

# Examining Artificial Intelligence (AI) Literacy Among First-Year Students in Korean Higher Education

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## Abstract

This study examined generative AI (GenAI) literacy for learning among 181 first-year undergraduates at a Korean national university using the Generative AI Literacy for Learning Scale (GenAI-LLS) developed by Gümüş and Kara (2025). Adopting a survey design, data were analyzed through descriptive statistics, one-way analysis of variance (ANOVA), independent-samples t-tests, and Scheffé post hoc comparisons. Study results showed that students reported moderate-to-high self-assessed AI literacy overall, with critical thinking scoring highest and prompt and language skills lowest, revealing a structural imbalance between evaluative awareness and communicative competence. ANOVA results confirmed significant differences across the four GenAI literacy dimensions, with post hoc tests indicating that Prompt and Language Skills were significantly weaker than both autonomous learning and critical thinking. No gender differences emerged; however, significant variations were observed across academic disciplines and prior AI education experience, with the latter being the strongest predictor of AI literacy levels. Findings indicate the need for targeted prompt engineering instruction in freshman curricula.

**Keywords:** AI, GenAI, AI literacy, freshman, first-year students, higher education

## 1. Introduction

Generative artificial intelligence (GenAI) tools have fundamentally altered how university students engage with academic work. Systems such as ChatGPT have shifted from novelties to central features of student learning, reshaping how university students retrieve information, draft written assignments, and prepare for professional futures (Hwang et al., 2023; Johnston et al., 2024; Ning et al., 2025; Nong et al., 2024). In South Korea, this transformation has coincided with sustained governmental commitment to AI integration in education through the 2022 Revised National Curriculum (Jeong, 2025), prompting many universities to expand AI-related coursework and, in a growing number of cases, designate AI modules as mandatory components of general education (Alamäki et al., 2024). Yet access to AI tools does not constitute meaningful competence.

AI literacy, understood as a multidimensional construct encompassing technical comprehension, critical evaluation of AI outputs, and ethical judgment (Hou et al., 2025; Ng et al., 2024), requires deliberate pedagogical cultivation. Without AI literacy, university students risk becoming passive consumers of AI-generated content, accepting biased or inaccurate outputs without scrutiny and gradually eroding their own cognitive engagement (Karaoglan Yilmaz et al., 2024; Ma & Chen, 2024). Recent empirical work in higher education has begun to map this challenge. Studies of non-computing majors reveal that most students recognize AI's relevance to their academic and professional prospects. Yet, foundational knowledge and technical confidence remain uneven across disciplines: STEM-oriented students tend to report higher AI knowledge and self-efficacy, while their peers in the humanities and social sciences express interest but lack structured pathways to develop AI competencies (Lee & Davis, 2025; Lee et al., 2024). Across these populations, coding knowledge, mathematical understanding, and computer literacy consistently emerge as the most salient perceived barriers, cognitive and educational obstacles, rather than issues of device access or infrastructure (Kong et al., 2025; Laupichler et al., 2023).

What remains less well understood is how these dynamics manifest among first-year undergraduates. Freshmen occupy

a critical juncture in AI literacy development for three reasons. First, they arrive at university bearing the most recent imprint of K-12 educational reforms, including expanded AI content and mandatory software education, and how secondary-level policy translates into competence at university entry. Second, they have not yet been extensively socialized into university-level disciplinary norms around AI use, meaning their literacy profiles reflect pre-university formation rather than higher education intervention. Third, from a developmental standpoint, the transition from secondary to tertiary education represents a period of heightened identity formation and academic habit consolidation; AI engagement patterns established during this period are likely to persist and shape subsequent academic trajectories. If competency gaps, particularly in productive skills such as prompt construction, go unaddressed at this stage, students risk entrenching superficial engagement patterns that undermine deeper learning throughout their university careers (Cardon et al., 2023; Chan & Hu, 2025). Understanding this population's GenAI literacy profile is therefore essential for designing effective onboarding curricula and for identifying intervention points before such gaps solidify.

This study addresses this gap by examining GenAI literacy among first-year students at a Korean university. The purpose of this study is to investigate university students' GenAI literacy for learning using the Generative AI Literacy for Learning Scale (GenAI-LLs), developed and validated by Gümüş and Kara (2025). By administering this validated instrument, the present study aims to assess current GenAI literacy for learning and examine how it varies across key demographic and academic variables. Three research questions guide the study: (1) What are the overall levels of university students' GenAI literacy for learning? (2) Are there statistically significant differences in university students' GenAI literacy for learning across the four dimensions of the GenAI-LLs (i.e., needs Analysis, prompt and language skills, autonomous learning, and critical thinking)? (3) Do university students' GenAI literacy for learning levels differ significantly according to demographic variables such as gender, academic discipline, and AI education (courses) previously taken?

## 2. Literature Review

### 2.1 Definition of AI Literacy

AI literacy draws on the definitional traditions established for other digital literacies. Across the growing body of scholarship, a set of recurring dimensions has emerged: understanding how AI systems operate, using AI tools effectively, solving problems through AI applications, exercising critical thinking when engaging with AI outputs, and navigating the ethical considerations that AI use entails (Kong et al., 2023; Ng et al., 2021). Yet the specific configurations of these dimensions vary considerably across frameworks, and a comparative examination reveals both convergences and consequential divergences in how researchers conceptualize what it means to be AI-literate. Kong et al. (2023) proposed a definition of AI literacy as the cognitive, affective, and sociocultural competencies required to understand AI's operational principles, solve ethical problems using AI resources, and apply critical thinking. Their framework, developed through a structured literacy program for university students, emphasizes three broad domains: conceptual understanding of AI, ethical reasoning, and empowerment through hands-on engagement.

Empirically, Kong et al. (2023) reported significant pre-to-post gains in students' conceptual understanding and empowerment following completion of their AI literacy program. However, ethical awareness showed more modest improvement, a pattern suggesting that ethical reasoning may require longer developmental trajectories than technical competence. Ng et al. (2024) advanced a four-dimensional model, affective, behavioral, cognitive, and ethical, validated through confirmatory factor analysis with secondary school students. Their model shares common ground with Kong et al. (2023) in foregrounding ethical awareness and conceptual knowledge, but diverges by explicitly incorporating affective dispositions (attitudes, motivation, self-efficacy toward AI) and behavioral dimensions (actual patterns of AI tool use). This inclusion of affective and behavioral components addresses a gap in frameworks that focus exclusively on knowledge and skill, recognizing that literacy involves not only what learners know and can do, but also how they feel about and actually engage with AI systems.

Recently, Gümüş and Kara (2025) explicitly articulated this conceptual distinction: the duality of learning about GenAI versus learning with GenAI. Learning about GenAI encompasses technical and ethical knowledge, how generative systems function, their capabilities and limitations, and the principles that should govern their use. This orientation has dominated the design of existing instruments. Learning with GenAI, by contrast, refers to the knowledge, skills, and dispositions that learners need for effective learning experiences with generative AI tools. This reorientation places the learning process, rather than the technology itself, at the center of the literacy construct.

Gümüş and Kara (2025) operationalized this distinction through the Generative AI Literacy for Learning Scale (GenAI-LLs), a 29-item instrument grounded in qualitative research using grounded theory methodology. The scale comprises four dimensions. Needs analysis captures learners' ability to identify their learning needs, select appropriate GenAI

tools to address them, and evaluate whether generated content meets intended learning objectives. Prompt and language skills assess the communicative competency required to interact with GenAI systems through well-formulated prompts, a dimension absent from prior frameworks that nonetheless fundamentally shapes the quality of AI-mediated learning. Autonomous learning evaluates self-regulation skills for both individual and collaborative learning with GenAI, encompassing goal-setting, strategy monitoring, and individualized learning experiences. Critical thinking measures the evaluative competency needed to question, assess, and judge the accuracy, reliability, and potential biases of GenAI-generated content, a dimension shared with virtually all existing frameworks but here situated specifically within the learning-with-AI paradigm.

## *2.2 University Freshmen's AI Literacy*

South Korea's approach to AI education in universities has developed along two parallel tracks. The first targets specialist training: AI-related departments have expanded enrollment, industry-academia collaborations have intensified, and curriculum design increasingly reflects workforce demand (Lee & Jeong, 2023; Jeong, 2025). The second track focuses on AI literacy as a component of liberal education for the general student population. A growing number of institutions now offer AI-related courses as part of general education requirements, and several have designated them mandatory. This dual structure reflects a policy recognition that AI competency is not exclusively the domain of computing specialists but a cross-cutting skill relevant to all graduates (Lee et al., 2024; Lee & Davis, 2025).

Empirical research on university students' AI literacy has produced a consistent set of findings. However, most studies have relied on instruments designed to measure AI literacy rather than AI literacy for learning with AI. Lee et al. (2024) surveyed university students across multiple disciplines at a Korean institution. They reported moderate overall AI literacy levels, with notable disciplinary disparities: STEM-oriented students scored higher on technical knowledge and self-efficacy dimensions. In contrast, humanities and social science students expressed interest in AI but lacked structured pathways to develop the competencies needed. Cetindamar et al. (2024) documented a parallel phenomenon in the workplace context, finding that widespread AI tool adoption coexisted with limited formal training and an understanding gap in which individuals increasingly rely on AI without sufficient technical grounding or critical evaluation skills. Ma and Chen (2024) validated a literacy scale for Chinese college students and similarly observed moderate self-assessed literacy with significant variation by academic background, gender, and prior computing experience. Across these studies, coding knowledge, mathematical understanding, and computer literacy emerge as the most salient perceived barriers to AI literacy, rather than issues of access or infrastructure (Kong et al., 2025; Laupichler et al., 2023).

First-year university students represent a distinctive population within this landscape. They arrive at university bearing the latest imprint of K-12 educational reforms, including the 2022 Revised Curriculum's expanded AI content and mandatory software education, while simultaneously navigating the transition to self-directed university-level learning. Their literacy profiles thus reflect both the cumulative effects of secondary education and the early stages of disciplinary socialization. Lee et al. (2024) and Lee and Davis (2025) reported that a substantial majority of freshmen had some prior AI learning experience, primarily through K-12 software education, and that most had engaged in text-based coding. An overwhelming majority expressed willingness to pursue further AI education, a finding that signals strong intrinsic motivation even among students with modest current competency.

Yet this attitudinal readiness coexists with substantive competency gaps. Chan and Hu (2023) found that while university students readily perceive generative AI as a collaborative resource, they often lack the structured skills to leverage it for deep learning. Cardon et al. (2023) warned more pointedly that students adopting AI tools without adequate grounding risk developing superficial engagement patterns that undermine academic integrity and higher-order thinking. Christ-Brendemühl (2025), analyzing university guidelines for the use of generative AI, documented that institutions increasingly acknowledge students' limited capacity to engage with AI tools critically and productively, despite high rates of voluntary adoption. These converging findings describe a population that is eager and active but inadequately equipped, a gap with practical consequences for learning quality, most amenable to intervention at the point of university entry, before such patterns become entrenched.

Despite the growing body of evidence, most existing studies either aggregate students across year levels or focus on upper-division undergraduates, leaving first-year students, the cohort most directly shaped by recent K-12 reforms and least exposed to university-level AI instruction, underexamined as a distinct population. The present study addresses both gaps by administering the GenAI-LLs (Gümüş & Kara, 2025), a learning-oriented instrument, to first-year undergraduates and by examining how their literacy profiles vary across dimensions and demographic variables. In doing so, it provides the first empirical application of the GenAI-LLs to a Korean freshman population, generating evidence directly relevant to the design of entry-level AI literacy curricula.

### 3. Research Methods

#### 3.1 Study Participants

This study employed purposive convenience sampling, targeting first-year undergraduates during a mandatory freshman orientation session at a Korean university. The orientation provided access to a broad cross-section of incoming students across all enrolled colleges, and all attendees were invited to participate in the survey on a voluntary basis. This sampling strategy was selected because the orientation represented the earliest institutional contact point with the incoming cohort, before students had received any university-level AI instruction, thereby capturing pre-intervention literacy profiles uncontaminated by higher education exposure.

Regarding gender composition, 108 respondents (59.7%) identified as female and 73 (40.3%) as male. The sample encompassed diverse academic backgrounds. STEM majors constituted the largest disciplinary group (24.3%,  $n = 44$ ), followed by business (17.1%,  $n = 31$ ) and social sciences (15.5%,  $n = 28$ ). Humanities students represented 11.6% ( $n = 21$ ), while natural sciences accounted for 7.2% ( $n = 13$ ). Smaller cohorts were drawn from the college of arts and engineering (6.1%,  $n = 11$ ), education-related programs (5.5%,  $n = 10$ ), and arts (5.0%,  $n = 9$ ), with an additional 7.7% ( $n = 14$ ) reporting other fields of study. This disciplinary distribution broadly mirrors the university's proportional enrollment structure, in which STEM and social science programs constitute the largest colleges, lending the sample reasonable structural correspondence with the institutional population.

**Table 1.** Demographic of Survey Participants

Category		Frequency (N=181)	Percentage (%)
Gender	Male	73	40.3
	Female	108	59.7
Majors	Humanities	21	11.6
	Social Sciences	28	15.5
	Business	31	17.1
	STEM majors	44	24.3
	Arts	9	5.0
	Natural Sciences	13	7.2
	College of Arts and Engineering	11	6.1
	The College of Education	10	5.5
	Etc	14	7.7
	AI education (courses) previously	Yes	145
No		36	19.9
Type of AI Learning	K-12 Software education	115	63.5
	University courses	18	9.9
	non-credit / extra-curricular courses	12	6.7
	None	36	19.9
Type of coding education	Unplugged Education	4	2.2
	Block coding	54	29.8
	Text-based coding	93	51.4
	None	30	16.6
Willingness to receive AI-related education in the future	Yes	170	93.9
	No	11	6.1

Regarding prior AI learning experiences, most participants (80.1%,  $n = 145$ ) reported receiving some form of AI-related instruction, whereas 19.9% ( $n = 36$ ) had no such background. Among those with previous exposure, the majority attributed their learning to K–12 software education initiatives (63.5%,  $n = 115$ ). In contrast, fewer respondents gained AI knowledge through university coursework (9.9%,  $n = 18$ ) or non-credit and extra-curricular activities (6.7%,  $n = 12$ ). Coding experience also varied considerably among participants. Over half (51.4%,  $n = 93$ )

reported familiarity with text-based programming, while 29.8% (n = 54) had engaged with block-based coding environments. A small subset had participated in unplugged computing activities (2.2%, n = 4), and 16.6% (n = 30) reported no prior coding instruction. Lastly, respondents demonstrated overwhelmingly positive attitudes toward future AI learning opportunities. A substantial majority (93.9%, n = 170) expressed willingness to engage in AI-related education, while 6.1% (n = 11) indicated no interest.

### 3.2 Survey Instrument

To measure GenAI, this study employed an adapted version of the Generative Artificial Intelligence Literacy for Learning Scale (GenAI-LLs), originally developed by Gümüş and Kara (2025). The GenAI-LLs is a 29-item Likert-type instrument designed to assess university students' competencies in learning with generative AI. All items were rated on a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). The scale conceptualizes GenAI literacy as a multidimensional construct encompassing four core dimensions: needs analysis, prompt and language skills, autonomous learning, and critical thinking. Collectively, these dimensions provide a comprehensive framework for understanding students' capacity to engage effectively with generative AI technologies in learning contexts.

Because the original GenAI-LLs was developed in English, adaptation for the Korean university context required a systematic translation and localization process. The translation followed a forward-backward procedure consistent with established guidelines for cross-cultural instrument adaptation. In the forward translation stage, two bilingual researchers with expertise in educational technology independently translated the 29 items from English into Korean. The two Korean versions were then compared, and discrepancies in wording, nuance, and disciplinary terminology were resolved through consensus discussion between the translators. The back-translated version was compared with the original to verify semantic equivalence, and minor adjustments were made where the back-translation revealed divergences in meaning. Throughout this process, particular attention was paid to culturally grounded expressions.

In the present study, the original 29-item four-factor structure was retained. As shown in Table 2, the instrument demonstrated high internal consistency across all subscales. The needs analysis dimension, comprising eight items, yielded a Cronbach's  $\alpha$  of .941. The five-item prompt and language skills subscale achieved an  $\alpha$  of .932. The nine-item autonomous learning subscale showed strong reliability ( $\alpha = .946$ ), as did the seven-item critical thinking subscale ( $\alpha = .905$ ). The overall reliability coefficient for the full scale was  $\alpha = .969$ , indicating excellent internal consistency and confirming the instrument's suitability for assessing GenAI literacy among the participants in this study.

**Table 2.** Questionnaire Composition and Reliability Analysis

Category	Question	Number of questions	Cronbach's alpha
Needs Analysis	1-8	8	.941
Prompt and Language Skills	9-13	5	.932
Autonomous learning	14-22	9	.946
Critical Thinking	23-29	7	.905
Total	1-29	29	.969

### 3.3 Data Collection and Analysis

Data for the present study were collected during the last week of February 2025, immediately preceding the start of the spring semester. The survey was administered during a centrally organized freshman orientation program held on the university campus. The orientation, which all incoming first-year students were expected to attend, spanned two days and included sessions on academic advising, campus resources, and general education requirements. The survey was administered during a designated break period on the first day of the orientation, thereby minimizing disruption to scheduled programming.

The survey was administered during a freshman orientation session. An online questionnaire was distributed via Google Forms to incoming first-year students attending the orientation. Participation in the study was entirely voluntary; students were free to decide whether to take part based on their own willingness. Before completing the survey, all participants received a thorough explanation of the research purpose, the nature of the questionnaire items, and the intended use of the collected data. Informed consent was obtained from each participant before they began responding to the survey items. No compensation was offered for participation, and respondents were assured that their responses would remain anonymous and confidential and would be used solely for academic research purposes. The first author's institution's IRB approved the research before it was conducted.

Several potential sources of bias associated with the orientation setting warrant acknowledgment. First, administering the survey in a group setting during an institutional event may have introduced social desirability effects, as students surrounded by peers and institutional staff might have reported more favorable self-assessments of their AI competencies than they would have in a private, unsupervised context. Second, the orientation environment, characterized by institutional formality and the implicit authority of university personnel, may have produced acquiescence bias, leading some respondents to agree with positively worded statements. Third, the timing of data collection during orientation week, a period of heightened novelty and adjustment for incoming students, may have influenced response patterns in ways that differ from data collected during the regular academic term. While the voluntary nature of participation and the anonymity of responses were designed to mitigate these pressures, the possibility that the orientation context inflated self-reported literacy scores cannot be entirely excluded and should be considered when interpreting the findings.

Collected data were analyzed using SPSS (version 29.0). Before the main analyses, the dataset was screened for missing values and outliers, and no cases were excluded. To address the first research question, descriptive statistics were computed to examine students' overall GenAI literacy for learning. Specifically, means and standard deviations were calculated for all 29 items and for each of the four GenAI-LL dimensions to describe the general distribution of students' self-assessed literacy levels.

To address the second research question, a one-way analysis of variance (ANOVA) was conducted to examine whether statistically significant differences existed among the four dimensions of GenAI literacy for learning. Before conducting the ANOVA, the key statistical assumptions were evaluated. The homogeneity-of-variance assumption was examined using Levene's test, which indicated it was satisfied ( $p > .05$ ). When the omnibus ANOVA was significant, Scheffé post hoc comparisons were conducted to identify specific pairwise differences among the dimensions.

To address the third research question, independent-samples t-tests were conducted to examine differences in GenAI literacy according to gender and prior AI education experience. Before conducting each t-test, the equality of variances was assessed using Levene's test, and the appropriate t-statistic (equal or unequal variances assumed) was reported accordingly. In addition, a one-way ANOVA was performed to examine differences across academic disciplines, followed by Scheffé post hoc tests when the omnibus test was significant.

To complement statistical significance testing, effect sizes were calculated for all inferential analyses. For ANOVA comparisons, partial eta-squared ( $\eta^2$ ) was reported, with values of .01, .06, and .14 interpreted as small, medium, and large effects, respectively (Cohen, 1988). For independent-samples t-tests, Cohen's  $d$  was calculated, with thresholds of .20, .50, and .80 indicating small, medium, and large effects (Cohen, 1988). The significance level for all inferential analyses was set at  $\alpha = .05$ . Finally, the internal consistency reliability of each subscale and the full instrument was evaluated using Cronbach's alpha, as reported in the survey instrument section.

## 4. Survey Results

### 4.1 Descriptive Statistics of Generative AI Literacy for Learning

Table 3 presents descriptive statistics for students' GenAI literacy for learning. Overall, first-year university students reported moderate to relatively high levels of perceived competence in using generative AI for academic purposes. Across the 29 items, mean scores ranged from 3.46 (SD = .946) to 4.24 (SD = .852) on a five-point Likert scale. The first dimension assessed students' ability to recognize when and how generative AI tools can support their learning tasks. Mean scores ranged from 3.46 (SD = .946) to 4.06 (SD = .861). Students expressed relatively high confidence in determining whether AI-generated information addressed specific learning problems ( $M = 4.06$ ,  $SD = .861$ ) and in applying generative AI tools to assist with problem-solving ( $M = 4.02$ ,  $SD = .894$ ). They also reported general competence in using AI to elaborate ( $M = 3.96$ ,  $SD = .945$ ) or simplify learning content ( $M = 3.95$ ,  $SD = .933$ ).

However, a comparatively lower score emerged for selecting the most appropriate generative AI tool for a particular learning need ( $M = 3.46$ ,  $SD = .946$ ), showing that tool discrimination remains an emerging competency among this cohort. The second dimension examined students' ability to communicate effectively with generative AI systems through prompt construction and refinement. Mean scores ranged from 3.60 (SD = 1.026) to 3.77 (SD = .982). Students reported moderate confidence in formulating detailed prompts to obtain desired information ( $M = 3.77$ ,  $SD = .982$ ) and in refining prompts to improve AI-generated outputs ( $M = 3.70$ ,  $SD = 1.005$ ). Lower scores were observed for identifying weaknesses in their prompts ( $M = 3.69$ ,  $SD = 1.036$ ;  $M = 3.62$ ,  $SD = 1.072$ ) and constructing prompts adaptable across different AI tools ( $M = 3.60$ ,  $SD = 1.026$ ).

The third dimension captured students' ability to utilize generative AI tools for self-regulated and collaborative learning. Mean scores ranged from 3.80 (SD = 1.035) to 4.08 (SD = .891). Students demonstrated relatively strong agreement with statements reflecting AI use in collaborative tasks and group work (M = 4.08, SD = .891; M = 4.06, SD = .895). They also perceived generative AI as capable of functioning as a supportive learning partner (M = 4.01, SD = 1.043) and useful for obtaining feedback on learning progress (M = 3.99, SD = .925).

**Table 3.** Descriptive statistics for learning using the Generative AI Literacy for Learning (N=181)

Category	Question	M	SD
Needs Analysis	1. I can select the right generative AI tool for the content I need.	3.46	.946
	2. I can use generative AI tools to solve a problem.	4.02	.894
	3. I can determine the content type I need through generative AI tools.	3.86	.938
	4. I can decide whether I need generative AI tools at any stage of solving a problem.	3.84	1.012
	5. I can determine whether the content I will get from the generative AI tools is the knowledge I need to use to solve the current problem.	4.06	.861
	6. I know how to benefit from the generative AI tools to achieve my learning goals.	3.91	.899
	7. I can use generative AI tools to simplify a topic.	3.95	.933
	8. I can use generative AI tools to detail a topic.	3.96	.945
Prompt and Language Skills	9. I can enter detailed prompts into the generative AI tools to get access to the content I need.	3.77	.982
	10. I can improve the prompts I enter into the generative AI tools to reach the content I need.	3.70	1.005
	11. I can detect the deficiencies in my prompts depending on the content generated by generative AI.	3.69	1.036
	12. I can design prompts to make the content generated by generative AI more meaningful.	3.62	1.072
	13. I can create prompts appropriate to diverse generative AI tools to reach the content I need.	3.60	1.026
Autonomous learning	14. I can use generative AI to get feedback on what I learn.	3.99	.925
	15. I can use generative AI to evaluate my performance on a specific issue.	3.88	.968
	16. I can gain awareness through generative AI for my general learning progress in a field.	3.81	.965
	17. I can use generative AI as a classmate role.	4.01	1.043
	18. I can use generative AI to improve my dialogue with my teammates in group work.	3.80	1.035
	19. I can use generative AI to collaborate with my teammates to solve a problem.	4.06	.895
	20. I can use generative AI to facilitate group problem-solving.	3.99	.916
	21. I can evaluate the quality of the tasks I have completed by using generative AI tools.	3.88	.979
	22. I can complete my tasks in group work by using diverse generative AI tools.	4.08	.891
Critical Thinking	23. I can question the content generated by generative AI.	4.18	.790
	24. I can reason about the accuracy of the content presented by generative AI.	3.99	.850
	25. I can draw a logical conclusion about the bias in the content presented by generative AI.	3.83	.936
	26. I reference other sources to decide on the accuracy of the content presented by generative AI.	4.24	.852
	27. I reference other sources to decide on the objectivity of the content presented by generative AI.	4.24	.859
	28. I can decide whether the content presented by generative AI is scientific knowledge or a subjective view.	3.91	.921
	29. I verify the accuracy of the content presented by generative AI before using it.	4.17	.885

The fourth dimension assessed students' ability to critically evaluate and verify AI-generated information, yielding the highest mean scores across the four constructs (range: 3.83–4.24). Students reported strong agreement with behaviors related to verifying AI-generated information through additional sources ( $M = 4.24$ ,  $SD = .852$ ;  $M = 4.24$ ,  $SD = .859$ ). They also demonstrated high awareness of questioning AI-generated content ( $M = 4.18$ ,  $SD = .790$ ) and checking its accuracy before use ( $M = 4.17$ ,  $SD = .885$ ).

#### 4.2 Differences in Generative AI Literacy Across Dimensions

To examine whether significant differences existed among the four dimensions of students' GenAI literacy for learning, a one-way analysis of variance (ANOVA) was conducted. As shown in Table 4, the results revealed a statistically significant difference among the four dimensions,  $F(3, 177) = 7.975$ ,  $p < .001$ . Among the four constructs, critical thinking demonstrated the highest mean score ( $M = 4.07$ ,  $SD = .695$ ), indicating that students had relatively strong confidence in evaluating and verifying information generated by AI systems. This was followed by autonomous learning ( $M = 3.94$ ,  $SD = .801$ ) and needs analysis ( $M = 3.88$ ,  $SD = .781$ ), indicating that students generally perceived generative AI as helpful for supporting independent learning processes and identifying learning needs. In contrast, prompt and language skills recorded the lowest mean score ( $M = 3.67$ ,  $SD = .908$ ), showing that students felt comparatively less confident in their ability to formulate and refine prompts when interacting with generative AI tools.

To further explore the differences between dimensions, a Scheffé post hoc test was conducted. The results indicated that prompt and language skills were significantly lower than those of autonomous learning and critical thinking ( $p < .001$ ). These findings show that while students demonstrate relatively strong awareness of evaluating AI-generated information and using AI for learning support, their skills in constructing and communicating prompts when interacting with AI systems remain comparatively underdeveloped.

**Table 4.** Differences in University Students' GenAI Literacy for Learning Across the Four Dimensions of the GenAI-LLs (N=181)

Category	M±SD	F	p	Scheffé
Needs Analysis (a)	3.88±.781			
Prompt and Language Skills(b)	3.67±.908	7.975	.000***	b<c,d
Autonomous learning (c)	3.94±.801			
Critical thinking (d)	4.07±.695			

#### 4.3 Differences in GenAI Literacy According to Demographic Variables

To examine whether students' GenAI literacy for learning differed across demographic characteristics, independent-samples t-tests and a one-way ANOVA were conducted. The results are presented in Table 5. First, regarding gender, no statistically significant difference was observed between male and female students. Male students reported a mean score of 3.92 ( $SD = .726$ ), while female students reported a similar level of literacy ( $M = 3.90$ ,  $SD = .662$ ). The independent samples t-test indicated that this difference was not statistically significant ( $t = .205$ ,  $p = .873$ ).

Second, differences across academic majors were examined using one-way ANOVA. The results revealed a statistically significant difference among majors ( $F(8, 172) = 2.198$ ,  $p = .030$ ). Among the groups, students from the college of arts and engineering showed the highest level of GenAI literacy ( $M = 4.33$ ,  $SD = .407$ ), followed by arts majors ( $M = 4.31$ ,  $SD = .497$ ) and humanities majors ( $M = 4.14$ ,  $SD = .503$ ). In contrast, relatively lower mean scores were observed among business majors ( $M = 3.66$ ,  $SD = .854$ ) and social sciences majors ( $M = 3.74$ ,  $SD = .614$ ). Results of the Scheffé post hoc test indicated that students in the college of arts and engineering demonstrated significantly higher levels of generative AI literacy than those in the social sciences and business fields.

Finally, the analysis examined whether prior experience with AI-related education influenced students' levels of generative AI literacy. The results indicated a statistically significant difference between students who had previously received AI-related education and those who had not ( $t = 3.40$ ,  $p < .001$ ). Students with prior AI learning experience reported a higher level of generative AI literacy ( $M = 3.99$ ,  $SD = .639$ ) compared to those without such experience ( $M = 3.57$ ,  $SD = .774$ ).

**Table 5.** Differences in University Students' GenAI Literacy for Learning Levels According to Demographic Variables (N=181)

	Category	M±SD	t/F	p	Scheffé
Gender	Male	3.92±.726	.205	.873	-
	Female	3.90±.662			
Majors	Humanities (a)	4.14±.503	2.198	.030*	b, c< g
	Social Sciences (b)	3.74±.614			
	Business (c)	3.66±.854			
	STEM majors (d)	3.96±.597			
	Arts (e)	4.31±.497			
	Natural Sciences (f)	3.85±.692			
	College of Arts and Engineering (g)	4.33±.407			
	College of Education affiliated (h)	3.96±.540			
	Etc (i)	3.73±.982			
AI education (courses) previously	Yes	3.99±.639	3.40	.000* **	-
	No	3.57±.774			

## 5. Discussion

The first research question examined the overall levels of university freshmen's GenAI literacy for learning. Students in this cohort reported moderate-to-high self-assessed competence across the 29-item GenAI-LLs, a result consistent with the broader pattern in which university students report growing familiarity with generative AI tools even in the absence of systematic instruction (Cetindamar et al., 2024; Lee et al., 2024). Contextual factors specific to the Korean setting help account for these relatively positive self-assessments: the 2022 Revised National Curriculum expanded AI-related content in secondary education (Jeong, 2025), and the overwhelming majority of participants reported prior AI learning experience, predominantly through K–12 software education. These conditions appear to have generated a baseline of confidence that aligns with Lee and Davis's (2025) finding that prior coding experience bolsters comfort with AI-related academic tasks. These aggregate self-assessments, however, warrant cautious interpretation. Students who interact with ChatGPT regularly may conflate tool familiarity with genuine literacy, a distinction Gümüſ and Kara (2025) deliberately embedded in the GenAI-LLs by separating operational skill dimensions from evaluative and metacognitive ones. That scores remained in the moderate range rather than producing ceiling effects suggests that students themselves recognize limits to their competence, an encouraging indicator for targeted instructional intervention.

The second research question investigated differences among the four dimensions of the GenAI-LLs. The ANOVA results confirmed a statistically significant disparity, with critical thinking scoring highest, followed by autonomous learning and needs analysis, and prompt and language skills ranking substantially lower. Scheffé post hoc comparisons confirmed that prompt and language skills were significantly weaker than both autonomous learning and critical thinking. This dimensional profile, strong evaluative awareness alongside weak communicative competence, constitutes one of the study's most consequential findings and invites interpretation at both theoretical and practical levels. The relatively high critical thinking scores suggest that freshmen are not uncritical consumers of AI-generated information, at least in their self-perceptions. Students strongly endorsed behaviors such as verifying AI outputs through additional sources and questioning AI-generated content before use.

This finding resonates with Kong et al.'s (2023) framework, which positions critical evaluation as a defining attribute of AI-literate individuals, and with Ning et al. (2025), who characterized critical reasoning as the competency distinguishing literate users from passive ones. That such evaluative dispositions are present before substantial university-level instruction may reflect the cumulative influence of K–12 digital literacy education or generational experience assessing online content. The autonomous learning dimension also performed well, with students expressing particular confidence in collaborative AI applications, using AI in group work, and treating it as a learning partner, a pattern consistent with Chan and Hu's (2023) observation that university students readily perceive generative

AI as a collaborative resource. The significantly lower prompt and language skills scores reveal a critical bottleneck of substantial theoretical weight. As Gümüş and Kara (2025) emphasized, the quality of AI-mediated learning is fundamentally shaped by the learner's ability to communicate with these tools through natural language.

In the context of human–AI interaction, prompt engineering functions as a productive literacy, one that demands not merely familiarity with AI tools but the ability to formulate, diagnose, and iteratively refine communicative inputs. Within needs analysis, the lowest single item across the entire instrument, selecting the most appropriate generative AI tool for a given learning need, points to a related gap in tool discrimination, a competency of growing importance as the generative AI ecosystem diversifies (Hou et al., 2025; Ng et al., 2024). These results collectively suggest that K–12 software education, while effective in building general awareness and critical dispositions, has not adequately addressed the communicative and strategic dimensions of human–AI interaction, corroborating concerns raised by Laupichler et al. (2023) and Kong et al. (2025) regarding persistent barriers to literacy development.

The third research question explored whether GenAI literacy levels differed by gender, academic discipline, and prior AI education. No gender difference was detected, a finding that diverges from studies reporting male advantages in AI-related self-efficacy (Ma & Chen, 2024) but aligns with research suggesting that gender gaps in digital literacy narrow when prior educational exposure is relatively uniform (Ng et al., 2024). The mandatory nature of K–12 software education in Korea may have served as an equalizing mechanism, providing male and female students with comparable foundational experiences before university entry. Significant disciplinary differences emerged, but in a pattern that complicates prevailing assumptions. Arts and engineering students scored highest, followed by arts and humanities majors, while business and social sciences students scored lowest. This pattern partially confirms and partially disrupts the findings of Lee et al. (2024) and Kong et al. (2025), who reported that STEM-oriented students demonstrated stronger AI competencies. The present results challenge a simple STEM-versus-non-STEM binary: Humanities students outperformed peers in business and social sciences, and arts and engineering students, integrating creative practice with technical design, exceeded even the conventional STEM category.

One plausible interpretation is that students in creative and design-oriented programs engage with generative AI in qualitatively different ways, using it for ideation, iterative production, and multimodal exploration, which may cultivate a broader literacy profile than standard STEM coursework focused primarily on coding or data analysis. The relatively low scores among business and social sciences students represent a practical concern, as graduates in these fields will inevitably encounter AI in professional settings. Lee and Davis (2025) identified structured pathways as a critical gap for non-computing students, and the present data reinforce the urgency of discipline-specific AI literacy interventions. The most robust demographic predictor was prior AI education experience. Students with previous instruction reported substantially higher literacy than those without, a gap whose practical significance is confirmed by the effect size. Because most prior experience was derived from K–12 software education, this finding suggests that secondary-level AI instruction, even when introductory, produces measurable returns at university entry (Jeong, 2025). Conversely, approximately one-fifth of students who arrived without any prior AI exposure enter at a distinct disadvantage. Cardon et al. (2023) warned that students adopting AI tools without adequate grounding risk developing superficial engagement patterns. The present results sharpen that concern: students lacking structured prior education reported lower confidence across all GenAI-LL dimensions, placing them at elevated risk of passive consumption behaviors that Karaoglan Yilmaz et al. (2024) and Ma and Chen (2024) linked to diminished learning quality and academic integrity.

## 6. Conclusion

This study examined GenAI literacy for learning among 181 first-year undergraduate students at a Korean university using the GenAI-LLs developed by Gümüş and Kara (2025). The findings suggest three main conclusions. First, the participants reported a moderate to relatively high level of GenAI literacy. This pattern may reflect both recent developments in K–12 software education and students' growing informal exposure to generative AI tools. However, this result should be interpreted with caution, as self-reported literacy may not fully reflect actual performance. Second, the findings revealed an uneven distribution across the four literacy dimensions. Students reported relatively stronger critical thinking and autonomous learning, but weaker prompt and language skills. This result suggests that, while students may already show awareness of AI use and a degree of independent learning readiness, they still need support in the practical skills required to interact with AI effectively for academic purposes. In particular, prompt construction, revision, and platform selection appear to be important areas for instructional development.

Third, prior AI education experience was the factor most clearly associated with higher literacy levels. Gender did not show a significant difference, whereas academic discipline showed a more nuanced pattern than a simple STEM-

versus-non-STEM distinction. Students in creative or design-related programs reported relatively higher literacy than some students in traditionally technical fields. This finding suggests that the form and quality of AI engagement may matter more than the disciplinary category alone. In addition, students in Business and Social Sciences, as well as those without prior AI instruction, may require earlier and more targeted support.

These findings have practical implications for higher education. Most importantly, AI literacy education should move beyond general awareness and provide structured opportunities for skill development. Freshman general education courses may serve as an effective site for such instruction. In particular, scaffolded training in prompt use should be incorporated across the first semester rather than delivered as a single introductory session. Such instruction may begin with analyzing effective and ineffective prompts, followed by guided practice in drafting, testing, and revising prompts across multiple AI platforms. It may then be extended through reflective activities such as prompt journals, which can help students evaluate outputs and refine their strategies over time. In addition, discipline-specific workshops may be beneficial for students in fields with lower baseline literacy, especially when AI use is linked to authentic academic tasks within each discipline. Students entering university without prior AI education may also benefit from short bridge programs that introduce basic concepts, tool use, and critical evaluation strategies.

## 7. Limitations and Directions for Future Research

This study is not without limitations, and each limitation points toward a productive avenue for future inquiry. Reliance on self-report data from a single institution limits generalizability and raises concerns about the correspondence between perceived and demonstrated competence. The cross-sectional design captures a snapshot of literacy at a single point in time. Still, it precludes causal inference about the effects of prior education or the developmental trajectory of literacy across the university career. Additionally, several academic majors had small sample sizes (e.g., Arts, Education, Arts and Engineering), which may limit the generalizability of the ANOVA results. Future studies should recruit larger and more balanced samples across majors.

Future research should address these limitations through several complementary lines of investigation. First, multi-institutional comparative studies are needed to establish whether the dimensional patterns observed here, particularly the structural imbalance between critical thinking and prompt skills, generalize across different institutional types. Extending such comparisons internationally, to include university cohorts in East Asian contexts (e.g., China, Japan, Taiwan) where generative AI adoption rates and educational policy trajectories differ from those in South Korea, would test the cross-cultural robustness of the findings and contribute to a genuinely global understanding of freshman AI literacy.

Second, longitudinal panel studies should track the same student cohort across multiple time points—at university entry, at the end of the first semester, and at the conclusion of the first year—to document how literacy dimensions develop in response to university instruction and informal AI use. Such designs would permit the identification of critical periods during which language skills are most amenable to instructional intervention. They would clarify whether the evaluative-productive gap narrows, persists, or widens over the course of university education. Coupling longitudinal self-report data with performance-based assessments, for instance, scoring prompt construction tasks, evaluating AI-output analysis exercises, or portfolio-based demonstrations of iterative prompt refinement, would provide convergent validity evidence that the present study, relying solely on self-report, could not offer.

Third, intervention studies employing quasi-experimental or experimental designs should evaluate the effectiveness of the specific instructional strategies proposed above. Comparing freshman cohorts who receive scaffolded prompt engineering modules with control groups that receive standard AI literacy instruction would yield direct evidence of whether targeted prompt training closes the dimensional gap documented here. Such studies should measure not only changes in self-assessed literacy but also performance outcomes: the quality of prompts students construct, the accuracy of their evaluations of AI outputs, and the depth of learning achieved through AI-mediated tasks.

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