trends in higher education

MDPI

Article

AI Literacy: University Students' Perceptions and Practices

Shawnee Wakeman [1], Holly Johnson [1,*], Justin Cary [2], Camille Endacott [2], Carl Westine [1] and Qiao Liu [1]

1 Cato College of Education, University of North Carolina at Charlotte, Charlotte, NC 28223, USA; slwakema@charlotte.edu (S.W.); cwestine@charlotte.edu (C.W.); qliu14@charlotte.edu (Q.L.)
2 College of Humanities and Earth and Social Sciences, University of North Carolina at Charlottet, Charlotte, NC 28223, USA; cendacot@charlotte.edu (C.E.)
* Correspondence: holly.johnson@charlotte.edu

Abstract

Understanding student artificial intelligence (AI) literacy in the context of higher education is crucial as technology advances and AI use increases. The purpose of this study is to better understand how university students perceive, define, and apply AI literacy within their own educational experiences and from their own disciplinary lens. Collecting electronic survey responses from 130 graduate and undergraduate students across several disciplines including First-Year Writing, Communication Studies, and Education, this study attempts to elucidate how students articulate and perceive their own degree of AI literacy—Access, Understanding, Critical Thinking, Application, and Ethics—in the educational context. Overall, students reported infrequent use, using ChatGPT most often. Education students reported a lower understanding of AI than non-education students. Undergraduates reported higher rates within ethics than graduate students. No significant differences in AI literacy were found between students who were or were not first-generation students, students who did or did not receive financial aid, or by gender. Students reporting higher rates of use also reported higher rates of AI literacy. Crucially, this study provides key qualitative and quantitative insights exploring how students perceive their own AI literacy. Understanding the current state of students' AI literacy is important to facilitating holistic student success in academic environments and career readiness as institutions of higher education adapt and prepare curricula, programs, and interventions addressing AI literacy across disciplines.

Keywords: AI literacy; artificial intelligence; AI perspectives and practices; AI in higher education; university student perspectives and practices

1. Introduction

As it reshapes how students learn, create, and make decisions, artificial intelligence (AI) has rapidly transitioned from a specialized area of research to an everyday presence in higher education. As a result, it is imperative that institutions of higher education (IHEs) aid in the development of students' understanding of what AI is and how it functions, intentionally designing opportunities for students to engage with AI tools in informed and purposeful ways. Without foundational knowledge of AI and its inner workings, there is an increased likelihood that students may overestimate the accuracy and objectivity of AI-generated responses, restricting their ability to be critical consumers of information, make ethical and informed decisions, and retain learner agency in their academic work [1,2]. This challenge is amplified by the increasing presence of generative AI systems that offer human-like responses, which may create a false impression of certainty in their outputs [3].

Check for updates

Academic Editor: Hee Jun Choi

Received: 10 February 2026
Revised: 1 May 2026
Accepted: 15 May 2026
Published: 19 May 2026

Consequently, research has shown that individuals' understanding of AI fundamentally shapes how they perceive, trust, interpret, and use AI systems [4]. This is especially important to recognize in higher education, given that AI use is not only informed by access to tools but also by faculty and students' understanding and beliefs regarding those tools. Furthermore, there are substantial variations in how departments and academic areas across IHEs define, integrate, and regulate the use of AI tools. For example, some disciplines emphasize AI as a technical skill or research tool, while others view it as a writing and communication aid, and still others resist its use and see it as a threat to potential academic integrity [5]. Inconsistency in expectations across disciplines could potentially cause confusion for students, forcing them to navigate competing interests and established norms as they transition between courses and programs. Additionally, as students transition into the workforce, these disciplinary variances may also create inequities in readiness and preparation, leaving some graduates more equipped than others to access and responsibly use AI effectively in professional contexts. In part for these reasons, AI literacy has become a key construct for examining direct influences AI has on learning, decision-making, and academic practice.

1.1. Review of AI Literacy Frameworks and Definitions

AI literacy is a widely used and applied term throughout higher education with definitions and frameworks ranging across disciplines and academic institutions designed to increase understanding and incorporation of AI literacy into curricula and pedagogy. Identified as one of the most commonly recognized definitions, Long and Magerko [6] proposed AI literacy to be "a set of competencies that enable individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (p. 2). Based on this definition, many attempts have been made to identify, operationally define, and effectively communicate essential components of AI literacy, resulting in several proposed frameworks [7]. These frameworks present many commonalities and themes and all attempt to approach AI from holistic perspectives, focusing on broad characteristics, skills, and competencies involving the establishment of best practices for AI use and study.

In one framework, Becker et al. [8] proposed an AI literacy framework that included four principles: (a) ethics and responsible use, (b) understanding the shift from previous digital technologies to more powerful AI, (c) accessibility and use by everyone in a higher education community, and (d) malleability within the higher education context to meet the needs of various groups. This specific framework was designed to support higher education decision makers in recognizing and addressing concerns regarding use and ethical practice. Although this framework offers important guidance for institutional decision makers, questions remain regarding how students themselves understand, experience, and enact these principles in their academic practices.

Similarly, Tadimalla and Maher [9] designed a curricular AI literacy framework that attempts to "promote an interdisciplinary understanding of AI, its socio-technical implications, and its practical applications for all levels of education" (pg. 1). Defining AI literacy in terms of technical and non-technical learning outcomes in socio-technical contexts, this framework presents highly flexible and adjustable AI literacy definitions that attempt to go beyond Computer Science and "advocates for a fundamental shift in how AI literacy is conceptualized and delivered. By adopting a comprehensive interdisciplinary socio-technical approach, AI literacy can be transformed into a foundational element of education at all levels" (pg. 8). While this framework provides insight into an interdisciplinary approach to AI literacy, the implementation of such frameworks within higher education still remains unclear, with special considerations needing to be given to how AI literacy is interpreted, operationalized, and aligned with students' existing knowledge, beliefs, and everyday practices.

Another framework, developed at Stanford University, positions a human-centered perspective at the core of AI literacy and emphasizes students' engagement with AI. This framework conceptualizes AI literacy through exploring four distinct lenses (i.e., functional, ethical, rhetorical, pedagogical), highlighting the varied ways learners interact with, reason about, and apply AI within and across educational contexts [10]. Although this framework articulates a comprehensive vision of AI literacy, it is still unclear the extent to which students attending IHEs possess the knowledge, beliefs, and practices required to engage with AI across each of these domains in their academic work.

Moreover, in their development of a proposed AI literacy framework, Hervieux and Wheatley [7] interviewed instructional university libraries about AI and its complexities. From their research, the authors identified six critical areas of focus: (a) knowing the basic principles of AI, (b) understanding the fundamental differences in AI types, (c) experimenting with AI tools, (d) reviewing the outputs and outcomes of AI tools, (e) evaluating the impact of AI on a societal scale, and (f) engaging with AI discourse. This framework further underscores the evolving consensus that students' AI literacy extends beyond technical proficiency to include elements of critical thinking, ethical reasoning, and societal awareness; however, it does not empirically examine the scope to which students' existing knowledge, beliefs, and practices align with the proposed competencies.

Across these varied frameworks, it is clear that AI literacy is a multi-dimensional construct that involves some understanding about what to consider and how to directly use AI in higher education as well as awareness of the consequences of use. As some of these frameworks consider the context of higher education, it is necessary to best understand student perspectives that serve as the foundation or starting point for developing AI literacy. Despite the evolving alignment in conceptual definitions and essential competencies, existing AI frameworks largely remain conceptual in nature, with limited application to develop tools (e.g., [11–13]). These studies, designed to develop an AI literacy survey, used a single literacy framework from 2020. Without an empirical understanding of students' AI literacy founded in a range of current literacy frameworks, IHEs risk developing policies, curricula, and instructional practices that assume competencies and levels of familiarity within AI literacy frameworks that may not exist. Addressing this gap is essential to informing effective and equitable AI literacy practices within higher education.

The current study is situated using the major components of AI literacy identified across existing frameworks. More specifically, our study is designed using several core principles shaped from the Stanford [10] and Tadimalla and Maher [9] frameworks. Both frameworks address ethical literacy and building an understanding of how AI works in our world as both predictive and generative tools. While Stanford's framework considers how individuals use AI to achieve goals, the Tadimalla and Maher framework considers sustainability issues. Finally, both models consider how AI is used within a higher education context for teaching and learning.

The first component of agreement between the two frameworks, understanding the scope and technical dimensions of AI, addresses foundational technical aspects of AI literacy such as defining the difference between generative AI like generative pre-trained transformers (GPTs) and predictive AI like a chatbot on a website and the implications of the use of AI for society (e.g., the trustworthiness of the generated response). The second component addresses ethics and ethical practice. As we expect users to understand the benefits and consequences of their engagement with AI (e.g., using AI to complete an assignment can be expected as part of the process or identified as cheating depending upon the context and expectations by the instructor), it is necessary to determine to what degree users are operating from the same set of ethical understandings. The third and fourth components reflect on the degree to which students in higher education use AI, and if they do, it is important to understand what tools they are actually using, how they learned about those tools, and what they report as the reasons they use those tools (i.e., personal, social, or educational).

1.2. Understanding AI Literacy in Higher Education

As AI literacy frameworks are introduced, it is necessary to understand the knowledge and perspectives regarding the components within the framework. The users within IHEs are the faculty, staff, and students that potentially engage with AI, as both individuals and groups. It is critical that administrators understand how these users engage with AI as defined by AI literacy frameworks as they develop guidelines for use and select tools that are university sanctioned. For example, the adoption of a tool simply for economic and security reasons ignores accessibility, familiarity, and sustainability features, all of which could directly influence a user's decision about its use along with what to use in a given context. Previous research indicates that half of university students do not engage with AI in a university context due to worries about misuse or cheating [14].

There has been research on AI use by students in higher education in a variety of countries (e.g., [15–17]). However, AI policy and reported AI use often do not align with the suggestions from existing frameworks or research and may even be influenced by conflicting beliefs that portray AI as either inherently beneficial or extremely harmful [18,19]. Confusion is often further exacerbated by the substantial variation across and within disciplines, sending students conflicting messages about what constitutes appropriate AI use. For example, students may be expected to use AI tools in one class while being strictly prohibited from doing so in another. This disciplinary variability has direct implications for teaching and learning, as instructors encounter barriers to integrating AI into coursework in ways that are not only ethically responsible but also aligned to pedagogical best practices (e.g., [20]). Furthermore, despite common assumptions suggesting that young, college-aged students are inherently proficient with AI [21,22], research suggests IHEs cannot assume that AI adoption, perception, understanding, or application will happen "naturally" without intentional support and instruction. Rather, access and exposure help to formulate perceptions and engagement, meaning that with such variances in practice, some students may enter the workforce with advanced AI literacy while others may lack a foundational understanding. As expectations in AI competency increase within the workforce, imbalances in preparation may create inequities in career readiness and professional outcomes [23].

1.3. The Present Study

Therefore, the purpose of this study was to investigate undergraduate and graduate students' perceived understanding of AI literacy (technical knowledge, application, ethics, sociotechnical awareness across a range of academic programs and disciplines using the aforementioned four components. More specifically, this study sought to answer the following research questions:

1. What are the perceptions and self-reported practices related to AI literacy by university students? We hypothesize that students will report high levels of understanding and a cautious approach to use in a university context.
2. How do AI literacy perceptions and practices vary by academic program and student level? We hypothesize no difference in perception or practice by content area. We also hypothesize that graduate students will report higher levels of understanding, including ethics and undergraduates will use a wider variety of AI tools in practice.

3. How do students' AI literacy perceptions and practices vary by demographic characteristics? We hypothesize there will be differences in responses for first-generation students and those who receive financial aid than those who are or do not.

2. Materials and Methods

2.1. Participants and Setting

This study took place at a large university in a Southeastern state in the U.S. The university includes nine colleges of undergraduate students and a graduate school. Total enrollment at the university was greater than 30,000 students in 2024 and 2025. Females represented approximately 51% of the population in 2025. Ethnicity of enrolled students in 2025 was 43% White, 19% African American, 15% Hispanic, 10% Asian, 5% 2 or more races, and 0.3% American Indian. The remaining students identified themselves as International.

Respondents to the survey included 36 students in the assignment option, 82 in the extra credit option and 12 in the newsletter option for a total of 130 responses. The survey and all delivery options were approved by the Institutional Review Board prior to use. The assignment option was a completion grade with an alternative assignment if students chose not to complete the survey. Twenty-three responses came from graduate students, 107 from undergraduate students. Additional demographic characteristics (race/ethnicity, age, disability status, first-generation college status, financial assistance, and whether participants were education majors) are summarized in Table 1.

Table 1. Demographic characteristics of participants (*n* = 130).

Characteristic	*n*	%
Student Type		
Undergraduate	107	82.3%
Graduate	23	17.7%
Gender Identity		
Female	94	72.3%
Male	32	24.6%
Non-Binary	2	1.5%
Chose Not to Respond	2	1.5%
Ethnicity		
White	69	53.1%
African American	27	20.8%
Hispanic	13	10.0%
Asian	8	6.2%
Multi-Racial	7	5.4%
Native American	2	1.5%
An Ethnicity Not Listed	4	3.1%
Age		
Under 18	11	8.5%
18–22 Years Old	74	56.9%
23–27 Years Old	23	17.7%
28–32 Years Old	6	4.6%
33 or Older	16	12.3%
Disability Status		
Have Disabilities	21	16.2%
No Disabilities	101	77.7%
Chose Not to Respond	8	6.2%
First-Generation Student		
Yes	42	32.3%
No	87	66.9%
Don't Know	1	0.8%

https://doi.org/10.3390/higheredu5020044

Table 1. *Cont.*

Characteristic	*n*	%
Financial Assistance		
Yes	70	53.8%
No	53	40.8%
Don't Know	7	5.4%
Education Major		
Yes	68	52.3%
No	62	47.7%

2.2. Survey Instrument

All surveys were developed in Google Forms. Survey items were developed using several proposed AI literacy frameworks. First, we examined the content within the four domains of understanding within the AI literacy Framework from Stanford [10] described earlier to draft the first set of survey items. Second, we enhanced the content using the Hervieux and Wheatley [7] framework. Finally, we reviewed the four pillars described earlier within Tadimalla and Maher [9] to confirm the content and organization of the survey items. We selected these frameworks as a foundation for the survey to target considerations and decisions for understanding and using generative AI in higher education.

The three surveys included all the same content except the extra credit survey had a link that took students outside of the survey responses to a form to include their name and email address for extra credit. The surveys had 6 sections with 55 total items. The sections included Demographics ($n = 10$ items); Access to AI ($n = 7$ items); Understanding of AI ($n = 10$ items); Critical Thinking ($n = 6$ items); Application and Use ($n = 11$ items); and Ethics and Responsibility ($n = 11$ items). Most content items ($n = 39$) used a 5-point Likert scale from Strongly Agree (5) to Strongly Disagree (1) with a neutral option. One item asked, "How often do you use AI tools" with five options of "5 or more times a day" to "I don't have regular access to AI". There were also five open-ended questions. Samples of the survey items can be found in the Supplemental File (Figure S1).

Reliability and validity evidence associated with the instrument supported its intended use as a measure of AI literacy. Inter-item, item-subscale, and inter-subscale correlations along with Cronbach's α for each of the five subscales were examined for consistency of the measures. Inter-item correlations were nearly always greater than 0.20. Specifically, this was true for 86.7% of the correlations in Access, 97.2% in Understanding, 100% in Critical Thinking, 100% in Application, and 92.7% in Ethics. With few exceptions, item-subscale correlations were above 0.60. Specifically, item-subscale correlations ranged as follows: Access (0.59–0.76), Understanding (0.49–0.80), Critical Thinking (0.75–0.84), Application (0.72–0.90), and Ethics (0.56–0.78). A complete set of inter-item and item-subscale correlation tables (Tables S1–S5) is included in the Supplemental File. As shown in Table 2, inter-subscale correlations all fell below 0.80, indicating related, yet distinct dimensions which supported a multidimensional structure. Finally, although the number of items in each subscale varied from 4 to 11, Cronbach's α values were all in the acceptable to excellent range (0.78 to 0.93), indicating strong internal consistency (see Table 3).

A repeated measures ANOVA with Huynh-Feldt ($\varepsilon = 0.798$) correction, given the presence of a significant Mauchly's test of Sphericity $\chi(9) = 80.445$, $p < 0.001$, was run to compare subscale means. Estimated marginal means for the subscales are presented in Figure 1. Means differed statistically significantly between subscales ($F(3.191, 411.595) = 18.237$, $p < 0.001$). Post hoc analyses with Sidak adjustment revealed statistically significant differences between subscales as follows: Ethics greater than all other subscales, Application smaller than Critical Thinking, Critical Thinking greater than Understanding, and Understanding smaller than Access.

Table 2. Correlations among AI literacy subscale mean scores (n = 130).

Variable	1	2	3	4
Access				
Understanding	0.64 **			
Critical Thinking	0.51 **	0.74 **		
Application	0.59 **	0.66 **	0.65 **	
Ethics	0.48 **	0.61 **	0.74 **	0.38 **

Note. ** $p < 0.01$.

Table 3. Internal consistency for AI literacy subscales (n = 130).

Subscale	Number of Items	Cronbach's α
Access	6	0.78
Understanding	9	0.87
Critical Thinking	4	0.81
Application	9	0.93
Ethics	11	0.88

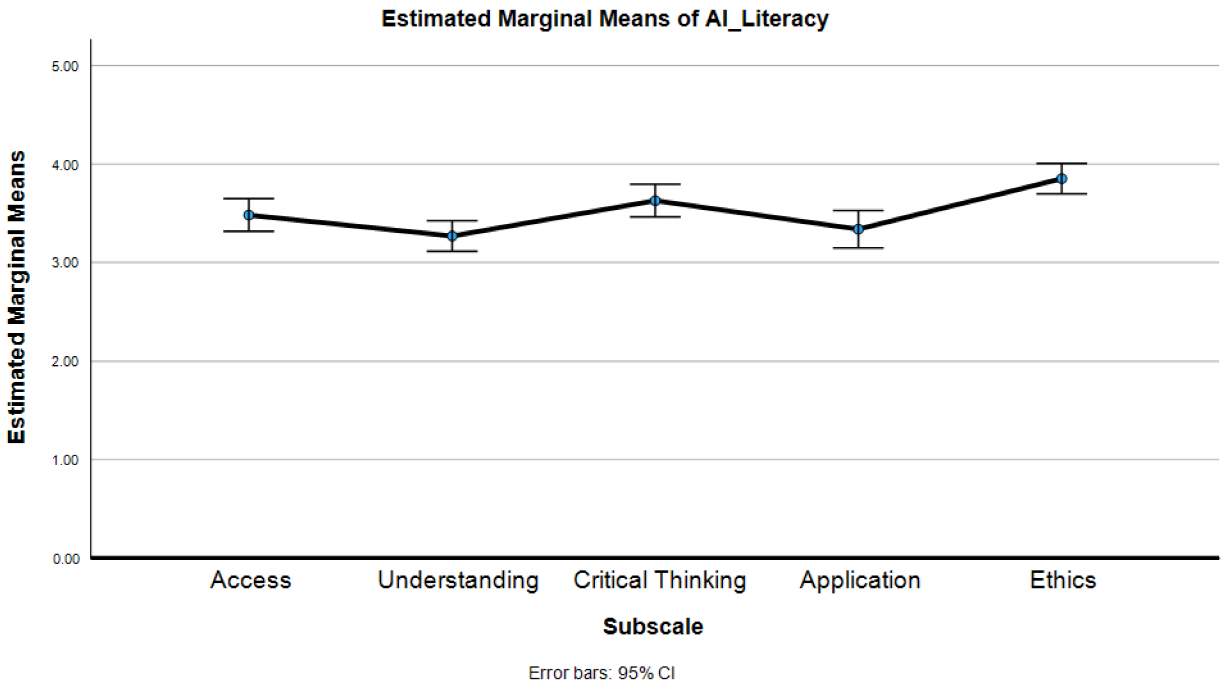

Figure 1. Estimated marginal means for the five subscales.

2.3. Survey Dissemination

The survey was shared in courses in 2024 and 2025 instructed by the first four authors as well as in newsletters for the Organizational Science program and the Department of Writing, Rhetoric, and Digital Studies. The instructors had two options for sharing the survey with students within each course. One option was completion for extra credit in the course and the other was as a course assignment with a completion grade with an alternate assignment option if students chose not to complete the survey. The survey for each option included the exact same set of questions in the same order other than a link to a separate survey for students to complete who were interested in extra credit. A specific link to each survey was provided for dissemination. Survey completion windows lasted approximately two weeks.

2.4. Data Analysis

2.4.1. Quantitative Analysis

All quantitative analyses were conducted using SPSS 28.0 [24]. First, descriptive statistics were examined, including distributions and assumption checks. For each subconstruct, a subscale mean score was computed by averaging items within that subscale, so scores remain on the original 1–5 metric. Internal consistency reliability was then evaluated using Cronbach's α for each subscale. Construct-level relations were examined using Pearson correlations among the five subscale mean scores.

To examine subgroup differences, independent samples t-tests were conducted comparing subscale means across key groups (e.g., education major vs. non-education major; undergraduate vs. graduate; gender; first-generation status; financial assistance status; and frequency grouping for AI use). A repeated measures ANOVA was performed to compare mean differences in the five subscales. Pairwise comparisons were performed to identify the pattern of statistically significant differences using a Sidak adjustment for multiple comparisons. Additionally, to examine subgroup differences, independent samples t-tests were conducted comparing subscale means across key groups (e.g., education major vs. non-education major; undergraduate vs. graduate; gender; first-generation status; financial assistance status; and frequency grouping for AI use).

2.4.2. Analysis of Open-Ended Responses

Several survey items included open-ended response prompts that generated two response formats: (a) single-word or short-phrase responses (e.g., naming an AI tool used most often) and (b) brief sentence responses (e.g., explaining how participants decide when to use AI). Because these formats differed in structure and analytic purpose, they were handled using two related procedures.

For the open-ended item asking participants to name AI tools they use, responses were treated as categorical nominations. Tool names were reviewed and standardized to combine minor spelling and naming variants (e.g., "chatgpt" vs. "Chat.GPT") into a single label. Each unique tool label was then counted, and frequencies and percentages were summarized to describe the distribution of tools reported by participants [25].

For items prompting brief sentence explanations, responses were analyzed using conventional qualitative content analysis [26]. We conducted iterative, inductive coding in which categories were developed from the data. First, responses were reviewed to generate an initial set of codes by one author. Similar responses were grouped into broader categories (e.g., Self-Directed Learning, Learning by Doing) and, when useful for clarity, further refined into subcategories (e.g., General Searching, Watching Videos, Reading). After initial codes and categories were created, coding categories were refined across repeated passes by three authors until category definitions were stable. Disagreements about category names, sub-category names and placement of content were resolved by consensus discussions. Once all content was categorized, the remaining authors then served as verification of the categories, subcategories and content.

2.5. Ethical Considerations

The recruitment materials, information regarding consent and surveys were approved for use by the Institutional Review Board for research as the institution of the authors. Student participation was optional in two of the surveys with only the survey used as an assignment in which the survey completion was graded as required. Responses were anonymous. Survey data was collected directly in Google Forms with the authors as the only people with access to the data.

3. Results

A total of 130 responses were collected across three waves of survey administration. Most of the students reported being undergraduate (82.3%), female (72.3%), a first-generation college student (66.9%), and having no disabilities (77.7%). Additionally, just over half of the respondents self-identified as White (53.1%), between 18 and 22 years old (56.9%), as an education major (52.3%), and as receiving financial assistance (53.8%). A full summary of the demographic characteristics of the sample is presented in Table 1.

3.1. Quantitative Results

To answer research question 1, averages for the 130 respondents by subscale were calculated. Overall, participants' average scores indicated agreement for all five subscales. For Access, the average score was 3.48; Understanding average score was 3.27; Critical Thinking average score was 3.63; Application average score was 3.34; and Ethics average score was 3.85.

The frequency of the AI tool use among participants is reported in Table 4. Only a third (35.4%) of the respondents indicated using AI tools at least once a day or more.

Table 4. Frequency of AI use among participants (n = 130).

Response Option	n	%
5 or more times a day	7	5.4%
2–4 times a day	22	16.9%
1 time a day	17	13.1%
Every once in a while	27	20.8%
Infrequently	40	30.8%
No regular access to AI	3	2.3%
Chose not to use AI	14	10.8%

To answer research questions 2 and 3, subgroup differences for the various subscales were examined for several demographic variables and presented in Tables 5–10. A comparison of education majors and non-education majors revealed a statistically significant difference for the Understanding subscale (p = 0.025, d = 0.399), with non-education majors scoring higher (see Table 5). Likewise, for the comparison of student types, a significant difference was found for the Ethics subscale (p = 0.031, d = 0.503), with undergraduates reporting higher scores than graduate students (see Table 6). No significant differences occurred for any of the subscales when considering the variables of gender, first-generation college student, or financial assistance (see Tables 7–9). With respect to the frequency of use of AI tools, significant differences were found in the Understanding (p = 0.015, d = −0.453), Critical Thinking (p = 0.030, d = −0.403), and Application (p < 0.001, d = −0.973) subscales when comparing students that reported using AI tools at least once a day to those that reported less frequent use (see Table 10). The negative direction of effect in each case indicates that students with more frequent use reported higher levels of AI literacy. For all independent samples t-tests, Levene's test was examined to assess homogeneity of variance; when violated, the Welch-adjusted results were interpreted.

Table 5. Independent sample *t*-tests comparing AI literacy subscale scores by major.

	Non-Education (n = 62)		Education (n = 68)				
Scale	**M**	**SD**	**M**	**SD**	t	p	**Cohen's d**
Access	3.63	0.97	3.35	0.93	1.66	0.100	0.291
Understanding	3.45	0.93	3.10	0.84	2.27	0.025 *	0.339
Critical Thinking	3.71	0.98	3.55	0.94	0.96	0.337	0.169
Application	3.52	1.03	3.17	1.13	1.84	0.068	0.323
Ethics	3.84	0.94	3.87	0.84	−0.20	0.839	−0.036

Note. * $p < 0.05$.

Table 6. Independent sample t-tests comparing AI literacy subscale scores by student type.

	Undergraduate (n = 107)		Graduate (n = 23)				
Scale	**M**	**SD**	**M**	**SD**	t	p	**Cohen's d**
Access	3.49	0.94	3.45	1.04	0.18	0.857	0.042
Understanding	3.32	0.87	3.02	0.98	1.48	0.141	0.340
Critical Thinking	3.70	0.89	3.30	1.20	1.81	0.073	0.415
Application	3.41	1.04	3.02	1.28	1.53	0.129	0.351
Ethics	3.93	0.85	3.49	0.97	2.19	0.031 *	0.503

Note. * $p < 0.05$.

Table 7. Independent sample t-tests comparing AI literacy subscale scores by gender.

	Female (n = 94)		Male (n = 32)				
Scale	**M**	**SD**	**M**	**SD**	t	p	**Cohen's d**
Access	3.49	0.91	3.56	1.05	−0.36	0.721	−0.073
Understanding	3.26	0.82	3.41	1.03	−0.81	0.417	−0.167
Critical Thinking	3.68	0.80	3.61	1.23	0.31	0.760	0.077
Application	3.31	1.07	3.53	1.12	−1.01	0.313	−0.207
Ethics	3.94	0.77	3.72	0.96	1.30	0.195	0.267

Table 8. Independent sample t-tests comparing AI literacy subscale scores by first-generation college student (FGCS).

	Non-FGCS (n = 87)		FGCS (n = 42)				
Scale	**M**	**SD**	**M**	**SD**	t	p	**Cohen's d**
Access	3.59	0.90	3.30	1.03	1.63	0.106	0.306
Understanding	3.29	0.84	3.25	1.02	0.21	0.838	0.039
Critical Thinking	3.68	0.87	3.51	1.12	0.95	0.343	0.179
Application	3.31	1.02	3.42	1.26	−0.55	0.587	−0.102
Ethics	3.94	0.84	3.65	0.98	1.77	0.080	0.332

Table 9. Independent sample t-tests comparing AI literacy subscale scores by financial assistance (FA).

	Non-FA (n = 53)		FA (n = 70)				
Scale	**M**	**SD**	**M**	**SD**	t	p	**Cohen's d**
Access	3.53	0.90	3.44	0.97	0.51	0.610	0.093
Understanding	3.16	0.87	3.37	0.91	−1.25	0.213	−0.228
Critical Thinking	3.57	0.97	3.71	0.93	−0.82	0.415	−0.149
Application	3.27	0.97	3.36	1.20	−0.45	0.652	−0.082
Ethics	3.81	0.97	3.92	0.79	−0.68	0.496	−0.124

Table 10. Independent sample t-tests comparing AI literacy subscale scores by frequency of AI use.

	Not Frequently (n = 84)		Frequently (n = 46)				
Scale	**M**	**SD**	**M**	**SD**	t	p	**Cohen's d**
Access	3.37	0.98	3.69	0.87	−1.84	0.068	−0.338
Understanding	3.13	0.94	3.53	0.76	−2.47	0.015 *	−0.453
Critical Thinking	3.49	1.03	3.88	0.76	−2.20	0.030 *	−0.403
Application	3.00	1.05	3.96	0.88	−5.31	<0.001 **	−0.973
Ethics	3.84	0.93	3.88	0.81	−0.26	0.799	−0.047

Note. * $p < 0.05$; ** $p < 0.01$.

3.2. Open-Ended Responses Results

In four of the AI literacy components of the instrument, students were asked to respond to an open-ended prompt to provide additional insight into their development of each AI literacy component or decision-making regarding the use of AI tools to better answer research question 1. Within Access, students were initially asked to self-identify whether they have access to AI tools that are not provided by the University. Of the 130 participants, 105 students reported external access to AI tools. Then, students with the additional access were asked to list the name of any tool(s) they used. Table 11 summarizes the list of 155 AI tools described; in 50 cases, students listed more than one tool. ChatGPT was the most commonly reported tool, followed by a long tail of other tools (e.g., Grammarly, Gemini*, Perplexity, Co-Pilot*- Note that Gemini and Co-Pilot are provided by the university). "None/Not sure" responses were also present.

Table 11. Access to AI tools reported from students (n = 105).

AI Tools Mentioned	n	%
ChatGPT	71	67.7%
Grammarly	14	13.3%
Gemini *	5	4.8%
Perplexity	4	3.8%
MagicSchool AI	4	3.8%
Co-Pilot *	4	3.8%
All Other Tools (N $\leq$ 3)	27	25.7%
None Listed	10	9.5%

* University provided tools.

Within Understanding, students were prompted to "Describe what you do to learn about AI.", and responses were categorized into five broad categories with additional subcategory descriptions which defined the learning sources. Table 12 captures this framework with example responses for illustration purposes. The majority of participants either pursued self-directed learning through research/online indirect resources (e.g., general research/searches, watching videos, scholarly reading), interacting with the tool directing/learning through use, learning through direct instruction (e.g., from an instructor, from a friend/colleague), or provided multiple responses. A smaller group of respondents indicated inactivity with respect to learning. Finally, some responses did not align with the question being asked, suggesting that the question was interpreted by some as "What have you learned about AI?" These 17 responses were excluded from the analysis.

Table 12. Categorization of participant responses to "Describe what you do to learn about AI."

Category	Subcategory	Example Response
Self-Directed Learning (n = 34)	General Searching	"I will Google or search online for information on AI."
	Watching Videos	"I learned about AI by watching the tutorial on an AI website."
	Reading	"I read journals, publications, technology magazines."
Learning by Doing (n = 11)	Trial and Error	"I engage with it and learn through practice."
Learning Through Direct Instruction (n = 14)	Instructor	"My professor introduced it to me to use for sources."
	Friend or Colleague	"Ask people who are aware of the program."
Multiple Responses (n = 6)	Multiple	"I have attended seminars on AI as well as doing my own research on the internet."
Nothing (n = 12)	No Use	"I don't do anything to learn about it because I rarely use it unless I need ideas."

Within Critical Thinking, students were asked to respond to two open-ended items. In the first, students were prompted to "Describe how you decide when to use or not use AI." This item elicited a range of standards individuals use for governing the use of AI. Responses were categorized into five broad categories with additional subcategory descriptions: Personal Use, Augmentation, Imposed by Policy, User-Defined Rules, and Abstainers. Table 13 captures the framework with example responses for illustration purposes.

Table 13. Categorization of participant responses to "Describe how you decide when to use or not use AI."

Category	Subcategory	Example Response
Personal Use (n = 10)	Personal	"I only use AI for personal matters like asking it to create a training plan for a race."
Augmentation (n = 47)	Starting Point	"I will use it if I am confused with the starting point. I will use it as a guide to influence thinking. I will use it if I need more information."
	Clarification	"I only use it if I'm having difficulty understanding a task."
	Searching	"I only use AI to create a very basic organization or framework for things like lesson plans."
	Automation	"I have only used it to summarize articles."
	Ending Point	"I only use it to correct my grammar for important papers and when apps/companies make it unavoidable."
	General Studying	"I use it to make study guides for tests."
Imposed by Policy (n = 21)	School/Teacher Policies	"When I use it I have permission from a professor or it's an informal assignment. I don't use AI for papers or tests.
Use-Defined Rules (n = 4)	Social/Educational Context	"I believe that when you need to use AI it would be studying and When not to use it would be on assignments, and tests, etc."
	Internal Ethical Guidelines	"When it feels right, it's hard to explain. Like when I know I'm not cheating."
	User's Understanding of How AI Affects Learning	"I don't use AI to do the work for me. I use AI to facilitate my learning process as I go about doing the work."
Abstainers (n = 24)	Purposeful Abstainers	"I do not use AI on assignments because they need to be a representation of my learning."
	Rare Users	"I don't like AI, so I've only ever used it once. For the most part I'd rather use resources created by humans."
	Doesn't Know How to Use It	"I do not use it. I would benefit from learning when to use it."
Multiple Responses (n = 4)	Multiple	I choose to use AI to check work that I have already completed (like Grammarly) or when I need help coming up with a prompt for something informal. I don't use AI as a general search engine.

For the second open-ended item in Critical Thinking, the participants were prompted to "Describe how you decide what AI to use." Responses were categorized into four broad categories with additional subcategory descriptions: Convenience (e.g., Price, Accessibility, Default/Preferred), Recommendation, Contextual (e.g., Accuracy, Ethical, Purpose-Driven), and Avoidance. Table 14 captures the broad groups with example responses for illustration purposes. Finally, some responses did not align with the question being asked. Some students responded that they didn't understand the question, while other responses implied the question was interpreted as "What do you use AI for?" These 19 responses were excluded from the analysis.

Table 14. Categorization of participant responses to "Describe how you decide what AI to use."

Category	Subcategory	Example Response
Convenience (n = 9)	Price	"Free resources are the best resources."
	Accessibility	"I use what is most easily accessible like Co-pilot on my computer or ChatGPT on my phone."
Recommendation (n = 50)	Default/Preferred	"I only use ChatGPT."
	Popularity	"I use the AI that I know of and is being most used by other students."
	Instructional	"When we are told to in class I use what is being used in the classroom."
Contextual (n = 39)	Accuracy	"Depends on how good the responses are."
	Ethical	"I see which one is based more on facts and not what the system learned from me."
	Purpose Driven	"The specific type of AI that I use depends on the specific task or process I am faced with."
Avoidance (n = 13)	No Use	"I don't use AI and I don't really understand what it is. I kind of do but I've never used one before."

Finally, within Application, students were asked to describe the two most frequent AI tools that they use beyond what is provided by the university. As shown in Table 15, over half of the students listed ChatGPT; however, several other tools, including Grammarly, Notebook LM, and Perplexity, received multiple mentions. Some students included university-provided tools in their response. In total, 48 students provided at least two responses (two students listed three tools).

Table 15. Student reports of AI tools they use (n = 130).

Tools Mentioned	n	%
ChatGPT	68	52.3%
Grammarly	16	12.3%
Notebook LM *	5	3.8%
Perplexity	5	3.8%
Gemini *	4	3.1%
Co-Pilot *	3	2.3%
Google AI	3	2.3%
MagicSchool AI	3	2.3%
QuillBot	2	1.5%
All Other Tools (n = 1)	18	13.8%
None	51	39.2%

Note. Percentages do not sum to 100% because some students listed more than one tool. * University provided tools.

4. Discussion

This study investigated students' self-reported perceptions of their own AI literacy in the areas of Access, Understanding, Critical Thinking, Application, and Ethics. These findings have several implications for understanding how students navigate the use of AI and perceive their own AI literacy in the educational domain. Overall, AI literacy scores from students within this study support research findings from other studies of this population (e.g., [15,27]). Both quantitative and qualitative results illuminate that overall students at one IHE feel relatively confident in their AI literacy skills. While there were differences across demographics for specific components, there were also promising results indicated by insignificant differences.

4.1. Points of Interest

Our results illuminated several interesting findings crossing several of the subscales within the survey. One of the more interesting descriptive findings from research question 1, crossing the subscales of Access, Application and Ethics, is the report from more than half of the respondents of their infrequent use of AI (i.e., 51.6% reported either every once in a while or infrequently), similar to previous studies [14]. There could be multiple interpretations of that data. First, students could have limited access to AI but given the lack of difference in students' perceptions regarding those students who are first-generation or receive financial aid, access for this sample is likely not the case, which does not align with our fourth hypothesis. Another possibility is that students potentially fear using AI in an educational setting. As noted in the qualitative statements, some students reported they did not understand policies for AI use or did not want to take a chance in case using AI could be construed as cheating, which does align with our first hypothesis. A third possibility is a lack of understanding of when and how they are using AI tools (for example, students may not know when they are encountering AI tools, such as when reading AI-generated summaries). As there was a significant difference between education and non-education student scores for the Understanding subscale, students in education may be more reluctant to use AI, which does not align with our second hypothesis. As many students' career plans are to become teachers, those students may also be pre-disposed to question the use of AI in an educational context without more explicit training in coursework. Students discussed this variability qualitatively (see Table 13). Conversely, students may be so acclimated to AI as part of the fabric of their daily lives that they may not recognize their use of AI (e.g., Siri on a cell phone or Alexa in a home). Finally, the reported frequency of use may speak to the expectations and experiences within the programs of the students. If students are not exposed to tools and their uses within coursework, they may be reluctant to use AI.

Our research question 1 findings crossing subscales of Understanding, Critical Thinking and Application point to a relationship between AI literacy and use such that more frequent use is correlated with higher perceptions of literacy. In fact, significant differences were found for these three subscales based upon the respondents' reported frequency of use. Participants who indicated use of at least once a day indicated higher agreement with statements within those literacy subscales. This finding suggests that the ability to try out and experiment with AI tools may build comfort with these tools for students who are interested and open to using AI [28]. Other research (e.g., [29]) found that self-efficacy regarding AI tools is related to higher reported AI literacy. Future research might investigate the mechanism through which more frequent use of AI tools is related to AI literacy, including comparing students' self-reported AI literacy to behavioral measures.

Related to Access, it is not surprising that ChatGPT is the most commonly used AI tool, findings supported by other research (e.g., [15,16]), even though at this IHE, ChatGPT is not one of the approved AI tools freely available to the students. Students overwhelmingly report using ChatGPT as opposed to other types of AI tools, including different GenAI tools (e.g., Microsoft Co-Pilot, Google Gemini; see Table 15). Only approximately 7% of the students reported using the IHE-approved tools. This type of information should be very useful for decision makers regarding the adoption of tools to meet the needs of the students.

We also found that graduate students reported their knowledge of AI Ethics as significantly lower than undergraduate students, which does not align with our third hypothesis. One interpretation could be that undergraduates may be more familiar with technology, reflecting a higher understanding of the implications of ethical use. Alternatively, graduate students may have been exposed to more scholarship about ethical technology use, leading them to be more aware of the limits of their knowledge than undergraduate students. It is possible that the current generation of students are more cognizant of sustainability and honesty issues related to AI use, impacting their ethical perspectives. For example, Yang et al. [30] found that overwhelmingly, the biggest ethical concern of undergraduates related to ChatGPT was its use to cheat. It is important to note that the sample size within our study is skewed as only 18% of the respondents represent graduate students.

It is also important to note that there was no difference in the reported AI literacy between students who were and were not first-generation students, students who did and did not receive financial aid and gender across all subscales, which does not align with our fourth hypothesis. These outcomes speak directly to access. Although previous research has found that first-generation college students have less access to digital technology for educational purposes [31], our study showed no difference in self-reported AI literacy based on students' status as first-generation students. The digital divide [32] includes considerations in personal inequalities, distribution of resources, access, and participation in society [32]. These considerations within the divide are purported to be closed for gender [32] even though other research identified gender as a differentiating factor (e.g., [29]). Other considerations (i.e., resources, access and participation) may not be perceived as actualized within this sample due to free internet on campus, free resources such as library computers and laptops for checkout, and increased access via apps and social media on cell phones. Additionally, it is possible to use financial aid to purchase a computer, providing resources and creating access.

As the quantitative data illustrate, AI literacy reported by university students in this sample averaged scores in the middle range leaning towards Agree for all five subscales. As students report a range of understandings, beliefs and practices regarding AI, it is imperative that early university instruction is provided to help students navigate what AI is and is not, how it may or may not be used, and the implications of its use on their own critical thinking and society. For example, there are benefits and consequences related to the cognitive offloading of the use of generative AI. With crafted prompts, students experience a presentation of content generated by AI that may extend their thinking in new and creative ways. Conversely, through the overuse of generative AI, students may not consider how to tackle problems, but instead widely accept the output of AI when presented with challenging content. Students indicate variable levels of understanding about AI and how it works. Although some students appreciate the ease at which AI generates information and ideas, others report caution about using it as permissible or trustworthy, providing mixed results for our first hypothesis. Concerns about how data is used and protected was also shared. As universities consider guidelines for the use of AI, it is imperative that courses address AI literacy- what it is, how it works, and considerations for use- early in a student's college career.

4.2. Limitations

The study has some limitations that reduce generalization of results. First, our survey was not piloted with university students nor reviewed by a content expert prior to use. For example, for two of the open-ended questions (i.e., Please describe how you decide what AI to use; Please describe what you do to learn about AI), some students did not answer the question as asked. If we had piloted the survey with students, these questions may have been refined for clarity of what was being asked. We developed the survey items using existing literacy frameworks, and while our students did not report any issues completing the survey or confusion with items, the potential for confusion with individual items remains a possibility. Second, our sample of students represented the social sciences/humanities from one university, but not the hard sciences. It is possible that students in the hard sciences or students from other universities have different levels of familiarity, beliefs and patterns of use with AI and therefore, the results should be interpreted with caution. Finally, the study relies on students' self-reported attitudes. Future research should include students' self-reported data alongside behavioral or observational measures to understand how students' perceptions of their AI literacy compare with their behavior or competence (for example, testing students' ability to distinguish AI-generated output).

4.3. Implications for Policy, Practice, and Research

Although there is not one currently accepted AI literacy framework, many of the current frameworks developed in recent years have several of the same or similar components. The frameworks include considerations surrounding understanding how AI works, access to the tools, ethical practice and use, including security, and the rhetoric and discourse of AI. It is essential for IHEs to not only recognize the need for AI literacy but also understand where in a student's university coursework and experiences AI literacy should occur. Universities may decide to adopt one or more of these frameworks to design and develop both faculty professional development and early AI coursework for students. Interdisciplinary teams within and across universities should come together and discuss expectations for AI literacy across fields. It is essential that IHEs have a plan to consider and communicate clearly the expectations of AI literacy for the future workforce and regularly examine their implementation efforts.

Given the speed at which organizations' adoption of AI tools is presently expanding, it is also imperative that IHEs commit resources and attention to their adopted AI literacy framework and the subsequent guidelines. This recommendation aligns with recommendations from other research (e.g., [15]). Regular review of these resources is necessary, but it is unclear how frequent would be appropriate for these reviews. If IHEs work to create the foundation of understanding of AI for career-ready students, that foundation must keep up with technological advances. Research would be beneficial to examine the understandings and practices of graduates of IHE programs and the needs of their employers.

Expertise is needed to influence policy and practice in IHEs. Even with support from technology departments on university campuses, AI literacy—exposure to critical understandings and applications related to AI—will not occur without direct experiences and opportunities for students. Subsequently, it is our view that IHEs and the faculty within should not ignore the potential of AI to influence student outcomes. We would advise that all faculty commit to expanding their own knowledge and skillset in regard to AI literacy, even if they ultimately decide not to use AI in their courses. Qualitatively, students in this study report variability in their ability to use AI within their coursework (e.g., "When we are told to in class, I use what is being used in the classroom."; "I have only used AI that I am aware of once and that was under the direct instruction of my professor. I learned how to use AI to write an abstract for an assignment."; and "I learn from my

https://doi.org/10.3390/higheredu5020044

professors as well as online apps, like Tik Tok shows me tips."), which indicates even with guidance from the IHE, faculty remain extremely variable in exposure, experience and use of AI within coursework [23]. It may be the case that both faculty and students do not understand when they are engaging with AI tools or if they do, what is actually occurring within the AI tool with the information. A student's college education remains a unique opportunity to develop knowledge and competencies related to digital technologies and, as such, college educators represent an influential group that can shape students' readiness for technologically mediated workplaces. Additional research is needed in this area.

Our findings suggest that use of AI is directly related to access to AI, which is supported by previous research [15,33]. The adoption of AI tools by the IHEs can impact what AI students regularly interact with, even though in our study, students used a non-university-sanctioned tool most often. It is apparent within this self-report data that even when IHEs commit to a tool, students seem to use tools with which they are most comfortable and can easily access as individuals. It is critical that students are represented in the adoption of tools. Support for the use of AI tools that students are more familiar with may need to be provided, even if the tools are not university sanctioned [34]. Students reported they will access and use tools that their faculty or peers expose them to. If IHEs invest in specific AI tools, faculty must be encouraged to engage with those tools if students are going to use them.

In practice, it is very important that students understand the ethical responsibility for the use of AI. The outcomes of this survey illustrate that students report varied understanding of ethics with some students expressing misgivings about AI ("I don't like AI, so I have only ever used it once.") or purposefully abstaining from use ("If I can avoid using it, I avoid using it."), while others have some form of internal "ethical" check (such as decisions within the social or educational context ("I decide to use AI based upon what type of project I am working on."), some personal view of ethical practice ("When it feels right, it's hard to explain. Like when I know I'm not cheating."), or an evaluation of how the use of AI impacts the individual's learning ("I use it when it can help me learn, and not hinder and not provide any shortcuts."). As students in this and other studies (e.g., [15]) report recognizing the ethical implications of AI, understanding what that looks like in practice requires ongoing communication. As many faculty have the autonomy to decide the policies about how they advise students to use AI within coursework, students need a level of understanding about what is and is not ethical practice. Research is needed to understand how faculty instruct, advise and support AI use within coursework. As one of the major concerns at IHEs for its use is cheating or misrepresenting student understanding, students need more than a policy to navigate AI-appropriate use.

A second major concern of the use of AI is data security. Data security at the IHE is likely the highest concern with the adoption of AI tools, influencing both policy and practice. Students (and faculty) may not understand how the AI works and as such, they put themselves or others at risk for data exposure or breach of privacy. However, security and privacy were not discussed by many respondents. One reported, "Most of my interest is in learning how to work around it, like disabling features that train Large Language Models using my data or switching browsers to avoid using automatic AI features in search engines. I also listen to digital privacy and digital security reporters and seek out their concerns and safety tips." Explicit instruction regarding the way in which data is used within AI is essential for individuals to fully develop their AI literacy. Although there are different uses of data within generative and predictive AI, data security in both types is essential to understand.

Within the output of the AI tools, it is also critical that the user understands the biases and inaccuracies that exist [15,35]. Several students in the current study commented on decisions for use based upon the accuracy of the responses within the tool (e.g., "I decided to use an AI system based on the answers I receive. If one AI system provides answers that are closely related to the question I asked, then I will use that system."). Research (e.g., [30]) has clearly shown that the biases within AI models are prevalent, as AI systems rely on patterns learned from existing data to make decisions probabilistically. For instance, generative AI tools are trained from existing datasets of language, which may include societal prejudices, exclude certain language patterns, or reproduce other intersectionality biases. Therefore, it is essential that the users develop and retain a discerning eye of AI outputs. Understanding that the quality of the AI output depends on the quality of the dataset on which it was trained is a critical aspect of AI literacy. Additionally, AI often produces inaccurate information, called artificial hallucinations. These hallucinations may or may not be recognizable by the user [15]. It is incredibly important as part of AI literacy that students not only know inaccuracies are possible but also learn to identify when they occur and how to interpret AI outcomes appropriately. Continued research in this area of student understanding is needed.

5. Conclusions

Based on current patterns of AI implementation, we see AI literacy as necessary for the present and future workforce. This study was designed to better understand what current university students report regarding AI literacy in terms of their Access, Understanding, Critical Thinking, Application, and Ethics. Using a survey designed from several AI literacy frameworks, the study found that less than half the students reported using AI daily. Differences were reported between education and non-education students for Understanding of AI and between undergraduates and graduate students for Ethics. No differences were reported by students based upon gender, first-generation attendance, or receiving financial aid. Students reported variability for how they made decisions about when to use AI and the type of AI used, with ChatGPT being the most popular tool. Qualitative data documented students' reported distrust of AI, supporting their infrequent use and highlighting their reliance on faculty for experience. Unfortunately, students reported variability across faculty for inclusion in coursework. Understanding student perceptions and use is an essential first step in designing and supporting AI content within IHE programs. It is vital that IHEs consider how to infuse AI literacy across and within all programs.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/higheredu5020044/s1, Figure S1: Samples from the AI literacy Survey; Table S1: Inter-item and Inter-subscale Correlations for the AI Access Subscale; Table S2: Inter-item and Inter-subscale Correlations for the AI Understanding Subscale; Table S3: Inter-item and Inter-subscale Correlations for the AI Critical Thinking Subscale; Table S4: Inter-item and Inter-subscale Correlations for the AI Application Subscale; Table S5: Inter-item and Inter-subscale Correlations for the AI Ethics Subscale.

Author Contributions: The following paragraph specifies individual contributions of authors: conceptualization, S.W., H.J., J.C. and C.E.; methodology, S.W., H.J., J.C. and C.E.; formal analysis, C.W. and Q.L.; investigation, S.W., H.J., J.C. and C.E.; data curation, S.W. and H.J.; writing—original draft preparation, S.W., H.J., J.C., C.W. and Q.L.; writing—review and editing, S.W., H.J., J.C. and C.E. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of University of North Carolina at Charlotte (protocol code IRB-25-0926 approved 1 April 2025).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data supporting reported results can be accessed by contacting the authors.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
GPT	Generative pre-trained transformers
IHE	Institutions of Higher Education
ANOVA	Analysis of Variance

References

1. Krugel, S.; Ostermaier, A.; Uhl, M. Zombies in the loop? Humans trust untrustworthy AI- advisors for ethical decisions. *Philos. Technol.* **2021**, *35*, 17. [CrossRef]
2. Pitts, G.; Rani, N.; Mildort, W.; Cook, E.M. Students' reliance on ai in higher education: Identifying contributing factors. In *International Conference on Human-Computer Interaction*; Springer: Cham, Switzerland, 2025; pp. 86–97. [CrossRef]
3. Zhang, A.; Gao, Y.; Suraworachet, W.; Nazarestky, T.; Cukurova, M. Evaluating trust in AI, human, and co-produced feedback among undergraduate students. *arXiv* **2025**. [CrossRef]
4. Zhao, X.; You, W.; Zheng, Z.; Shi, S.; Sun, L. How do consumers trust and accept AI agents? An extended theoretical framework and empirical evidence. *Behav. Sci.* **2025**, *15*, 337. [CrossRef] [PubMed]
5. Lund, B.; Mannuru, N.R.; Teel, Z.A.; Lee, T.H.; Ortega, N.J.; Simmons, S.; Ward, E. Student perceptions of AI-assisted writing and academic integrity: Ethical concerns, academic misconduct, and use of generative AI in higher education. *AI Educ.* **2025**, *1*, 2. [CrossRef]
6. Long, D.; Magerko, B. What Is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*; Association for Computing Machinery: New York, NY, USA, 2020; pp. 1–16. [CrossRef]
7. Hervieux, S.; Wheatley, A. *Building an AI Literacy Framework: Perspectives from Instruction Librarians and Current Information Literacy Tools*; White Paper; Choice: Chicago, IL, USA, 2024. Available online: https://www.choice360.org/research/white-paper-building-an-ai-literacy-framework-perspectives-from-instruction-librarians-and-current-information-literacy-tools/ (accessed on 6 October 2024).
8. Becker, K.; Parker, J.; Richter, D. *Framework for the Future: Building AI Literacy in Higher Education*; White Paper; Moxie: San Bruno, CA, USA, 2024. Available online: https://www.researchgate.net/publication/381660503_Framework_for_the_Future_Building_AI_Literacy_in_Higher_Education_White_Paper (accessed on 6 October 2024).
9. Tadimalla, S.Y.; Maher, M.L. AI literacy for all: Adjustable interdisciplinary socio-technical curriculum. *arXiv* **2024**, arXiv:2409.10552. [CrossRef]
10. Stanford Teaching Commons. Understanding AI Literacy. Available online: https://teachingcommons.stanford.edu/teaching-guides/artificial-intelligence-teaching-guide/understanding-ai-literacy (accessed on 6 October 2024).
11. Hornberger, M.; Bewersdorff, A.; Nerdel, C. What do university students know about Artificial Intelligence? Development and validation of an AI literacy test. *Comput. Educ. Artif. Intell.* **2023**, *5*, 100165. [CrossRef]
12. Hornberger, M.; Bewersdorff, A.; Schiff, D.S.; Nerdel, C. Development and validation of a short AI literacy test (AILIT-S) for university students. *Comput. Hum. Behav. Artif. Hum.* **2025**, *5*, 100176. [CrossRef]
13. O'Dea, X.; Tsz Kit Ng, D.; O'Dea, M.; Shkuratskyy, V. Factors affecting university students' generative AI literacy: Evidence and evaluation in the UK and Hong Kong contexts. *Policy Futur. Educ.* **2026**, *24*, 13–34. [CrossRef]
14. Welding, L. Half of College Students Say Using AI on Schoolwork Is Cheating or Plagiarism. Retrieved from BestColleges.com. 2023. Available online: https://www.bestcolleges.com/research/college-students-ai-tools-survey/ (accessed on 6 October 2024).
15. Chan, C.K.Y.; Hu, W. Students' voices on generative AI: Perceptions, benefits, and challenges in higher education: Revista de universidad y sociedad del conocimiento. *Int. J. Educ. Technol. High. Educ.* **2023**, *20*, 43. [CrossRef]
16. Folmeg, M.; Fekete, I.; Koris, R. Towards identifying the components of students' AI literacy: An exploratory study based on Hungarian higher education students' perceptions. *J. Univ. Teach. Learn. Pract.* **2024**, *21*, 92–107. [CrossRef]
17. Roe, J.; Perkins, M.; Ruelle, D. Understanding Student and Academic Staff Perceptions of AI Use in Assessment and Feedback. *arXiv* **2024**. [CrossRef]
18. Ghimire, A.; Edwards, J. From guidelines to governance: A study of AI policies in education. *arXiv* **2024**, arXiv:2403.15601. [CrossRef]

19. Kamali, J.; Alpat, M.F.; Bozkurt, A. AI ethics as a complex and multifaceted challenge: Decoding educators' AI ethics alignment through the lens of activity theory. *Int. J. Educ. Technol. High. Educ.* **2024**, *21*, 62. [CrossRef]
20. Karaduman, C. Pre-service EFL teachers' perceived AI literacy and competency: The integration of ChatGPT into English Language teacher education. *SAGE Open* **2025**, *15*, 1–16. [CrossRef]
21. Sousa, A.E.; Cardoso, P. Use of generative AI by high education students. *Electronics* **2025**, *14*, 1258. [CrossRef]
22. Zheng, J.; Hao, L.; Lu, K.; Garg, A.; Reese, M.; Yap, M.-J.; Wang, I.-J.; Wu, X.; Hoffman, J.; Kelly, A.; et al. Do students rely on AI? Analysis of student-ChatGPT conversations from a field study. *arXiv* **2025**, arXiv:2508.20244. [CrossRef]
23. Portocarrero Ramos, H.C.; Cruz Caro, O.; Sánchez Bardales, E.; Quiñones Huatangari, L.; Campos Trigoso, J.A.; Maicelo Guevara, J.L.; Chávez Santos, R. Artificial intelligence skills and their impact on the employability of university graduates. *Front. Artif. Intell.* **2025**, *8*, 1629320. [CrossRef]
24. IBM Corp. *ISM SPSS Statistics for Windows*, Version 28.0; Computer Software; IBM Corp: Armonk, NY, USA, 2021.
25. Morgan, D.L. Qualitative content analysis: A guide to paths not taken. *Qual. Health Res.* **1993**, *3*, 112–121. [CrossRef]
26. Hsieh, H.-F.; Shannon, S.E. Three approaches to qualitative content analysis. *Qual. Health Res.* **2005**, *15*, 1277–1288. [CrossRef]
27. Salhab, R.; Aboushi, M.M. Influence of AI literacy and 21st-century skills on the acceptance of generative artificial intelligence among college students. *Front. Educ.* **2025**, *10*, 1640212. [CrossRef]
28. Xu, S.; Kee, K.F.; Li, W.; Yamamoto, M.; Riggs, R.E. Examining the diffusion of innovations from a dynamic, differential-effects perspective: A longitudinal study on an adoption among employees. *Commun. Res.* **2024**, *51*, 843–866. [CrossRef]
29. Kong, J.; Liu, J.; Chen, G.; Shang, W. Assessing AI literacy in college students: The mediating role of self-efficacy in motivational commitment pathways. *Educ. Inf. Technol.* **2025**, *30*, 23957–23979. [CrossRef]
30. Yang, T.; Cheon, J.; Cho, M.-H.; Huang, M.; Cusson, N. Undergraduate students' perspectives of generative AI ethics. *Int. J. Educ. Technol. High. Educ.* **2025**, *22*, 35. [CrossRef]
31. Reisdorf, B.C.; Triwibowo, W.; Yankelevich, A. Laptop or bust: How lack of technology affects student achievement. *Am. Behav. Sci.* **2020**, *64*, 927–949. [CrossRef]
32. Van Dijk, J.A.G.M. *The Deepening Divide: Inequality in the Information Society*; Sage: Thousand Oaks, CA, USA, 2005.
33. Bailey, D.; Southam, A.; Costley, J. Digital storytelling with chatbots: Mapping L2 participation and perception patterns. *Interact. Technol. Smart Educ.* **2021**, *18*, 85–103. [CrossRef]
34. Chen, K.; Tallant, A.C.; Selig, I. Exploring generative AI literacy in higher education: Student adoption, interaction, evaluation and ethical perceptions. *Inf. Learn. Sci.* **2025**, *126*, 132–148. [CrossRef]
35. Fazil, A.W.; Hakimi, M.; Shahidzay, A.K. A comprehensive review of bias in AI algorithms. *Nusant. Hasana J.* **2024**, *3*, 1–11. [CrossRef]

https://doi.org/10.3390/higheredu5020044