uncertainties. This justifies efforts to formally integrate AI literacy into curricula as a way to boost confidence, skills, and nuanced understanding.

AI Literacy: Definitions and Frameworks

AI literacy has emerged as a crucial concept for preparing students to navigate AI tools critically and effectively. Generally, AI literacy can be defined as "the ability to understand, use, evaluate, and ethically navigate AI" (Southworth et al., 2023, p. 4; see also Laupichler et al., 2022; Long & Magerko, 2020; Ng et al., 2021). It builds on the idea of technology literacy but focuses on competencies specific to AI. Long and Magerko (2020) proposed one of the early comprehensive frameworks, defining AI literacy as a set of core competencies that enable individuals to critically evaluate AI technologies and interact with them as informed users or collaborators. These competencies span understanding fundamental AI concepts (e.g., how machine learning algorithms work), recognizing AI applications in everyday life, knowing AI's limitations, and awareness of ethical considerations (such as fairness, transparency, and accountability)

Similarly, Touretzky et al. (2019) spearheaded the AI4K12 initiative, which distilled AI knowledge into "five big ideas" for K-12 education, from how computers perceive the world through sensors to the societal impacts of AI, thereby providing a scaffold for AI literacy at the precollege level. Kong et al. (2021) extended these ideas into higher education by piloting an AI literacy course for university students from diverse majors, demonstrating that even nontechnical undergraduates can learn core AI concepts and skills. These efforts collectively emphasize that AI literacy is multidimensional, involving not just technical know-how but also the ability to apply AI in context and reflect on its human implications.

Despite these emerging frameworks, there is consensus that higher education has lagged in adopting AI literacy compared to industry and even K-12 education. As Zipf et al. (2024) noted, "calls…to build artificial intelligence literacy" have persisted for over a decade, yet "very little work has been done outside expert fields, such as information technologies, to attempt to build AIL models" for the general student population (p. 285). Literature on AI literacy in higher and adult education is only just emerging and lacks a consistent definition or approach, and many studies use different terms, such as "AI readiness," or focus narrowly on computer science contexts (Guidry, 2024). Casal-Otero et al. (2023), in a systematic review of K-12 AI literacy initiatives, concluded that AI should not be taught as an isolated new subject but rather infused into existing subjects through collaboration between educators and AI experts. To be effective at scale, AI literacy must be integrated across the curriculum.

AI Literacy in Communication

One particularly underexplored area is the integration of AI literacy into communication studies and liberal arts curricula. Given that GenAI tools (e.g., ChatGPT) are fundamentally language and media technologies, their impact on communication education is highly relevant. Media ecology scholars argue that GenAI systems can be viewed as a new form of "media" and thus fall squarely within the domain of communication inquiry (Petricini, 2024b). From a pedagogical perspective, communication instructors have begun discussing how to address AI in the classroom. Early commentaries suggested incorporating AI-related discussions into topics such as media literacy, rhetoric, and ethics, so that students learn to critically evaluate AI-generated content and understand its influence on public discourse. Connor and Cali (2024), for example, have proposed a communication course in graduate studies that teaches students about AI.

Such integration remains nascent in practice; scholarly literature contains very few empirical studies on AI literacy interventions in liberal arts courses or communication courses. The user's study, therefore, addresses a clear gap: It examines what happens when AI literacy content is embedded in a basic communication course (a general education public speaking class). By doing so, it investigates whether introducing AI-focused modules in a non-technical discipline can enhance students' understanding of AI and its relationship to communication. This contributes to the broader conversation by assessing AI literacy in context which is an important step beyond conceptual frameworks and into pedagogical implementation.

AI and Uncertainty

Perceptions of AI in higher education are consistently marked by uncertainty, a phenomenon intensified by limited direct experience and ambiguity surrounding AI's capacities and ethical implications (Cave et al., 2020; Ng et al., 2021). Scholars have highlighted how uncertainty emerges from the inherent complexity of GenAI and large language models, as these tools produce outputs that appear authoritative yet can be opaque or unreliable (Long & Magerko, 2020; Southworth et al., 2023). Recent studies directly examining student and faculty perceptions reinforce this uncertainty. For instance, a survey of 733 undergraduates revealed mixed familiarity with GenAI, with students more often reporting feelings of nervousness rather than excitement, due to unclear institutional policies and expectations (Stone, 2024). Research involving students and faculty has explored how ambiguity around AI's educational roles leads to mistrust, primarily stemming from insufficient institutional guidance and training (Lyu et al., 2025). Another study involving 399 students found participants simultaneously recognized AI's educational benefits while voicing concerns about accuracy, ethical implications, and potential impacts on personal development (Chan & Hu, 2023).

Zipf et al. (2024) further demonstrated that although faculty and students acknowledge AI's inevitability, significant apprehension persists, reinforcing that uncertainty can be amplified by exaggerated public narratives oscillating between dystopian fear and utopian optimism Petricini, 2024a; Petricini et al., 2024).

Communication and Uncertainty

Uncertainty and anxiety have long been central concerns in communication research, particularly through the lens of communication apprehension. Rooted in both trait and situational variables, communication apprehension describes an individual's fear or anxiety associated with actual or anticipated communication with others (McCroskey, 1977). This apprehension often emerges in contexts marked by ambiguity, lack of control, or unfamiliarity—conditions that disrupt one's sense of communicative efficacy. In digital and technologically mediated environments, these anxieties can be compounded by evolving norms, unfamiliar interfaces, and shifting expectations about credibility and participation.

Research on communication apprehension has evolved to address the distinct anxieties that arise in digitally mediated environments, leading to the development of the concept of computer-mediated communication apprehension (CMCA). Originally defined by Clarke (1991, p. 5) as "an individual's level of fear, apprehension, or anxiety associated with using or anticipation of using computers as a medium to interact with another person or persons," CMCA is now recognized as a distinct construct, separate from general communication apprehension or computer anxiety. This conceptualization is important as it draws attention to the fact that individuals may feel entirely comfortable using computers for solitary tasks but experience notable apprehension when required to engage with others via digital platforms.

Scott and Rockwell (1997) demonstrated that CMCA, writing apprehension, and general technology apprehension collectively reduce individuals' likelihood to adopt and use communication technologies, particularly those involving written or synchronous interaction. Scott and Timmerman (2005) provided a more comprehensive model, confirming that CMCA accounts for unique variance in technology use beyond other apprehension forms and should be treated as a situational barrier to digital communication competence. These findings are still relevant today, as new and often unfamiliar technologies such as GenAI tools become routine platforms for learning and professional interaction.

In digital and technologically mediated environments, communication-related anxieties can be intensified by evolving norms, unfamiliar interfaces, and shifting expectations about credibility and participation. Agrawal and Krishna (2021) have noted that students in virtual learning environments experience elevated levels of stress and anxiety, particularly when required to interact with peers and instructors in online formats that lack clear social cues and predictable norms. This is compounded by what they describe as a broader "discourse on how education, learning, and technology need to be reimagined in a dynamic world of spiraling complexity, uncertainty, and precarity" (p. 1). Similarly, Farris et al. (2024) highlighted that faculty experiencing CMCA reported diminished satisfaction and motivation in remote teaching contexts. CMCA, they argued, is not just technological discomfort, but a distinct communicative barrier that surfaces when individuals are asked to interact through platforms that feel unfamiliar, often under conditions of urgency or institutional pressure.

This pattern extends well beyond higher education. As AI becomes embedded in everyday decision-making systems, public uncertainty and anxiety reflect broader societal tensions. People often experience a disconnect between the ubiquity of AI and their limited understanding of its mechanics, capabilities, or intentions. This gap fosters a cultural climate of suspicion or unease,

intensified by media portrayals and inconsistent policy responses. The present study, while rooted in general education, holds broader relevance.

The Intervention

To embed AI literacy meaningfully within a communication course context, a series of low-stakes, scaffolded interventions was integrated across the semester in a section of CAS 100A: Effective Speech. These weekly activities were designed to introduce students to GenAI tools, particularly Microsoft Copilot, and to develop their critical awareness, ethical understanding, and practical application of AI in communication-related tasks. Each intervention was aligned with existing course objectives and speech assignments, ensuring that AI literacy was treated not as an add-on but rather as an embedded competency that evolved alongside students' public speaking skills. Table 1 outlines the sequence and focus of each intervention. These ranged from exploratory engagements and content analysis to professional skill building and ethical reflection. By progressively building students' confidence and fluency with AI, the interventions supported the development of both technical proficiency and critical consciousness, which were further analyzed through reflective assignments and final course assessments. The instructor used feedback from students' reflections in previous years to revise and strengthen how current assignments were structured and communicated.

Table 1. Weekly AI literacy interventions embedded in Effective Speech course.

Week	Title of intervention	AI literacy focus	Primary skill developed
2	Exploring Conversations with Copilot	Introduction to generative AI interaction	AI dialogue, critical thinking, tool exploration
3	AI Risks Video	Ethical considerations and real-world impacts of AI	Risk evaluation, media literacy
4	Limitations of AI in Personalized Content	AI fallibility in emotional and contextual tasks	Reflection, comparison of human vs. AI content
5	Evaluating AI as a Travel Planner	AI-generated planning and personalization	Comparative analysis, creativity, adaptability
6	Using AI as a Brainstorming Tool	AI as ideation partner	Topic generation, reflection on creative process
7	The Elevator Pitch Challenge	AI-generated summarization	Concision, delivery, performance evaluation
8	Showcasing AI Skills on Your Resume	AI in professional communication and self-presentation	Resume writing, career development

Week	Title of intervention	AI literacy focus	Primary skill developed
9	Reflecting on Informative Speech Outlines with AI Assistance	AI-aided structural and content revision	Organization, revision planning, self-assessment
10	Exploring Image Generation and Copyright	Visual generative AI and legal/ethical implications	Visual literacy, copyright awareness
11	Using AI to Simulate Audience Analysis	AI-generated audience profiling	Audience adaptation, critical AI evaluation

Note. AI = Artificial intelligence.

The Study

This survey-based research study used a pre- and posttest design to gain insight into the impact of AI-related interventions (described above, see Table 1) across multiple sections of an introductory communication class, offered in an asynchronous, online format. All participating sections of the course are required to use the same instructional design, materials, and assessment, making a quasi-experimental design (i.e., with a control group for comparison) not possible in this case. Indeed, practical considerations are one of the primary reasons why pre- and posttest designs (without control groups) are among the most commonly used for pedagogical intervention studies (Alessandri et al., 2017; Bartsch, 2013; Bernstein, 2018; Grauerholz & Main, 2013).

The introductory communication course being studied is offered as part of the general education curriculum for a large, public, research-intensive university with competitive admission standards. Course enrollment typically includes a mixture of students enrolled in fully online degree programs through the university's virtual college and students enrolled in traditional (face-to-face) degree programs for whom the online course offers specific affordances, often the convenience of scheduling. The same instructor taught all four course sections included in this study between the fall semester of 2024 and the spring of 2025.

The study received ethical approval by applying and joining a pre-existing, and previously approved, Institutional Review Board protocol (at the exempt level) for general education courses. A member of the research team who was not the instructor recruited participants and administered the survey at the beginning and end of the semester for each course. Participating students received low-stakes extra credit for their participation, and nonconsenting students could complete an alternative assignment (not included in the study) to receive the same credit. A total of 136 students participated in the study, with three surveys removed for noncompletion, leading to an approximate response rate of 66.5% (133 of 200). The researchers disseminated the survey electronically, using institutionally owned Qualtrics. The pre- and posttest instruments were identical with the exception of verb tenses in selected questions (from future to past). The majority of students accessed the survey via a QR code posted in their respective learning management system course shells.

The Instrument

The research question focuses on student motivation to engage with AI tools, so we selected a long-standing, previously validated survey instrument that measures multiple facets of motivation—the

Intrinsic Motivation Inventory (IMI), which is grounded in Deci and Ryan's self-determination theory (Ryan, 1982; Vallerand, 2000). The validity and reliability of the IMI is well established, with the most widely cited version used with undergraduate students reporting an overall Cronbach's alpha coefficient of .85 (good; McAuley et al., 1989, p. 51). The version of the IMI used measured interest/enjoyment (three items), perceived competence (three items), pressure/tension (three items) and value (four items), the constructs of which were lightly modified to focus specifically on motivation to engage with AI tools in the course. Two other subscales—Perceived Choice and Relatedness—were not used because they either did not apply to the intervention(s) or because they were not germane to the research question. For the survey, students rated their agreement with a series of statements on a Likert scale of 1 (*strongly disagree*) to 7 (*strongly agree*). The survey also included five demographic questions in multiple-choice format (with options to self-disclose or decline to state: major, semester standing, gender identity, race/ethnicity/heritage, and first-generation status.

Data Analysis

We compared pre- and posttest responses to scaled survey items using descriptive statistics (mean, median, frequency) as well as Wilcoxon signed rank tests, as is commonly used for nonparametric data such as scaled items, especially with pre- and posttests being administered to a relatively small sample size (deWinter et al., 2010). Because of ethical restrictions on capturing identifiable data in research surveys, pre- and posttest responses could not be individually paired, so the semesters were combined and compared as pre- and posttest groups (Grabchak, 2023). We chose not to conduct an independent samples test because the pre- and posttest groups, though statistically distinct, consisted of the same cohort of students. The researchers conducted further comparisons, starting with analysis of variance tests, using two demographic subgroups (gender identity and race/ethnicity). No other demographic variable produced groups of sufficiently commensurate size to allow for similar statistical comparisons. All data analysis was conducted using statistical packages in (open source) R.

Findings

Participants

The prevalent demographics of the participant population were 1st- or 2nd-year students enrolled in science, technology, engineering, and mathematics majors who identified as White and male (see Table 2). The latter characteristics are roughly comparable with the student population of *Penn State University* as a whole, which might be expected with a required general education course at the same institution.

Table 2. Survey respondents by demographic variable (presurvey).

Variable	*N*	%
Gender identity		
Male	70	53
Female	53	40
Nonbinary	1	1
Declined to state	9	7
Race/ethnicity/heritage		
Self-Described	5	4

Variable	*N*	%
Asian or Pacific Islander	21	16
Black or African-American	4	3
Hispanic origin	5	4
Middle Eastern or Northern African	2	2
Multiracial or biracial	2	2
White	91	68
Academic year		
1st	41	33
2nd	37	28
3rd	27	20
4th	17	13
Graduate	3	2
Other	8	6
Major		
Business	17	14
STEM	58	49
Arts & humanities	4	3
Health	7	6
Social science	7	6
Other	26	24
First-generation college student		
Yes	32	24
No	101	76

Note. $N = 133$. STEM = Science, technology, engineering, mathematics.

AI and Intrinsic Motivation

Overall, the results from the IMI (Table 3) suggest that the students generally saw the relevance of learning to use AI tools in a communication context (Figure 1, Value subscale) and that they found it increasingly enjoyable to do so (Figure 1, Interest/Enjoyment subscale), with at least one item in each subscale registering statistically significant gains from pre- to posttest. They also indicated relatively low degrees of initial stress or anxiety regarding the use of AI tools in the course (Figure 1, Pressure/Tension subscale), and those stress levels appeared to continue to fall, despite scores indicating that their perception of competence in using AI tools, both within and outside of the course, fell across two constructs (Figure 1, Perceived Competence subscale). This suggests that students may have begun the course overconfident in their abilities to work with AI tools and that direct experience applying AI enabled them to perceive areas of future growth. In other words, they learned more about what they did not know about the use of these tools, but they appear to have experienced this (largely) as positive uncertainty. Aggregate results are reflected in Figure 1.

Table 3. Intrinsic Motivation Inventory (IMI) survey responses (pre- and posttest comparisons, all participants, by subscale)

Subscale	Question	*t* statistic	*df*	t test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
IE	Excited about participating in this public speaking course	-0.24	152	.81	.65	4.67	4.79	4.84	133	77
IE	I think the course will be enjoyable	-2.23	160	.03 *	.02*	3.86	5.09	5.55	133	76
IE	I find the idea of using new technologies in this course interesting	-0.57	152	.57	.49	4.58	5.46	5.57	133	77
PC	Capable of doing well in this course	2.63	119	.00**	.03*	5.71	6.02	5.51	133	77
PC	Confident I can master the skills taught in this course	3.04	161	.00**	.00**	6.07	5.63	5.12	133	77
PC	I think I can effectively use any new tools in this course	1.57	156	.12	.11	5.38	5.60	5.35	133	77
V	I believe this course will be valuable for my	2.16	128	.03*	.06	5.56	6.03	5.64	133	77

Subscale	Question	*t* statistic	*df*	t test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
	personal development									
V	Learning about AI tools will be useful for my future career	0.90	144	.37	.54	5.09	5.73	5.53	133	77
V	I think skills I learn will be important for my success	1.20	133	.23	.45	5.14	5.96	5.74	133	77
PT	Anxious to use AI tools in this course	1.40	158	.16	.11	5.48	3.25	2.86	133	77
PT	Worried I might not perform well if AI tools are involved	1.93	170	.05	.04*	5.56	2.63	2.16	133	76
PT	The thought of learning about AI makes me feel stressed	1.37	163	.17	.10	5.458	2.52	2.17	133	77

Note. AI = Artificial intelligence; IE = Interest/Enjoyment; PC = Perceived Competence; V = Value; PT = Pressure/Tension.
* $p < .05$. ** $p < .01$.

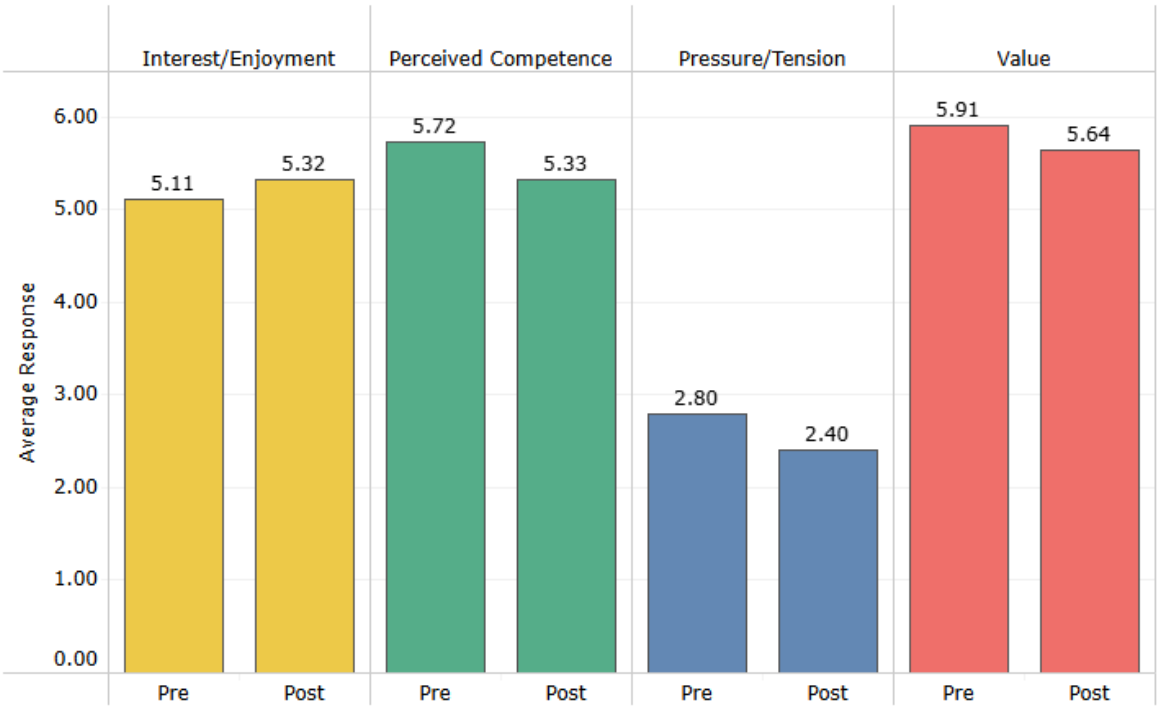

Figure 1. Intrinsic Motivation Inventory survey responses (pre- and posttest comparisons, all participants, aggregated by subscale)

AI, Intrinsic Motivation, and Gender Identity

The findings indicate modest differences by gender identity on the IMI subscales (Figure 2). There was one statistically significant difference by gender identity between respondents who identified as male and those who identified as female on the posttest (see Table 4)—those who identified as male indicated higher perceived competency for the item "I think I can effectively use any new tools in this course" than their female-identifying peers. However, those who identified as female registered statistically significant decreases (pre- to posttest) for items on the Perceived Competency subscale ("I am capable of doing well in this course" and "I am confident I can master the skills taught in this course"; see Table 5). Those who identified as male registered decreases in one of the Perceived Competency constructs for which their female-identifying peers registered decreases ("I am confident I can master the skills taught in this course") but not the other. Those who identified as male also registered gains (and higher overall scores) for one item on the Value subscale ("I believe this course will be [has been] valuable for my personal development"; see Table 6).

Table 4. Intrinsic Motivation Inventory survey responses (posttest survey comparisons by gender identity (ID).

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Group 1 (Male ID)	Group 2 (Female ID)	Group 1 (Male ID)	Group 2 (Female ID)
IE	Excited about participating in this public speaking course	0.22	62.34	.83	.63	685.0	4.88	4.79	43	34
IE	I think course will be enjoyable	-0.35	64.12	.73	.43	640.0	5.50	5.62	42	34
IE	I find the idea of using new technologies in this course interesting	-0.57	61.80	.57	.29	631.0	5.49	5.68	43	34
PC	Capable of doing well in this course	0.03	71.98	.97	.90	743.5	5.51	5.50	43	34
PC	Confident I can master the skills taught in this course	-1.19	70.27	.24	.17	604.0	4.98	5.29	43	34
PC	I think I can effectively use any new tools in this course	-1.84	65.31	.07	.02*	520.5	5.14	5.62	43	34
V	I believe this course will be valuable for my personal development	-0.86	62.29	.39	.13	587.5	5.51	5.79	43	34
V	Learning about AI tools will be useful for my future career	0.42	54.08	.67	.70	694.5	5.60	5.44	43	34
V	I think skills I learn will be important for my success	-1.32	71.16	.19	.12	587.0	5.56	5.97	43	34
PT	Anxious to use AI tools in this course	-1.00	63.50	.32	.49	666.5	2.65	3.12	43	34
PT	Worried I might not perform well if AI tools are involved	-0.50	65.97	.62	.71	681.5	2.07	2.26	42	34
PT	The thought of learning about AI makes me feel stressed	-0/56	64.00	.11	.24	660.0	2.50	2.12	42	34

Note. AI = Artificial intelligence; IE = Interest/Enjoyment; PC = Perceived Competence; V = Value; PT = Pressure/Tension.
* $p < .05$.

Table 5. Intrinsic Motivation Inventory survey responses (pre- and posttest comparisons, respondents indicating female identity)

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
PC	Capable of doing well in this course	2.18	51.12	.03*	.04*	1,190.5	6.12	5.50	56	34
PC	Confident I can master the skills taught in this course	2.00	70.43	.05*	.03*	1,210.0	5.80	5.29	56	34

Note. PC = Perceived Competence. * $p < .05$.

Table 6. Intrinsic Motivation Inventory survey responses (pre- and posttest comparisons, respondents indicating male identity)

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
PC	Confident I can master the skills taught in this course	2.30	88.69	.02*	0.02*	1,870.5	5.49	4.98	70	43
V	I believe this course will be valuable for my personal development	2.02	77.81	.05*	0.05*	1,814.5	5.97	5.51	70	43

Note. PC = Perceived Competence; V = Value. * $p < .05$.

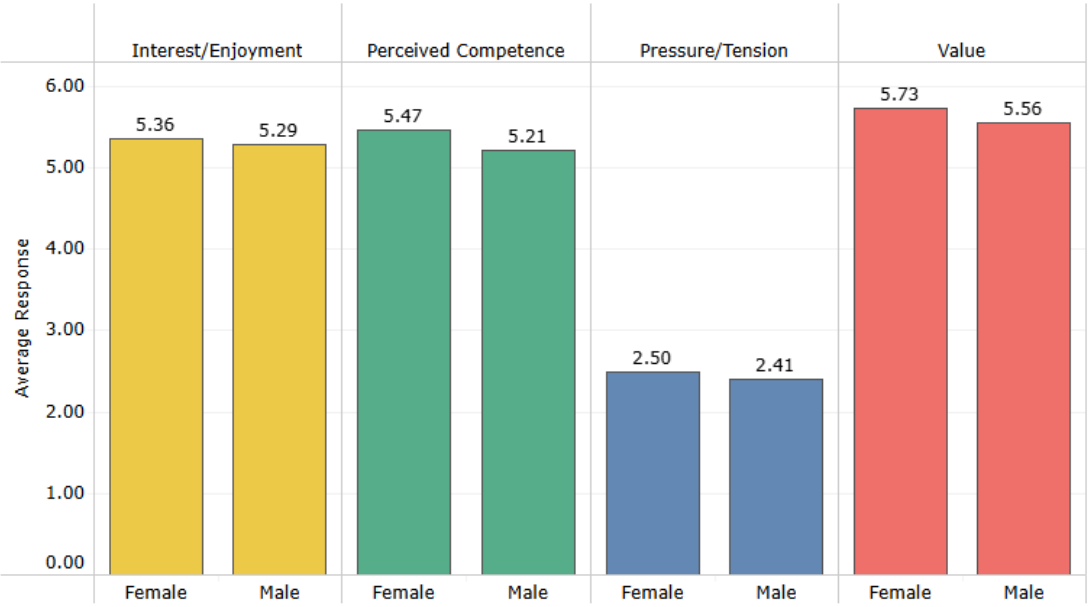

Figure 2. Intrinsic Motivation Inventory survey responses (comparisons by gender identity, aggregated by subscale).

AI, Intrinsic Motivation, and Race/Ethnicity

In the posttest survey, students who identified as White registered similar levels of perceived interest/enjoyment, competence, and value on the IMI as their peers who identified as belonging to other racial, ethnic, or heritage populations (see Table 7). The groups differed markedly, however, in their perceived levels of negative affect regarding the use of AI communication tools, with those who identified primarily as White registering statistically significant lower levels of stress, tension, or anxiety about their use in this class (and potentially other classes as well). Indeed, those students who identified as White registered statistically significant drops (from pre- to posttest) in levels of negative affect across all three measures in the Pressure/Tension subscale (see Table 8); those students who identified as belonging to other racial, ethic, or heritage populations did not register significant changes, either positive or negative, from pre- to posttest in terms of AI-related stress (see Table 9).

Table 7. Intrinsic Motivation Inventory survey responses (posttest survey comparisons, all participants, by race/ethnicity/heritage identity).

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Group 1 (White)	Group 2	Group 1 (White)	Group 2
IE	Excited about participating in this public speaking course	-1.39	48.46	.17	.05	488.0	4.65	5.23	51	26
IE	I think course will be enjoyable	-0.82	58.23	.41	.51	591.0	5.46	5.73	50	26
IE	I find the idea of using new technologies in this course interesting,	-1.21	46.90	.23	.12	523.0	5.43	5.85	51	26
PC	Capable of doing well in this course	-1.44	69.86	.15	.42	590.0	5.35	5.81	51	26
PC	Confident I can master the skills taught in this course	-2.34	65.29	.02*	.08	505.5	4.92	5.50	51	26
PC	I think I can effectively use any new tools in this course	-1.25	49.90	.22	.20	547.5	5.23\	5.58	51	26
V	I believe this course will be valuable for my personal development	0.42	45.45	.67	.74	693.5	5.69	5.54	51	26

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Group 1 (White)	Group 2	Group 1 (White)	Group 2
V	Learning about AI tools will be useful for my future career	-1.41	53.10	.16	.11	521.0	5.35	5.88	51	26
V	I think skills I learn will be important for my success	0.21	44.27	.84	.99	664.5	5.76	5.69	51	26
PT	Anxious to use AI tools in this course	-1.72	43.36	.09	.10	518.5	2.57	3.42	51	26
PT	Worried I might not perform well if AI tools are involved	-1.85	44.50	.07	.04*	481.5	1.90	2.65	50	26
PT	The thought of learning about AI makes me feel stressed	-1.94	45.02	.05*	.03*	490.0	1.88	2.73	51	26

Note. AI = Artificial intelligence; IE = Interest/Enjoyment; PC = Perceived Competence; V = Value; PT = Pressure/Tension.
* $p < .05$.

Table 8. Intrinsic Motivation Inventory survey responses (pre- and posttest comparisons, respondents indicating White identity).

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
PT	Anxious to use AI tools in this course	2.20	109.06	.03*	.03*	2,829.0	3.28	2.57	91	51
PT	Worried I might not perform well if AI tools are involved	2.69	117.04	.00**	.00**	2,858.0	2.67	1.90	91	50
PT	The thought of learning about AI makes me feel stressed	2.35	114.06	.02*	.01*	2,857.0	2.59	1.88	91	51

Note. AI = Artificial intelligence; PT = Pressure/Tension.
* $p < .05$. ** $p < .01$.

Table 9. Intrinsic Motivation Inventory survey responses (pre- and posttest comparisons, respondents indicating racial/ethnic/heritage identity other than White)

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
PT	Anxious to use AI tools	-0.47	50.73	.64	.76	434.0	3.17	3.42	35	26

Subscale	Question	*t* statistic	*df*	*t* test *p* value	Wilcoxon *p* value	*W* statistic	Average		*N*	
							Pretest	Posttest	Pretest	Posttest
	in this course									
PT	Worried I might not perform well if AI tools are involved	-0.24	54.40	.81	.84	441.0	2.54	2.65	35	26
PT	The thought of learning about AI makes me feel stressed	-0.83	50.26	.41	.46	407.5	2.34	2.73	35	26

Note. AI = Artificial intelligence; PT = Pressure/Tension.

Limitations

The design of this study is intended to provide descriptive insights into the motivational impact of a specific intervention (a series of scaffolded assignments focused on AI literacy)—an approach that presents limitations in scope (i.e., it is not a direct measure of learning) and reliability. Indeed, there are known limitations to pre- and posttest designs, notably that they do not take into account history, maturation, or other confounding variables (Marsden & Torgerson, 2012). While it is not possible to completely control for all of these variables, the language of the survey was adapted to focus specifically on the use of AI tools in the communication course.

Second, the analysis of pre- and posttest data can be subject to issues with regression to the mean, such as when survey items register initially high responses, which may limit the effectiveness of tests of significant difference (Alessandri et al., 2017). For this reason, we report on and address descriptive statistics in addition to *p* values. The use of grouped samples rather than paired data limits the power of the statistical inferences made, as does the unequal sizes of the comparison groups, which suggests that caution should be taken when considering the potential generalizability of these results. That generalizability is further limited by the nature of the population surveyed, which is limited to a single instructor at a single institution, over the course of an academic year. The insights presented would need to be replicated in more contexts, with larger and more diverse student populations, to strengthen their validity and reliability.

Discussion

This study demonstrates that embedding a series of brief, low-stakes, and scaffolded AI activities within a basic communication course has the potential to productively shift students' motivational calculus. Across the semester, students reported higher enjoyment and perceived value of learning with AI and lower anxiety about using AI tools. At the same time, perceived competence declined. We interpret this pattern not as a deficit but as a productive recalibration of self-assessment. We believe that authentic practice surfaced unknowns and limitations, which tempered initial overconfidence with a more accurate understanding of what effective, ethical AI use actually is. For a literacy initiative oriented toward critical engagement rather than mere tool engagement, this is a motivating trajectory.

Public speaking is an especially suitable site for AI literacy because its core aims, including audience analysis, message design, ethical reasoning, and credible evidence use, map directly onto the opportunities and risks of generative tools. The scaffolded activities used here (e.g., brainstorming, summarization, outline review, audience simulation) allowed students to interrogate AI's advantages and limits in context. Treating AI literacy as embedded communicative practice, rather than an add-on or purely technical module, might help normalize reflection on more complex topics such as authorship, disclosure, bias, and credibility.

The pattern of results suggests a potentially interesting learning arc. First, value and interest increased as students saw personal and professional relevance and experienced authentic use cases. Second, pressure and tension decreased when initial contact occurred in low-stakes, exploratory tasks before higher stakes applications. Third, perceived competence decreased as students encountered boundary cases (e.g., emotional tone, audience nuance, copyright). We speculate that this shows a recognition of limits that is a sign of maturing judgment. In this study, students became more discerning about when and how to use AI, what to double-check, and what still requires human expertise. Designing for this arc of curiosity, calibration, and then durable confidence may be more important than maximizing early self-efficacy scores.

While the results are encouraging, there are still clear areas for growth. The subgroup analyses show that not all students benefited equally. Female-identifying students reported larger drops in perceived competence, and students from racially minoritized groups did not experience the same reductions in AI-related stress that their White peers did. What this tells us is that embedding AI literacy cannot be treated as one-size-fits-all. Efforts to integrate these tools have to be more responsive to differences in how students encounter and interpret technology. That might mean slowing down at certain points, creating space for students to surface their own experiences, or rethinking examples and applications so they resonate across diverse groups. Building equitable AI literacy requires as much attention to climate and representation as it does to content and skill building.

We see two potentially constructive avenues for future research beyond replication. First, it may prove to be insightful to move beyond self-reported attitudes to observable practices. For example, when and how do students disclose AI assistance, justify its use, and integrate or reject AI suggestions in drafts and speeches? Second, we recommend further research on the codesign of targeted supports with students historically underserved by tech-rich curricula. Further testing could probe whether these approaches narrow gaps in anxiety and perceived competence without dampening critical scrutiny. Replicating across instructors, modalities, and institutions will clarify which scaffolds travel well and which require local adaptation.

As AI technologies continue to reshape communication practices and professional expectations, embedding data-informed, critically engaged AI literacy across disciplines will be essential to preparing students not merely as users, but as thoughtful, ethical participants in an AI-mediated world. Future work should continue to interrogate how different student populations experience AI learning environments and refine pedagogical models to ensure that the benefits of AI literacy are accessible to all learners.

Taken together, these findings suggest that embedding AI literacy in the basic communication course not only enhanced motivation and reduced anxiety but also potentially prompted a healthy recalibration of competence. This is an important step toward critical rather than uncritical use. By treating AI literacy as part of the communicative process, instructors can help students approach these tools with curiosity, discernment, and ethical awareness. At the same time, the uneven benefits across student subgroups remind us that equitable AI education requires attention to climate, representation, and inclusive design. As higher education continues to grapple with AI's place in the curriculum, this study points to the promise of scaffolded, discipline-specific interventions that prepare students not just to use AI but to engage it thoughtfully, responsibly, and with confidence.

Appendix

Appendix 1: Detailed Descriptions of Weekly AI Literacy Interventions.

Week 2—Exploring Conversations With Copilot
Students engaged in a low-stakes interaction with Microsoft Copilot, prompting it with informal questions and reflecting on its conversational tone, helpfulness, and limitations. This activity introduced students to GenAI in a hands-on, approachable way.
Week 3—AI Risks Video
Students viewed a video outlining key societal and ethical risks associated with AI use. They responded to reflection questions that tied the video's themes to both course concepts and real-world applications, prompting early critical engagement with AI's broader implications.

Week 4—Limitations of AI in Personalized Content
Students analyzed a real-life AI error in generating an obituary, highlighting the limitations of AI in handling emotional or personal content. They then used AI to generate a celebratory toast and evaluated the result's effectiveness, tone, and appropriateness.
Week 5—Evaluating AI as a Travel Planner
Students used Copilot to plan a trip they had previously taken, introduced "plot twists" to test AI flexibility, and compared AI-generated plans to their own experiences. Reflections focused on AI's practical utility and creative problem-solving capabilities.
Week 6—Using AI as a Brainstorming Tool
After brainstorming speech topics on their own the previous week, students asked Copilot to generate ideas for their informative speech. They compared the AI's suggestions with their solo ideas and discussed effectiveness, creativity, and alignment with assignment requirements.
Week 7—The Elevator Pitch Challenge
Students drafted a full speech on a fun, informal topic, then used AI to condense it into a 50-word elevator pitch. They practiced delivering their condensed version and reflected on AI's summarization ability and its implications for public speaking.
Week 8—Showcasing AI Skills on Your Resume
Students received a guide for articulating AI skills gained in class on their resumes. They explored ways to frame AI competencies under categories including technical skills, coursework, ethical reasoning, and soft skills, promoting transferability of their learning to the workplace.
Week 9—Reflecting on Informative Speech Outlines With AI Assistance
Students uploaded their informative speech outlines to Copilot and received feedback on structure, clarity, and transitions. They wrote reflections assessing Copilot's suggestions and considered how AI could support future writing and revision tasks.
Week 10—Exploring Image Generation With Copilot and Copyright Issues
This multimedia assignment introduced students to AI-generated images. Students used Copilot to create a visual based on a speech-related prompt and then reflected on how image generation works, including legal and ethical debates about copyright and AI art.
Week 11—Using AI to Simulate Audience Analysis
Students prompted Copilot to generate an audience profile for their persuasive speech. They reflected on the strengths and limitations of using AI for audience analysis and considered its impact on message tailoring and speaker–audience connection.

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