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MAP Education and Humanities

Volume 7

MAP Education and Humanities (MAPEH) is a scholarly peer-reviewed international scientific journal published by **MAP** - *Multidisciplinary Academic Publishing*, focusing on empirical and theoretical research in all fields of education and humanities.

E-ISSN: **2744-2373**

ORIGINAL RESEARCH PAPER

AI LITERACY AMONG UNIVERSITY STUDENTS: A MULTIDIMENSIONAL ANALYSIS OF GENDER, AGE, AND EDUCATIONAL-LEVEL DIFFERENCES

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ABSTRACT

AI literacy has become an essential competence in higher education, encompassing distinct technical, practical, critical, and ethical dimensions. This study aimed to examine whether students' AI literacy, as well as its dimensions, namely AI technical understanding, AI practical application, AI critical appraisal, and AI ethics, differed according to gender, age, and educational level. An online survey was conducted across five Austrian higher education institutions to collect data from 245 students. The results showed a moderate overall level of AI literacy. AI critical appraisal showed the highest mean score, whereas AI technical understanding was markedly lower than the practical, critical, and ethical dimensions. All four dimensions were positively and significantly correlated, with the strongest association between AI critical appraisal and AI practical application. Male students scored significantly higher on overall AI literacy and on AI technical understanding, AI critical appraisal, and AI practical application than female students, while no gender difference was found for AI ethics. No statistically significant differences emerged across age groups. Educational-level differences were identified for overall AI literacy, AI technical understanding, and AI critical appraisal, with master's-level students demonstrating the highest scores; no differences were found for AI practical application or AI ethics. Theoretically, the findings support a multidimensional conceptualization of AI literacy, showing that demographic differences are not homogeneous across individual dimensions and may be masked when AI literacy is treated only as an overall construct. Practically, they emphasize the necessity of dimension-specific, inclusive AI literacy initiatives, which greatly enhance technical understanding and critical appraisal, and embed ethical competence across student groups.

MAP Multidisciplinary Academic Publishing

MAP EDUCATION AND HUMANITIES

Volume 7

ISSN: 2744-2373/ © The Authors.
Published by **MAP** - *Multidisciplinary Academic Publishing.*

Article Submitted: **22 June 2026**
Article Accepted: **30 August 2026**
Article Published: **31 August 2026**

Publisher's Note: **MAP** *stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.*

https://doi.org/10.53880/2744-2373.2026.7.47

MAP EDUCATION AND HUMANITIES Volume 7

HOW TO CITE THIS ARTICLE

Bećirović S., Beck-Saiz J. (2026). **AI Literacy Among University Students: A Multidimensional Analysis of Gender, Age, and Educational-Level Differences**.
MAP Education and Humanities, 7, 47-61. doi: https://doi.org/10.53880/2744-2373.2026.7.47

1. Introduction

Artificial intelligence (AI) is becoming increasingly important in higher education and is transforming teaching and processes. AI literacy is regarded as a key competence for the competent, reflective, and responsible use of AI (Bećirović, Polz, et al., 2025a; Long & Magerko, 2020; Tzirides et al., 2024). Similarly, AI literacy is understood as a multidimensional construct encompassing technical understanding, practical application, critical appraisal, and ethical reflection regarding AI systems (Biagini, 2025; Long & Magerko, 2020; Ng et al., 2021a, 2021b; Żywiołek et al., 2026). The Scale for the Assessment of Non-Experts' AI Literacy (SNAIL), developed by Laupichler et al. (2023), operationalizes AI literacy for non-experts through the three dimensions of AI technical understanding, AI practical application, and AI critical appraisal. Other conceptualizations and measurement instruments explicitly include ethical aspects as a distinct domain of AI literacy (Dong et al., 2025; Ng et al., 2024). In the present study, AI ethics is therefore included as a fourth dimension.

Empirical studies indicate that higher levels of AI literacy may be associated with more competent use of AI applications, greater acceptance of AI technologies, and stronger perceived self-efficacy (Carolus et al., 2023b; Dervić et al., 2025; Weng et al., 2024). At the same time, there is evidence that AI literacy may vary across groups of students (Bećirović, Karas, et al., 2026). However, previous findings concerning demographic characteristics are inconsistent. For example, a transnational study identified differences according to field of study and academic level, whereas no significant differences in the overall AI literacy score were found for gender or age (Mansoor et al., 2024). With regard to ethical reflection, Wang et al. (2025) likewise reported no overall differences by gender or between STEM and non-STEM disciplines; only in ethical awareness did female students achieve higher scores than male students. These inconsistent findings underline the need to examine the individual dimensions of AI literacy in a differentiated manner.

Recent research also suggests that the individual dimensions of AI literacy are associated differently with variables relevant to students' academic experiences (Bećirović & Mattoš, 2024). Positive relationships were found between technical understanding and practical application, respectively, and AI self-efficacy, whereas critical appraisal of AI was negatively associated with self-efficacy and the perceived quality of AI-generated outputs (Bećirović, Polz, et al., 2025b). In contrast, no significant effects of the examined AI literacy dimensions were found for academic performance (Bećirović, Polz, et al., 2025b). The additional inclusion of AI ethics makes it possible to capture not only knowledge, application, and appraisal-related competences, but also the normative and responsibility-related engagement with AI.

Although previous studies have examined demographic differences in AI literacy, the available evidence remains fragmented. Some studies rely primarily on overall AI literacy scores and selected demographic characteristics such as gender, age, academic degree, or field of study (Mansoor et al., 2024), whereas others examine only selected dimensions or demographic variables, for example gender differences in perceived AI knowledge, application, and attitudes (Cachero et al., 2025) or gender and academic-stage differences across functional, technical, and socio-critical competencies (Medina-Gual et al., 2025). In particular, limited attention has so far been paid to the simultaneous and dimension-specific examination of gender, age, and educational level in relation to AI technical understanding, AI practical application, AI critical appraisal, and AI ethics. In the Austrian higher education context, Bećirović et al. (2025b) have already provided a relevant study analyzing relationships between selected AI literacy dimensions and variables related to students' academic experiences. However, dimension-specific differences according to gender, age, and educational level, including AI ethics as a fourth dimension, were not the primary focus of that study. Against this background, the present study examines whether AI technical understanding, AI practical application, AI critical appraisal, and AI ethics differ according to gender, age, and educational level. Specifically, the study addresses the following three research questions:

1: Is there a significant influence of gender and students' AI literacy?

2: Is there a significant impact of students' age and their AI literacy?

3: Is there a significant influence of students' educational levels and their AI literacy?

By addressing these research questions, the study may contribute to the literature by providing a dimension-specific examination of students' AI literacy according to gender, age, and educational level within the Austrian higher education context. The findings may provide an empirical basis for the development of inclusive AI literacy curricula and educational initiatives, support university educators in adapting their teaching methods to different competence profiles, and help students strengthen the technical, practical, critical, and ethical competences required for the effective and responsible use of AI-powered technologies.

2. Literature Review and Theoretical Framework

2.1 AI Literacy as a Multidimensional Competence Construct

AI literacy is conceptualized in the literature in different ways, although these conceptualizations are based on largely overlapping core elements. Long and Magerko (2020) define AI literacy as a set of competences that enables individuals to critically evaluate AI, communicate and collaborate effectively with AI systems, and use AI appropriately across different areas of life and work. Ng et al. (2021a, 2021b) understand AI literacy as a multidimensional competence construct that encompasses knowledge and understanding, application, evaluation and creation, as well as engagement with ethical issues. A more recent conceptualization by Ng et al. (2024) distinguishes affective, behavioral, cognitive, and ethical components of AI literacy. In addition, the systematic literature review by Biagini (2025) shows that, alongside knowledge and application, the critical reflection on the ethical, societal, and practical implications of AI is among the recurring components of contemporary AI literacy concepts.

Despite their different emphases, these conceptualizations agree that AI literacy extends beyond the mere operation of AI applications and encompasses knowledge- and application-related, critical-reflective, and ethical competences. However, the specific configuration of this multidimensionality varies in terms of the subcompetences emphasized and the ways in which they are empirically assessed. In their systematic review, Almatrafi et al. (2024) identify recurring core areas such as understanding AI, using it in practice, and evaluating AI systems. Other conceptualizations additionally incorporate psychological and metacognitive aspects, such as AI self-efficacy (Carolus et al., 2023).

For non-experts, Laupichler et al. (2023) developed the SNAIL scale, which comprises the three empirically distinguishable dimensions of AI technical understanding, AI practical application, and AI critical appraisal. This three-dimensional structure has also been applied in the higher education context (Bećirović, Augustín, et al., 2026). However, ethical issues do not constitute a separate subscale within SNAIL. Other models explicitly integrate ethics into AI literacy. The AI Literacy Questionnaire developed by Ng et al. (2024) includes a distinct ethical domain, while Dong et al. (2025) validated a four-dimensional scale comprising technical understanding, practical application, critical appraisal, and AI ethics. Considering these four dimensions jointly enables a differentiated assessment of knowledge, application competence, epistemic evaluation, and ethical responsibility orientation.

2.2 AI Technical Understanding

AI technical understanding refers to a fundamental conceptual and functional understanding of artificial intelligence (2021a, 2021b). It includes knowledge of key operating principles, the role of data and algorithmic models, as well as the potential applications, limitations, and uncertainties of AI systems. For non-experts, this dimension primarily concerns understanding basic system logics and the role of data, models, and inputs in shaping AI outputs rather than advanced expertise in programming or AI system development (Laupichler et al., 2023; Ng et al., 2021a, 2021b; Stolpe & Hallström, 2024).

Technical understanding is represented as a distinct component across different multidimensional conceptualizations of AI literacy. In their systematic review of 47 studies, Almatrafi et al. (2024) identified "Know and Understand" as one of six recurring AI literacy constructs, alongside Recognize, Use and Apply, Evaluate, Create, and Navigate Ethically. More recent measurement research likewise treats technological understanding as a distinct dimension alongside critical appraisal, practical application, and AI ethics (Dong et al., 2025). These findings reinforce the conceptual distinction between understanding AI technologies and the practical, evaluative, and ethical dimensions of AI literacy. In higher education, technical AI understanding provides a foundation for informed decisions about the system use (Bećirović, 2023a). In Bećirović et al. (2025b), technical understanding was positively associated with AI self-efficacy but showed no significant relationships with perceived output quality or academic performance.

2.3 AI Practical Application

AI practical application refers to the ability to use AI applications purposefully and appropriately in specific learning, work, and problem-solving situations (Ng et al., 2021a, 2021b). In the higher education context, this may include information retrieval, idea generation, text revision, the use of feedback, and support with subject-specific tasks. This dimension corresponds to the competence area of "use and apply," in which existing knowledge of AI is transferred to different situations (Ng et al., 2021a, 2021b).

Practical application is identified as a recurring component of AI literacy across conceptual and measurement frameworks. In their systematic review, Almatrafi et al. (2024) identified "Use and Apply" as one of six recurring AI literacy constructs. Carolus et al. (2023) likewise conceptualize "Use & Apply AI" as a distinct facet that encompasses operating AI systems and using them meaningfully to achieve goals. More recent measurement research treats practical application as a separate dimension alongside technological understanding, critical appraisal, and AI ethics and emphasizes the application of AI knowledge and skills to concrete problems and contexts (Dong et al., 2025). From this perspective, practical application represents a goal-directed and context-sensitive competence rather than mere familiarity with AI technologies.

Recent empirical evidence further underscores the relevance of this dimension in higher education. Bećirović et al. (2026) found that AI practical application significantly predicted AI-supported problem-solving and AI ethics, indicating that the ability to apply AI meaningfully is associated with both task-oriented and ethical aspects of AI use. Bećirović et al. (2025b) also found positive relationships between AI practical application and both AI self-efficacy and the perceived quality of AI-supported outputs.

2.4 AI Critical Appraisal

AI critical appraisal describes the ability to critically evaluate AI systems and AI-generated outputs in terms of their reliability, accuracy, limitations, and appropriateness (Dong et al., 2025; Long & Magerko, 2020). This includes identifying potential errors, biases, and uncertainties and assessing whether AI-generated information is sufficiently reliable for a given context. Dong et al. (2025), for example, conceptualize critical appraisal in terms of questioning the reliability, accuracy, and limitations of AI-generated results and examining potential bias in the underlying data. This competence is particularly relevant in academic contexts, where AI-generated information requires critical evaluation rather than uncritical acceptance.

Critical appraisal is consistently represented as an evaluative component within multidimensional conceptualizations of AI literacy. In their systematic review, Almatrafi et al. (2024) identified "Evaluate" as one of six recurring AI literacy constructs. Laupichler et al. (2023) likewise identified Critical Appraisal as an empirically distinct dimension of AI literacy for non-experts alongside Technical Understanding and Practical Application. More recent measurement research retains critical appraisal as a separate dimension alongside technological understanding, practical application, and AI ethics (Dong et al., 2025). Taken together, these approaches position critical appraisal as the evaluative dimension of AI literacy, concerned with judging AI systems and their outputs rather than merely understanding how AI functions.

Empirical research further illustrates the distinct role of this dimension. Bećirović et al. (2025b) found that AI critical appraisal was negatively associated with AI self-efficacy and perceived output quality. More recently, Bećirović et al. (2026) found that critical appraisal significantly predicted AI ethics, whereas no significant effects were observed for AI-supported problem-solving or self-regulated learning. These findings further indicate that critical appraisal represents a distinct component of AI literacy whose relationships with other AI-related competences may vary across outcomes.

2.5 AI Ethics

In the context of AI literacy, AI ethics refers to the ability to recognize and reflect on ethical issues arising in the development, use, and evaluation of AI and to take them into account in decision-making (M. Stracke, Griffiths, et al., 2025). Key areas include fairness and inclusion, data protection and privacy, transparency, human-centredness, as well as responsibility and accountability (Ng et al., 2024; Wang et al., 2025; Yang et al., 2025). The model developed by Yang et al. distinguishes knowledge, attitudes, and competence in the field of AI ethics.

The ethical component is conceptualized differently across the literature. Ng et al. (2021a, 2021b, 2024) regard it as an integral component of AI literacy. Dong et al. (2025) likewise include AI ethics as a separate dimension of an AI literacy instrument alongside technical understanding, practical application, and critical appraisal. By contrast, Wang et al. (2025) treat AI ethical reflection as a related but conceptually distinct construct comprising ethical awareness, critical ethical evaluation, and orientation towards the social good of AI.

In higher education, AI ethics concerns the responsible use of AI, particularly with regard to privacy, fairness, transparency, academic integrity, and potential societal consequences (Memarian & Doleck, 2023; Ng et al., 2021b). Whereas AI critical appraisal primarily focuses on the factual reliability and appropriateness of AI-generated outputs, AI ethics extends the analysis to the normative evaluation of their use.

Technical understanding, practical application, critical appraisal, and AI ethics represent interconnected yet conceptually distinct areas. Together, they capture the knowledge-related, application-oriented, critical-reflective, and ethical prerequisites for the competent and responsible use of AI.

3. Methods

3.1 Participants

This quantitative study involved a sample of 254 Austrian university students from five different higher education institutions. Convenience sampling, which has benefits and drawbacks, was used to choose the participants. Convenience sampling is a non-random selection method that selects study participants based on their availability, proximity to the research site, and familiarity with the researcher (VanderStoep & Johnston, 2009). Convenience sampling has the benefit of being relatively easy to recruit participants, but like all non-random sampling techniques, it has the disadvantage of not being representative because those who are included may have different traits from the population to which the researcher hopes to generalize the findings (VanderStoep & Johnston, 2009). This constraint is mitigated in this study, nevertheless, by the fact that data were collected from students attending five different educational institutions in three different Austrian federal states. This allows for the generalization and application of findings to students enrolled in postsecondary education.

The educational level of the participants was classified into four groups: University entrance qualification (n = 95), Bachelor (n = 82), Master (n = 67), and Others (n = 10). Gender-wise, the study included more female students (N = 212; 83.5%) than male students (N = 42; 15.4%). The participants ranged in age from 18 to 60 (M = 34.6; SD = 11.3). They were divided into four groups: 18–24 years (n = 69), 25–34 years (n = 56), 35–44 years (n = 70), and 45–60 years (n = 59). This classification shows the wide range of ages among students in Austrian universities, where career transitions and ongoing education are common.

3.2 Instruments and procedures

The current study used a two-part online survey. The survey's first section on demographics (Table 1) included students' age, academic discipline, level of education, and gender. Each of the six variables in the second half of the questionnaire (Table 1) had four to fourteen items that were from studies that had undergone thorough validation. A seven-point Likert scale, with one denoting strong disagreement and seven denoting strong agreement, was used to evaluate each response. All variables demonstrated internal consistency, as indicated by Cronbach's alpha reliability values ranging from .839 to .964 (Table 1).

Table 1.
Data collection instruments

Variables included in the study	Items	Sources of the instruments
Technical Understanding (TU)	14	Laupichler et al. (2023)
Critical Appraisal (CA)	10	Laupichler et al. (2023)
Practical Application (PA)	7	Laupichler et al. (2023)
AI Ethics (ETH)	6	Carolus et al. (2023)

Students and educational administrators received detailed information and provided their explicit consent before data collection. The purpose of the study was clearly explained to each participant, along with instructions on completing the questionnaire. Respondents were told that participation was voluntary and that their confidentiality would be protected. Participants spent 15 to 20 minutes completing the online survey.

3.3 Data analysis

The data for this study were analyzed using SPSS (Statistical Package for the Social Sciences) version 29.0. To assess reliability, Cronbach's alpha was used. Normality was evaluated using skewness and kurtosis. Descriptive statistics, including frequencies, means, and standard deviations, were calculated. Pearson correlations were used to examine relationships among AI literacy dimensions. Hypotheses were tested using one-way ANOVA and independent-samples t-tests.

4. Results

4.1 Initial analysis

The descriptive statistics, Pearson correlation coefficients, and normalcy indices for each of the four AI literacy dimensions are shown in Table 2. Overall, AI Literacy had a mean score of 4.04 (SD = 1.24), indicating a moderate level of AI literacy among participants. Among the individual dimensions, AI Critical Appraisal demonstrated the highest mean (M = 4.64, SD = 1.54), followed by AI Practical Application (M = 4.49, SD = 1.47) and AI Ethics (M = 4.50, SD = 1.33). AI Technical Understanding exhibited the lowest average score (M = 2.52, SD = 1.48), suggesting that participants perceived their technical knowledge of AI to be less developed than their evaluative, practical, and ethical competencies. Assessment of univariate normality indicated that the variables were approximately normally distributed. Skewness values ranged from -.45 to 1.08, while kurtosis values ranged from -.82 to 0.36, all falling within commonly accepted thresholds for normality (i.e., ±2 for skewness and ±7 for kurtosis; Hair et al., 2022). Therefore, the data were considered suitable for subsequent parametric analyses. Pearson correlation analysis revealed that all AI literacy dimensions were positively and statistically significantly correlated with one another ($p < .001$). The strongest relationship among the dimensions was observed between AI Critical Appraisal and AI Practical Application (r = .797), indicating that participants with stronger abilities to critically evaluate AI-generated information also tended to report greater competence in applying AI tools in practical contexts. AI Technical Understanding showed moderate-to-strong positive associations with AI Critical Appraisal (r = .637), AI Practical Application (r = .644), and AI Ethics (r = .480). As expected, the overall AI Literacy score demonstrated very strong positive correlations with each of its constituent dimensions. The strongest association was observed with AI Critical Appraisal (r = .906), followed by AI Practical Application (r = .891), AI Technical Understanding (r = .818), and AI Ethics (r = .775). These findings provide strong evidence that the four dimensions represent closely related yet conceptually distinct aspects of AI literacy and collectively contribute to the overall construct. Our results show that while there is a significant relationship between the four AI literacy dimensions, the correlation coefficients stayed below the generally accepted threshold of.85, indicating sufficient discriminant validity among the variables.

4.2 Differences in AI Literacy Across Gender Groups

An independent-samples t-test was used to investigate gender differences in overall AI literacy and its four dimensions (Table 3). The results revealed a statistically significant difference in overall AI literacy, with male students (M = 4.59, SD = 1.18) reporting significantly higher levels of AI literacy than female students (M = 3.93, SD = 1.22), $t(252) = 3.24$, $p = .001$, $d = 0.55$. The effect size was moderate, indicating that male students perceived themselves as possessing higher overall AI literacy. The four domains of AI literacy were also examined for gender differences using an independent-samples t-test. While there was no statistically significant gender difference for AI Ethics, male students reported significantly higher levels of AI Technical Understanding, AI Critical Appraisal, and AI Practical Application than female students (Table 2). For AI Technical Understanding, male students (M = 3.38, SD = 1.65) demonstrated significantly higher

Table 2.
Descriptive Statistics, Normality Indices, and Pearson Correlations Among AI Literacy Dimensions

Variable	M	SD	Skew	Kurtosis	1	2	3	4	5
1. AI Technical Understanding	2.52	1.48	1.08	.36	—				
2. AI Critical Appraisal	4.64	1.54	-.29	-.82	.637***	—			
3. AI Practical Application	4.49	1.47	-.45	-.47	.644***	.797***	—		
4. AI Ethics	4.50	1.33	-.37	-.43	.480***	.622***	.569***	—	
5. Overall AI Literacy	4.04	1.24	.02	-.44	.818***	.906***	.891***	.775***	—

Note. M = mean; SD = standard deviation; ****p* < .001 (two-tailed).

Table 3.
Gender differences in AI literacy dimensions

Variable	Female *M* (*SD*)	Male *M* (*SD*)	*t*	*df*	*p*	Cohen's *d*
AI Technical Understanding	2.35 (1.39)	3.38 (1.65)	3.78	53.14	< .001	.72
AI Critical Appraisal	4.53 (1.55)	5.22 (1.32)	2.71	252	.007	.46
AI Practical Application	4.36 (1.47)	5.17 (1.28)	3.31	252	.001	.56
AI Ethics	4.48 (1.34)	4.61 (1.27)	.59	252	.559	.10
AI Literacy (Overall)	3.93 (1.22)	4.59 (1.18)	3.24	252	.001	.55

Note. *M* = mean; *SD* = standard deviation; *t* = independent-samples *t* test; *df* = degrees of freedom; *p* = probability value; *d* = Cohen's *d* (effect size).

levels of technical understanding of AI than female students (M = 2.35, SD = 1.39), t(53.14) = 3.78, p < .001, d = .72, representing a medium-to-large effect size. Similarly, male students (M = 5.22, SD = 1.32) scored significantly higher on AI Critical Appraisal than female students (M = 4.53, SD = 1.55), t(252) = 2.71, p = .007, d = .46, indicating a small-to-moderate effect size. For AI Practical Application, male students (M = 5.17, SD = 1.28) also obtained significantly higher scores than female students (M = 4.36, SD = 1.47), t(252) = 3.31, p = .001, d = .56, representing a moderate effect size. However, no statistically significant gender difference was found for AI Ethics, t(252) = .59, p = .559, d = .10. Male students reported slightly stronger AI ethical awareness than female students, although the difference was insignificant. The results suggest that male students possessed a higher level of competence in the practical application of AI, stronger AI critical evaluation skills, and a greater understanding of AI technical concepts. Nevertheless, the differences were not apparent in the areas of AI ethical awareness, indicating that female and male students share similar ethical considerations regarding AI usage.

4.3 Differences in AI Literacy Across Age Groups

To determine whether there were statistically significant differences in AI literacy among the four age groups of students: 18–24 years (n = 69), 25–34 years (n = 56), 35–44 years (n = 70), and 45–60 years (n = 59), a one-way analysis of variance (ANOVA) was used. As previously, the dependent variables included AI Technical Understanding, AI Critical Appraisal, AI Practical Application, and AI Ethics. The composite AI Literacy score showed no significant differences across the four age groups (F(3, 250) = 1.609, p =.188, η^2 =.019. Although individuals aged 25-34 years reported the highest average AI literacy (M = 4.29, SD = 1.21), and those aged 35-44 years reported the lowest (M = 3.81, SD = 1.32), these variations were not statistically significant. The effect size was minor, demonstrating that age explained approximately 1.9% of the variation in overall AI literacy. The results also indicated that there were no statistically significant differences among the age categories in any of the four individual AI literacy dimensions. For AI Technical Understanding, the ANOVA revealed no significant effect of age, F(3, 250) = 0.18, p = .913, η^2 = .002. Mean scores ranged from 2.45 (18–24 years) to 2.61 (25–34 years), indicating comparable levels of technical understanding across age groups. Similarly, no significant age differences were found for AI Critical Appraisal, F(3, 250) = 2.30, p = .078, η^2 = .027. Although participants aged 25–34 years reported the highest mean score (M = 4.99), the observed differences did not reach statistical significance. For AI Practical Application, the analysis also failed to identify significant differences among age groups, F(3, 250) = 1.81, p = .147, η^2 = .021. Participants aged 25–34 years again obtained the highest mean score (M = 4.82), whereas those aged 35–44 years reported the lowest mean (M = 4.24). However, these differences were not statistically significant. Likewise, AI Ethics did not significantly differ across age groups, F(3, 250) = 1.86, p = .138, η^2 = .022. Mean scores ranged from 4.21 to 4.75, suggesting relatively similar ethical awareness regardless of participants' age. In our sample, the results indicate that age was not a significant determinant of AI literacy. Despite the fact that participants aged 25–34 consistently exhibited slightly higher mean scores across several AI literacy dimensions, the observed differences were negligible and did not reach statistical significance (Table 4).

Table 4.
One-way ANOVA Examining Differences in AI Literacy Across Age Groups

Variable	18–24 M (SD)	25–34 M (SD)	35–44 M (SD)	45–60 M (SD)	F(3,250)	p	η²
AI Technical Understanding	2.45 (1.22)	2.61 (1.49)	2.47 (1.58)	2.58 (1.66)	0.18	.913	.002
AI Critical Appraisal	4.52 (1.35)	4.99 (1.60)	4.34 (1.55)	4.81 (1.60)	2.30	.078	.027
AI Practical Application	4.57 (1.34)	4.82 (1.39)	4.24 (1.53)	4.39 (1.59)	1.81	.147	.021
AI Ethics	4.56 (1.29)	4.75 (1.16)	4.21 (1.38)	4.55 (1.43)	1.86	.138	.022
Overall AI Literacy	4.02 (1.03)	4.29 (1.21)	3.81 (1.32)	4.08 (1.36)	1.61	.188	.019

Note. *p* = probability value; η^2 = eta squared.

4.4 Differences in AI Literacy Across Educational Levels

To determine whether there were any differences in the AI literacy of students based on their educational level (University entrance qualification, Bachelor, Master, and Others), a one-way analysis of variance (ANOVA) was carried out. The analysis demonstrated a statistically significant effect of educational level on overall AI literacy, $F(3, 250) = 2.92$, $p = .035$, $\eta^2 = .034$, indicating a small effect size. Descriptive statistics showed that Master's students obtained the highest overall AI literacy score ($M = 4.41$, $SD = 1.35$), followed by Bachelor's students ($M = 3.95$, $SD = 1.31$), participants with other educational qualifications ($M = 3.89$, $SD = 1.16$), and students with a University entrance qualification ($M = 3.87$, $SD = 1.04$). Bonferroni post hoc comparisons revealed that Master's students scored significantly higher than students with a University entrance qualification (mean difference = 0.55, $p = .034$). No other pairwise comparisons reached statistical significance after adjustment for multiple comparisons. These findings suggest that students enrolled in Master's programs demonstrate higher overall AI literacy than those entering higher education, whereas AI literacy levels among Bachelor's students and participants with other educational qualifications were no statistically different. Again, four individual dimensions of AI literacy were also analyzed: AI Technical Understanding, AI Critical Appraisal, AI Practical Application, and AI Ethics. The results suggested that two dimensions of AI literacy—AI Technical Understanding and AI Critical Appraisal—were significantly influenced by educational level. However, no significant differences were observed in AI Practical Application or AI Ethics. For AI Technical Understanding, a statistically significant difference was observed among the educational groups, $F(3, 250) = 4.22$, $p = .006$, $\eta^2 = .048$, indicating a small effect of educational level. Participants enrolled at the Master's level reported the highest level of AI Technical Understanding ($M = 3.05$, $SD = 1.80$), whereas those with a University entrance qualification reported the lowest scores ($M = 2.26$, $SD = 1.16$). Bonferroni post hoc comparisons showed that Master's students scored significantly higher than both students with a University entrance qualification (mean difference = 0.79, $p = .005$) and Bachelor's students (mean difference = 0.67, $p = .035$). No other pairwise comparisons reached statistical significance. Similarly, AI Critical Appraisal differed significantly across educational levels, $F(3, 250) = 3.57$, $p = .015$, $\eta^2 = .041$. Master's students again demonstrated the highest mean score ($M = 5.15$, $SD = 1.45$), followed by Bachelor students ($M = 4.56$), students with a University entrance qualification ($M = 4.38$), and the Others category ($M = 4.43$). Bonferroni post hoc analysis indicated that Master's students scored significantly higher than students with a University entrance qualification (mean difference = 0.77, $p = .010$), whereas all remaining pairwise comparisons were not statistically significant. In contrast, AI Practical Application did not significantly differ across educational levels, $F(3, 250) = 1.11$, $p = .347$, $\eta^2 = .013$. Although Master's students obtained the highest mean score ($M = 4.75$), the observed differences among the four educational groups were not statistically significant. Likewise, AI Ethics showed no statistically significant differences among educational levels, $F(3, 250) = 0.97$, $p = .409$, $\eta^2 = .011$. The observed mean scores were relatively consistent across all educational groups, indicating that students' educational attainment did not significantly influence their ethical awareness of artificial intelligence. These findings suggest that greater AI Technical Understanding and AI

Table 5.
One-Way ANOVA Comparing AI Literacy Across Educational Levels

AI Literacy Dimension	University Entrance Qualification M (SD)	Bachelor M (SD)	Master M (SD)	Others M (SD)	F(3,250)	p	η²
AI Technical Understanding	2.26 (1.16)	2.39 (1.49)	3.05 (1.80)	2.53 (1.04)	4.22	.006**	.048
AI Critical Appraisal	4.38 (1.39)	4.56 (1.67)	5.15 (1.45)	4.43 (1.70)	3.57	.015*	.041
AI Practical Application	4.33 (1.35)	4.48 (1.46)	4.75 (1.66)	4.39 (1.24)	1.11	.347	.013
AI Ethics	4.51 (1.29)	4.36 (1.37)	4.71 (1.32)	4.23 (1.47)	0.97	.409	.011
Overall AI Literacy	3.87 (1.04)	3.95 (1.31)	4.41 (1.35)	3.89 (1.16)	2.92	.035*	.034

Note. η^2 = eta squared. $p < .05$*, **$p < .01$.

Critical Appraisal are linked to higher educational attainment, particularly Master's-level education. Nevertheless, it does not seem that the educational level of students has significant effects on their AI Practical Application skills or their AI Ethics (Table 5).

5. Discussion

The aim of the present study was to assess students' AI literacy in a differentiated manner and to examine potential differences according to gender, age, and educational level. The following sections interpret the findings in relation to previous research and consider their theoretical and practical relevance for the higher education context.

5.1 Differences in AI Literacy by Gender

The results revealed significant gender differences in overall AI literacy as well as in its dimensions, namely AI technical understanding, AI critical appraisal, and AI practical application, with male students reporting higher scores in each case. The most pronounced difference was found in technical AI understanding. This pattern is particularly noteworthy because technical understanding was also the lowest-rated AI literacy dimension in the overall sample, suggesting that the observed gender difference was most pronounced in an area in which students generally reported comparatively limited competence. By contrast, no significant gender difference was identified for AI ethics. One possible explanation concerns gender differences in prior exposure to and use of AI as well as in self-perceived AI competence, which have also been reported in recent higher education research (Cachero et al., 2025; O'Dea et al., 2026). The finding of higher scores among male students is partly consistent with the study by O'Dea et al. (2026). In their investigation of generative AI literacy among university students in the United Kingdom and Hong Kong, gender was associated with several aspects of AI use and perceived competence. Male students more frequently reported knowing how to use AI for problem-solving and showed different patterns of AI use and intention to use AI in the future than female students. These findings suggest that differences in exposure to and engagement with AI may contribute to gender differences in self-reported AI literacy competences.

A particularly relevant comparison is provided by Cachero et al. (2025), who examined gender differences in university students' self-perceptions of AI. Female students reported significantly lower perceived AI knowledge and perceived ability to apply AI than male students. Given that the present study likewise relies on self-reported competence, this finding supports the possibility that the observed gender differences may reflect not only differences in AI-related experience but also gender-related differences in perceived competence.

However, the existing research does not present a consistent picture. In a transnational sample of 1,800 university students, Mansoor et al. (2024) found no significant gender difference in overall AI literacy; female students even achieved slightly higher, although non-significant, mean scores. The contrast with the present findings may partly reflect differences in sample composition, national contexts, and the operationalization of AI literacy. Importantly, Mansoor et al. (2024) primarily reported gender differences for an overall AI literacy score, whereas the present study additionally examined individual dimensions. This distinction may be relevant because the present results show that gender differences were not uniform across AI literacy dimensions, being strongest for technical understanding and absent for AI ethics.

The absence of a significant gender difference in AI ethics is broadly consistent with Wang et al. (2025), who found no significant differences either in the overall ethical reflection score or in the subdimensions of critical ethical evaluation and AI for social good. However, female students in their study reported higher ethical awareness than male students. This suggests that possible gender differences may depend on whether AI ethics is assessed as an overall construct or through individual subdimensions.

5.2 Differences in AI Literacy Across Age Groups

No statistically significant differences were found between the age groups in either overall AI literacy or any of the four dimensions examined. The corresponding effect sizes were small, suggesting that age explained only a small proportion of the variation in self-assessed competences within the present sample. Although the 25- to 34-year-old participants achieved the highest descriptive mean scores for overall AI literacy and for all four dimensions—AI technical understanding, AI critical appraisal, AI practical application, and AI ethics—these differences did not reach statistical significance and should therefore not be interpreted as a confirmed advantage of this age group.

This finding is consistent with the transnational study by Mansoor et al. (2024). In their sample of 1,800 university students from four countries, no significant age-related differences in AI literacy were identified. Whereas differences according to academic performance and field of study were observed, chronological age did not significantly differentiate AI literacy scores in their sample (Mansoor et al., 2024).

However, previous research does not provide a fully consistent picture of digital literacy (Bećirović, Dervic, et al., 2025; Yaman & Bećirović, 2016). Verduga-Alcívar et al. (2026) found significant differences according to age group and academic semester among 576 Ecuadorian university students. Their study, however, examined students attending or having attended statistics courses and employed a different four-dimensional conceptualization of AI literacy comprising affective, behavioral, cognitive, and ethical dimensions. These methodological and contextual differences, including the composition of the sample, the operationalization of AI literacy, and the formation of age groups, may partly account for the divergent findings. Taken together, the present findings suggest that chronological age alone may not be a sufficient indicator of students' AI literacy and that age-related differences may depend on the educational context and the way AI literacy is conceptualized and measured.

5.3 Differences in AI Literacy Across Educational Levels

The results revealed significant differences between educational level groups in overall AI literacy and in the dimensions of AI technical understanding and AI critical appraisal. Participants at the master's level achieved the highest mean scores in each of these areas. The post-hoc comparisons showed particularly higher scores for the master's group compared with participants holding a university entrance qualification; in technical AI understanding, the master's group also scored higher than the bachelor's group. By contrast, no significant differences were found for AI practical application or AI ethics.

The finding that AI literacy varies according to educational level is broadly consistent with previous research. In their transnational study of 1,800 university students, Mansoor et al. (2024) reported significant differences in AI literacy according to academic degree, although their study primarily assessed AI literacy at the overall level and was conducted across different national and disciplinary contexts. Similarly, Verduga-Alcívar et al. (2026) found significant differences in AI literacy according to academic semester among Ecuadorian university students, suggesting that AI-related competences may vary across stages of university education. However, this pattern is not consistent across studies. Butt et al. (2026), in a survey of 733 university students, found no significant differences in AI literacy according to program level, while significant differences emerged across academic disciplines. Taken together, these findings suggest that educational-level differences in AI literacy are context-dependent and may interact with other characteristics of students' academic experiences. One possible interpretation of the higher scores among master's-level participants in AI technical understanding and AI critical appraisal is that they reflect cumulative academic and AI-related learning experiences. The findings of Verduga-Alcívar et al. (2026), showing differences across academic semesters, are compatible with such an interpretation, although the cross-sectional designs of both studies do not permit conclusions about developmental or causal effects. Educational level itself may also not be the only factor underlying the differences (Dautbašić & Bećirović, 2022). Hornberger et al. (2023) found higher objectively assessed AI literacy among students with a technical study background and among those with prior formal or informal experience with AI. Thus, differences between educational-level groups may partly reflect disciplinary background and prior formal or informal exposure to AI rather than academic progression alone. The absence of significant educational-level differences in AI practical application and AI ethics further indicates that the relationship between educational progression and AI literacy was dimension-specific rather than uniform. AI-related learning and experience are not confined to progression through formal degree levels; prior formal and informal learning opportunities have also been associated with differences in students' AI literacy (Hornberger et al., 2023). With regard to AI ethics, higher education policy literature conceptualizes ethical and responsible AI use as a cross-cutting competence involving students, educators, administrators, and other stakeholders rather than as a responsibility tied to a particular stage of study (M. Stracke, Nahar, et al., 2025). Accordingly, the absence of educational-level differences in AI practical application and AI ethics should not be interpreted as evidence that these competences do not develop, but rather that they did not vary systematically according to formal educational level in the present sample. Across the three group comparisons, the findings illustrate that the dimensions of AI literacy do not vary uniformly according to demographic and educational characteristics. AI technical understanding emerged as a particularly salient dimension, as it was comparatively low in the overall competence profile and showed the most pronounced gender difference as well as significant differences across educational levels, while no age-related differences were observed. AI ethics, by contrast, did not differ significantly by gender, age, or educational level. At the same time, the positive correlations among all four dimensions indicate that technical, practical, critical, and ethical competences remain interconnected within a broader multidimensional AI literacy profile.

6. Conclusion

6.1. Summary of the results

The present study examined students' AI literacy as a multidimensional construct comprising AI Technical Understanding, AI Practical Application, AI Critical Appraisal, and AI Ethics. The results revealed an uneven self-reported competence profile. Overall, AI literacy was situated near the midpoint of the seven-point response scale. Among the four dimensions, AI Critical Appraisal showed the highest mean score, followed closely by AI Ethics and AI Practical Application, whereas AI Technical Understanding was markedly lower. All four dimensions were positively and significantly correlated. The strongest association was found between AI Critical Appraisal and AI Practical Application, indicating that students who rated themselves as more capable of evaluating AI-generated information also tended to report greater competence in applying AI tools. The pattern of correlations is consistent with viewing the four dimensions as related but distinguishable components of AI literacy.

The group comparisons showed that gender and educational level were associated with selected dimensions of AI literacy, whereas age was not. Male students reported significantly higher overall AI literacy and higher levels of AI Technical Understanding, AI Critical Appraisal, and AI Practical Application than female students. The largest gender difference occurred in AI Technical Understanding. No significant gender difference was found for AI Ethics.

No statistically significant differences emerged across the four age groups, either in overall AI literacy or in any of the individual dimensions. Although the mean scores varied descriptively, the differences were small and did not provide evidence of systematic age-related variation in the present sample.

Educational level was significantly associated with overall AI literacy, AI Technical Understanding, and AI Critical Appraisal. Master's-level students achieved the highest mean scores in these areas. Post-hoc comparisons showed that they scored significantly higher than students with a university entrance qualification in overall AI literacy, AI Technical Understanding, and AI Critical Appraisal; they also scored higher than bachelor's-level students in AI Technical Understanding. By contrast, no significant educational-level differences were identified for AI Practical Application or AI Ethics.

Taken together, the findings demonstrate the importance of examining AI literacy at the level of its individual dimensions rather than relying exclusively on an overall score. The comparatively low level of AI Technical Understanding would be less visible in an aggregate measure, as would the different patterns observed across gender and educational groups. AI Ethics, in contrast, showed no significant variation by gender, age, or educational level. By incorporating this ethical dimension alongside the three SNAIL dimensions, the study extends the differentiated empirical assessment of AI literacy in the Austrian higher education context.

6.2 Practical Implications and Theoretical Contributions

The findings suggest that the promotion of AI literacy in higher education should not be limited to the operation and practical use of current AI applications. In addition, students should be introduced to fundamental concepts and mechanisms of AI so that they can appropriately assess its possibilities, underlying conditions, and limitations. In this context, Hornberger et al. (2023) recommend broadly accessible educational opportunities that take students' different disciplinary backgrounds and prior knowledge into account. Similarly, to improve students' digital literacy, instructors must also have these skills (Bećirović, 2023b).

For higher education practice, the results further suggest that particular attention should be paid to ensuring equitable competence development in technical AI understanding, without interpreting the observed differences as fixed gender-specific characteristics. The study by Kong et al. (Kong et al., 2021) demonstrates that targeted educational interventions can reduce existing differences: following an AI literacy course, students of different genders and disciplinary backgrounds improved their understanding of AI concepts, while previously existing differences decreased.

As no significant differences were found between the age groups, it appears more appropriate in the higher education context to align support measures with students' specific prior knowledge and support needs rather than assuming different competence levels solely on the basis of age.

The differences according to educational level also suggest that students in earlier stages of their education should receive targeted support in developing technical understanding and critical appraisal. Studies of dedicated AI literacy courses indicate that structured educational programmes can promote conceptual understanding of AI among students from different disciplinary backgrounds (Kong et al., 2021, 2022).

The findings regarding AI ethics further support the promotion of this dimension as a fundamental component of AI literacy for all groups of students. As no single group achieved a markedly higher or lower score, corresponding educational initiatives should not be directed exclusively at particular age, gender, or educational groups. Instead, the curricular integration of ethical issues appears appropriate in order to enable students from all disciplines to evaluate specific AI applications in terms of fairness, data protection, transparency, and societal responsibility.

6.3 Study limitations and suggestions for future research

The findings should be interpreted in light of several limitations. As the four dimensions were assessed through self-reports, they reflect perceived competences; future studies could complement these measures with objective knowledge tests or performance-based tasks. The cross-sectional design does not permit conclusions about developmental trajectories or causality. In addition, the "Others" group consisted of only ten participants, and its mean scores should therefore be interpreted with caution. Future research should include larger and more balanced subgroups and should take into account frequency of use, field of study, as well as learning and application experiences.

Author contributions

Senad Bećirović conceived the idea, designed the study, prepared the questionnaire, collected data, wrote the methodology, handled software, performed data analysis, wrote the results, and reviewed and edited the entire manuscript. **Jennifer Beck-Saiz** wrote the abstract, introduction, literature review, discussion, and conclusion, and reviewed. Both authors read and approved the final manuscript.

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