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Article

Knowing Is Not Enough: Perceived Generative AI Literacy, Support Needs, and Critical Engagement Among Higher Education Students

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Abstract

Generative artificial intelligence (GenAI) tools are increasingly used in higher education, yet the relationship between students' self-assessed competence and their actual learning practices, support needs, and critical engagement remains underexplored. This quantitative survey study examined perceived GenAI literacy, learning-related use patterns, self-identified knowledge gaps, and responsible-use orientations among 449 students from four Slovenian faculties of education and arts. Results showed that perceived GenAI literacy was positively associated with the frequency, breadth, and diversity of learning-related GenAI use, though correlations were modest. Students at all literacy levels reported substantial support needs, particularly regarding responsible use. While lower-literacy students reported greater support needs descriptively, the adjusted logistic model indicated that higher perceived literacy was associated with greater odds of identifying a need for additional basic GenAI knowledge, suggesting a possible awareness-of-limits effect. Contrary to expectations, perceived literacy did not predict a critical and responsible orientation toward GenAI; instead, age was the stronger predictor. Perceived institutional support contributed little explanatory power across models. Overall, the findings indicate that self-assessed GenAI literacy facilitates broader tool adoption but does not automatically lead to ethically reflective use. The study underscores the need for structured, pedagogically embedded AI literacy initiatives that explicitly address critical and responsible engagement, rather than relying on tool exposure alone, and highlights the importance of distinguishing perceived competence from critical GenAI competence in future research.

Keywords: GenAI literacy; higher education; responsible AI use; student support needs; critical AI engagement

1. Introduction

Generative artificial intelligence (GenAI) tools, such as ChatGPT, DALL-E, and Midjourney, have rapidly entered educational practice and renewed attention to how students understand, evaluate, and use AI in learning contexts. In this context, GenAI literacy can be considered a more specific extension of broader AI literacy. Ng et al. (2021) conceptualized AI literacy as a multidimensional construct that includes knowing and understanding AI, using and applying AI, evaluating and creating with AI, and addressing ethical issues. This broader conceptualization is useful because it frames students' GenAI use not merely as a matter of access or frequency, but as a competence-based phenomenon shaped by understanding, judgment, and ethical awareness. At the same time, systematic review evidence indicates that ChatGPT is widely perceived as useful for personalized support, writing assistance, and teaching preparation, while also raising concerns about superficial outputs, bias, fabricated information, and overreliance (Mai et al., 2024). Together, these findings support the assumption that self-assessed GenAI literacy is likely to influence how confidently and extensively students use GenAI tools, although such confidence may not always correspond to critical or well-calibrated use (Campillo-Ferrer et al., 2025; Mai et al., 2024).

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Research grounded in technology acceptance provides a direct bridge to RQ1. Börekci and Çelik (2024) found that students with higher digital literacy perceived AI tools as more useful and easier to use, and that these perceptions positively influenced their behavioral intentions toward adoption. Similarly, Strzelecki (2024) showed that higher education students' acceptance and use of ChatGPT can be explained by perceived usefulness and related acceptance variables. Chan and Hu (2023) also reported that students perceive clear benefits in using generative AI in higher education, while identifying various challenges and reservations regarding its role in study practices. The study by Campillo-Ferrer et al. (2025) is relevant here because it directly examines student perceptions of GenAI use in a higher education program, reinforcing the inclusion of a perception- and confidence-related dimension in the model. Framed through Biggs's 3P model, these studies justify RQ1: whether self-assessed GenAI literacy, as a presage factor, predicts both the frequency of GenAI use and the learning-oriented modes through which students engage with these tools across educational levels.

GenAI-related knowledge gaps remain central to equitable and educationally meaningful adoption. Ng et al. (2021) already show in their conceptual review that AI literacy cannot be reduced to technical operation alone, as evaluation and ethical issues are integral to the construct. This is echoed in the ChatGPT literature synthesized by Mai et al. (2024), which identifies recurring weaknesses such as inaccuracy, hallucinated or fabricated references, and context-insensitive responses, as well as major threats including plagiarism, academic dishonesty, and uncritical dependency. Chan's (2023) AI policy education framework further supports this argument by emphasizing that higher education institutions need structured guidance for teaching and learning with AI, rather than leaving students to navigate these tools informally. Related systematic reviews also converge on the point that ethical use, pedagogical integration, and critical evaluation remain persistent challenges in educational applications of GenAI (Ogunleye et al., 2024). This leads directly to RQ2: which GenAI knowledge domains are most deficient, and how do these deficiencies vary across educational levels and learner groups?

The literature supports the shift from simple use to responsible and critical use in RQ3. Kasneci et al. (2023) explicitly described large language models in education as offering significant opportunities alongside serious challenges, arguing that productive use depends on learners' ability to evaluate outputs, recognize limitations, and use the tools responsibly. Mai et al. (2024) similarly found that ChatGPT can support idea generation, writing, and personalization, but these benefits diminish when learners rely on it uncritically or use it in ways that undermine independent thinking and academic integrity. Chan and Hu's (2023) analysis of students' perspectives complements this by showing that students themselves already articulate both benefits and risks, suggesting that responsible use is not a peripheral concern but part of everyday student meaning-making around GenAI. Together, these studies support RQ3 as a test of whether self-assessed GenAI literacy and specific GenAI-related knowledge gaps predict responsible, critical, and academically appropriate use, rather than mere frequency of use.

Perceived instructional and institutional support is also likely to influence students' GenAI literacy and actual use, making it an important fourth research focus. The literature suggests that students do not learn to use GenAI in isolation, but within classroom and institutional contexts that can normalize, guide, or constrain their engagement with these tools. Chan and Hu (2023) showed that students' views of GenAI include not only perceived benefits and risks, but also expectations about how teachers and institutions should respond, indicating that support structures are important for shaping confidence and practice. Similarly, Chan's (2023) policy-oriented framework argues that effective GenAI integration in higher education requires explicit institutional guidance, pedagogical support, and clear rules for use, rather than informal individual experimentation. Related reviews also highlight the importance of institutional policies, teacher competence, and structured support in enabling responsible educational use of GenAI and reducing uncertainty, inequity, and misuse (Nguyen et al., 2024; Ogunleye et al., 2024; Wu et al., 2025). On this basis, RQ4 extends the model by asking whether perceived instructional and institutional support is associated with students'

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perceived GenAI literacy and their learning-related use of GenAI, thereby capturing the contextual conditions under which competence and use are more likely to develop.

1.1. Aim of the Study

This study examines how higher education students' perceived GenAI literacy relates to their self-reported use of GenAI for learning, the areas where they perceive a need for further knowledge and skill development, and their perceptions of instructional and institutional support for GenAI use. The study addresses the growing need for research that goes beyond general attitudes and adoption measures to examine how perceived competence, support needs, and educational context shape students' learning-related engagement with GenAI in higher education (Chan, 2023; Ogunleye et al., 2024; Wu et al., 2025). By analyzing these relationships, the study aims to identify priority areas for GenAI literacy development and inform more responsible and pedagogically meaningful integration of GenAI into higher education (Chan, 2023; Tlili et al., 2023; Wu et al., 2025).

Accordingly, the study is guided by the following research questions:

- **RQ1.** How is perceived GenAI literacy related to students' self-reported frequency, breadth, and learning-related purposes of GenAI use in higher education?
- **RQ2.** Which areas of GenAI-related knowledge and skills do higher education students identify as requiring further support?
- **RQ3.** To what extent do perceived GenAI literacy and identified support needs predict students' critical and responsible orientation toward GenAI use?
- **RQ4.** How are perceived instructional and institutional support, perceived GenAI literacy, and critical and responsible orientation associated with students' learning-related use of GenAI?

2. Materials and Methods

Research Design

This study uses a quantitative survey design. This approach is appropriate because the instrument captures multiple dimensions of higher education students' experiences with GenAI at a single point in time, including self-assessed knowledge, self-reported use patterns, perceived knowledge gaps, and attitudes toward responsible and educational use. This design aligns with the current literature, where much research has focused on mapping patterns of adoption, perceptions, opportunities, and concerns related to GenAI in education through cross-sectional evidence (Nzenwata et al., 2024; Ogunleye et al., 2024; Wu et al., 2025). Although the present design collects data at one specific moment, the instrument's structure also allows for future replication across multiple waves.

2.1. Participants

The study included 449 participants. Ages ranged from 18 to 48 years (M = 21.60, SD = 3.69). The sample was predominantly female, with 408 women (90.9%), 38 men (8.5%), two individuals who preferred not to disclose their gender (0.4%), and one who identified as other (0.2%). Most students were enrolled in first-cycle academic bachelor's programs (n = 301, 67.0%), followed by second-cycle master's programs (n = 73, 16.3%) and professionally oriented bachelor's programs (n = 64, 14.3%). A small proportion were enrolled in doctoral programs (n = 10, 2.2%). The largest group of students was in their first year (45.7%), followed by third year (28.1%) and second year (18.3%). Students in higher years (fourth, fifth, and sixth) collectively accounted for less than 5% of the sample, while 4.5% held extended student status. Most participants (96.4%) did not have registered special needs status, 3.3% had this status, and one participant (0.2%) was in the process of obtaining it. The sample included students from four faculties: the Faculty of Education at the University of Maribor, the Faculty of Education at the University of Ljubljana, the Faculty of Education at the University of Primorska, and the Faculty of Arts at the University of Ljubljana. Because the sample was drawn

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from education and humanities-related faculties, this institutional composition may partly explain the predominance of female participants.

2.2. Measures

Data for this study were collected using a structured self-report survey. For this analysis, the dataset was limited to students enrolled in higher education institutions. The instrument addressed several dimensions of generative AI (GenAI) use in educational contexts, including perceived literacy, usage patterns, support needs, ethical awareness, and perceived instructional support. Where appropriate, composite scores for multi-item constructs were calculated by averaging item responses, while checklist-type variables were treated as binary indicators or summed counts, depending on the analysis purpose.

2.2.1. Perceived GenAI Literacy

Perceived GenAI literacy was measured with a self-assessment item aligned with RQ1, RQ3, and RQ4. This item asked students how well they know generative AI that can create different types of content, such as text, images, audio, and video. Responses were recorded on a 5-point ordinal scale ranging from no knowledge or very low familiarity to very good knowledge.

2.2.2. GenAI Use Patterns

Self-reported GenAI use for learning (RQ1) was assessed across three facets: frequency, breadth, and specific educational purposes.

- **Frequency of use** was measured with a single item asking how often students use GenAI for learning at home or in school, rated on an ordinal scale (e.g., 1 = Never, 5 = Daily).
- **Breadth of use** was captured with items that asked whether students use GenAI to generate different types of media, including text, images, audio, and video.
- **Learning-related purposes** were assessed using a multiple-response set of questions. Students indicated specific educational tasks for which they utilize GenAI, such as preparing for exams, drafting presentations, seeking additional explanations for difficult concepts, brainstorming ideas, and translating texts.

2.2.3. Perceived Support Needs

Perceived support needs were assessed with a checklist item that asked students which areas of GenAI-related knowledge they still needed or would like further support in, corresponding to RQ2 and RQ3. The options reflected both functional and critical dimensions of GenAI literacy and included knowing how to use GenAI in general, how to use it for learning, how to use it responsibly in general, how to use it responsibly for learning, and how GenAI works. Responses were coded dichotomously as selected or not selected, and a sum score was calculated to represent the overall breadth of perceived support needs. Higher scores indicate that students identified a greater number of areas in which they require additional guidance or training.

2.2.4. Perceived GenAI Benefits for Learning

Perceived GenAI benefits for learning were measured with six items assessing whether GenAI improves students' learning outcomes, productivity, creativity, speed of completing learning tasks, available free time, and knowledge gain. Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A composite score was calculated by averaging the six items, with higher scores indicating stronger perceived learning-related benefits of GenAI (Cronbach's alpha = .845).

2.2.5. Perceived GenAI Ease of Use

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Perceived GenAI ease of use was measured with five items assessing whether learning with GenAI is easier, requires little mental effort, enables students to achieve their goals easily, provides convenient access to needed learning content, and is generally easy to use. Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A composite score was calculated by averaging the five items, with higher scores indicating greater perceived ease of use (Cronbach's alpha = .728).

2.2.6. Critical and Responsible Orientation

Critical and responsible orientation toward GenAI was measured using items that assessed the perceived importance of ethical issues related to GenAI use in education, consistent with RQ3. Students rated the importance of issues such as plagiarism, intellectual property, bias and unfairness, data privacy, false or fabricated information, anthropomorphizing AI tools, environmental impact, broader social consequences, and dependence on GenAI. The questionnaire included brief examples to clarify each item's meaning; for example, plagiarism was illustrated as submitting an assignment fully written by GenAI, privacy as the possible misuse of personal data, and false information as situations in which GenAI invents or alters information. All items were rated on a 4-point scale from 1 (not important) to 4 (very important). A mean composite score was calculated, with higher values indicating a stronger critical and responsible orientation toward GenAI use in education (Cronbach's alpha = .834).

2.2.7. Perceived Educational Support for GenAI Use

Perceived support from the educational environment was measured using a six-item scale related to RQ4. The items assessed students' perceptions of whether teachers allow GenAI use in class, encourage its use for learning, recognize its potential benefits, value students' efforts when using it, provide appropriate technical support, and help students use GenAI for learning. Responses were recorded on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). A composite score was calculated by averaging the items, with higher scores indicating a more supportive instructional and institutional climate for GenAI use (Cronbach's alpha = .817).

2.3. Data Analysis

Descriptive statistics were first calculated for the main items and composite variables to summarize students' perceived GenAI literacy, learning-related GenAI use, perceived support needs, critical and responsible orientation, and perceived instructional and institutional support. Multi-item measures were then evaluated for internal consistency and, where applicable, for dimensional structure before calculating composite scores. RQ1 was examined using correlational and regression analyses to test whether perceived GenAI literacy was associated with the frequency, breadth, and purposes of GenAI use. For RQ2, group comparisons and domain-level analyses were conducted to identify differences in perceived knowledge gaps and to determine which areas students most frequently identified as requiring further support. RQ3 was addressed through regression models estimating whether perceived GenAI literacy and support needs were associated with students' self-reported responsibility and critical use of GenAI for learning. For RQ4, a composite indicator of learning-related GenAI use was created from three components: frequency of GenAI use for learning, breadth of use across media types, and the number of learning-related purposes for which GenAI was used. Because these components were measured on different scales, each component was standardized within the higher-education subsample and then combined into a single index using equal weights. Higher scores indicate more frequent, broader, and more diverse learning-related use of GenAI. Only cases with valid data on all component indicators were included in the model.

2.4. Ethical Considerations

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The study complied with the ethical principles of the Declaration of Helsinki for research involving human participants and was approved by the Institutional Ethics Committee of the University of Maribor (038-30-196/2024/42/FF/UM, 28 November 2024). Participation was voluntary, with the option to withdraw at any time without negative consequences. All participants received written information about the purpose, procedures, and use of the data before providing informed consent. No personally identifying information was collected; responses were treated as confidential, stored securely, and reported only in aggregated form.

2.5. Data Availability

The data supporting the findings of this study will be available after the project ends, following an embargo period.

2.6. Use of Generative AI

During the preparation of this manuscript, the authors used generative AI tools to assist with translation and language editing. All AI-assisted content was reviewed, verified, and revised by the authors, who take full responsibility for the accuracy and integrity of the published work.

3. Results

3.1. Associations Between Perceived GenAI Literacy and Learning-Related GenAI Use (RQ1)

Table 1 shows the Spearman correlations between perceived GenAI literacy and three indicators of learning-related GenAI use. Perceived GenAI literacy was positively associated with all three indicators: frequency of use for learning, breadth of use, and the number of learning-related purposes for which GenAI was used. The correlations were small to moderate in size: perceived GenAI literacy was associated with frequency of GenAI use for learning ($rs = .305$, $p < .001$), breadth of use ($rs = .411$, $p < .001$), and learning-related purposes of use ($rs = .327$, $p < .001$). The strongest association in the matrix was between frequency of use for learning and breadth of use ($rs = .527$, $p < .001$), while learning-related purposes of use was also positively related to both frequency ($rs = .481$, $p < .001$) and breadth ($rs = .406$, $p < .001$). Overall, the results suggest that students with higher perceived GenAI literacy tended to report more frequent, broader, and more varied learning-related use of GenAI tools.

Table 1. Spearman Correlations among Perceived GenAI Literacy and Learning-Related GenAI Use Variables.

Variable	1	2	3	4
1. Perceived GenAI literacy	—			
2. Frequency of GenAI use for learning	.305***	—		
3. Breadth of GenAI use	.411***	.527***	—	
4. Learning-related purposes of GenAI use	.327***	.481***	.406***	—

Note. Values are Spearman's rho coefficients. Pairwise sample sizes varied across coefficients, ranging from 194 to 401. *** $p < .001$.

3.2. Perceived Support Needs (RQ2)

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Table 2 shows the proportions of respondents reporting various GenAI-related support needs, comparing students with low and higher perceived GenAI literacy. Overall, students with lower perceived GenAI literacy reported greater support needs across all domains. The differences were statistically significant for general use, use for learning, and responsible use for learning, while the difference for understanding how GenAI works was not significant. The greatest support need was for learning how to use GenAI responsibly, especially among students with lower perceived literacy, whereas the smallest difference between groups was for understanding how GenAI works. Although the pattern is consistent, the effect sizes were small, indicating that perceived literacy is only modestly related to support needs.

Table 2. Identified Areas of GenAI Support Needs by Level of Perceived GenAI Literacy.

GenAI-related support need	Low literacy n (%)	Higher literacy n (%)	χ^2	*p*	Cramer's V
How to use GenAI in general	72.3%	59.4%	7.60	.006	0.130
How to use GenAI for learning	74.7%	60.4%	9.46	.002	0.145
How to use GenAI responsibly in general	80.7%	75.3%	1.78	.183	0.063
How to use GenAI responsibly for learning	70.5%	59.7%	5.24	.022	0.108
How GenAI works	61.4%	53.4%	2.78	.095	0.079

Note. Perceived GenAI literacy was recoded into two groups for the cross-tabulation: "Low literacy" includes original responses 1 (not familiar) and 2 (poor), while "Higher literacy" includes original responses 3 (moderately familiar), 4 (good), and 5 (very good). .

Table 3 presents the results of a binomial logistic regression examining students' likelihood of reporting a need for additional knowledge about how to use GenAI in general. The model included perceived GenAI literacy, perceived institutional support, GenAI use for learning, perceived benefits of GenAI for learning, perceived ease of use, age, and study level as predictors. Overall model fit was modest (R^2_{McF} = .084), suggesting that the model explained only a limited part of the variation in the outcome. Perceived GenAI literacy emerged as a significant positive predictor, indicating that students with higher self-rated literacy were more likely to report a need for additional basic knowledge about GenAI use. Perceived benefits of GenAI for learning were also significant, but with a negative coefficient, showing that students who viewed GenAI more positively in educational terms were less likely to report such a need. The remaining predictors, including age, study level, perceived institutional support, GenAI use for learning, and perceived ease of use, were not statistically significant

Table 3. Predictors of Students' Perceived Need for Support in How to Use GenAI in General.

Predictor	B	SE	p	OR	95% CI for OR
Intercept	-3.91	1.33	.003	—	—
Age	0.08	0.04	.057	1.09	[1.00, 1.18]

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Study level: 1st-cycle university / higher professional	-0.11	0.31	.722	0.89	[0.48, 1.64]
Study level: 2nd-cycle university / higher professional	-0.11	0.42	.789	0.89	[0.38, 2.00]
Study level: doctoral / higher professional	-1.09	0.95	.252	0.34	[0.05, 2.61]
Perceived GenAI literacy	1.01	0.19	< .001	2.75	[1.88, 4.03]
Perceived institutional support	-0.04	0.16	.792	0.96	[0.69, 1.33]
GenAI use for learning (yes vs no)	0.31	0.28	.270	1.37	[0.78, 2.39]
Perceived GenAI benefits for learning	-0.57	0.18	.001	0.56	[0.39, 0.79]
Perceived GenAI ease of use	0.25	0.19	.202	1.29	[0.88, 1.89]

Note. Model fit: Deviance = 474, AIC = 494, R^2_{McF} = .0844, N = 395.

3.3. Predictors of Responsible and Critical Orientation Toward GenAI (RQ3)

Table 4 presents the multiple regression model predicting students' critical and responsible orientation toward GenAI use. The model was statistically significant overall but explained only a small proportion of the variance in the outcome. Among the predictors, age and gender were the only variables that showed significant unique associations with critical and responsible orientation. Older students tended to report a somewhat stronger critical and responsible orientation toward GenAI use, while male students scored slightly lower than female students after accounting for the other variables in the model. In contrast, perceived GenAI literacy and support needs were not statistically significant predictors in the final model.

Table 4. Multiple Regression Predicting Critical and Responsible Orientation Toward GenAI Use.

Predictor	B	SE	β	t	p
Intercept	2.829	0.182	—	15.57	< .001
Perceived GenAI literacy	-0.048	0.028	-0.081	-1.70	.090
Support needs	0.029	0.015	0.091	1.91	.056
Gender	-0.145	0.070	-0.098	-2.07	.040
Age	0.018	0.006	0.133	2.85	.005

Note. Dependent variable = critical and responsible orientation toward GenAI use. *B* = unstandardized coefficient, *SE* = standard error, *β* = standardized coefficient. Model summary: adjusted R^2=.036, $F(4, 443) = 5.22$, $p < .001$. Gender coded 0 = female, 1 = male.

3.4. Predictors in the Reported Model for Instructional and Institutional Support Context (RQ4)

Table 5 presents the linear regression results for RQ4, examining instructional and institutional support, perceived GenAI literacy, and critical and responsible orientation as predictors of learning-

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related GenAI use. The model was statistically significant and explained a modest portion of the variance in the outcome. Perceived GenAI literacy was the only significant predictor, indicating that students who considered themselves more knowledgeable and competent in using GenAI also reported greater learning-related use of these tools. In contrast, perceived instructional and institutional support, as well as critical and responsible orientation, were not independently associated with learning-related use after accounting for the other predictors. This suggests that perceived competence is more closely related to students' learning-related use of GenAI than the broader support climate in this sample.

Table 5. Multiple Regression Predicting Learning-Related Use of GenAI.

Predictor	B	SE	β	t	p
Intercept	0.640	1.435	—	0.446	.656
Instructional and institutional support	0.115	0.235	0.034	0.492	.623
Perceived GenAI literacy	1.262	0.241	0.358	5.236	< .001
Critical and responsible orientation	0.146	0.352	0.029	0.414	.679

Note. Dependent variable: »Learning-related GenAI use«. Dependent variable is a standardized composite of frequency, breadth, and purposes of learning-related GenAI use. Model summary: R = .355, R^2 = .126, AdjR^2 = .112, $F(3, 192) = 9.20$, $p < .001$.

4. Discussion

The study shows that perceived GenAI literacy is positively related to how frequently and broadly students use GenAI for learning, but these relationships are modest and do not directly translate into a stronger critical-responsible orientation. At the same time, students across literacy levels express substantial support needs, especially regarding responsible use, and the regression models explain only a small share of the variance, suggesting that GenAI use and literacy are influenced by a wider set of contextual and personal factors. This pattern is important because it suggests that perceived competence may be sufficient for use, but not for ethical reflection or institutional alignment.

4.1. Perceived Literacy and Learning-Related GenAI Use

Perceived GenAI literacy was positively associated with the frequency of GenAI use for learning, the breadth of use across modalities, and the number of learning-related purposes, with small to moderate correlations. This pattern supports the idea that feeling more knowledgeable and competent with GenAI is linked to incorporating these tools more often and in more varied ways into study routines, such as exam preparation, drafting presentations, or seeking explanations of difficult concepts. These findings are consistent with recent survey and review work showing that students with higher AI or GenAI literacy tend to integrate such tools more deeply into their academic work, both in the UK and Hong Kong (O'Dea et al., 2026), and across a broader set of empirical GenAI-in-education studies (Zhang et al., 2024). At the same time, the modest effect sizes and the limited variance explained by the regression models indicate that perceived literacy is only one component of a more complex ecology that includes institutional policies, disciplinary norms, and students' motivation and trust in AI tools (Deng et al., 2025; Ogunleye et al., 2024).

4.2. Support Needs and the Paradox of Literate Users

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Students with lower perceived GenAI literacy reported higher support needs across domains, especially regarding how to use GenAI for learning and how to use it responsibly. This is an expected and encouraging pattern, as it suggests that students who feel less competent are aware of their limitations and actively signal a need for help in both functional and ethical areas. However, the logistic regression analysis adds an interesting twist: once other variables were controlled, higher perceived GenAI literacy actually increased the odds of reporting a need for additional knowledge about how to use GenAI in general, while students who perceived GenAI as more beneficial for learning were less likely to report such needs. This "awareness of ignorance" among more literate users echoes findings from generative AI literacy research showing that prior exposure and training can sharpen students' sense of what competent, safe use actually entails, and thus reveal more nuanced support needs (O'Dea et al., 2026). It also aligns with systematic reviews that emphasize unresolved questions about what constitutes sufficient GenAI literacy for students and call for multidimensional frameworks that connect functional skills, ethical judgment, and contextual understanding (Ogunleye et al., 2024; Zhang et al., 2024).

4.3. Critical and Responsible Orientation: More than a Function of Literacy

Contrary to expectations that higher GenAI literacy would directly lead to more responsible and critical orientations, the regression model for RQ3 showed that neither perceived literacy nor support needs made a meaningful contribution once demographic factors were included. Instead, older students reported a somewhat stronger critical-responsible orientation, and gender also showed a statistically significant but small effect, although the modest R^2 indicates that the overall predictive power of the model is low and the gender effect should be interpreted with caution. This pattern aligns with broader concerns in the literature that functional or self-assessed literacy alone does not ensure ethically reflective use of GenAI tools (Kasneci et al., 2023; Zhang & Tur, 2024). Reviews of empirical GenAI applications in education similarly highlight that students can be frequent and apparently skilled users while still overlooking issues such as bias, hallucinations, and academic integrity, particularly in short-term interventions that boost performance without necessarily deepening critical awareness (Deng et al., 2025; Zhang et al., 2024). Taken together, these findings underscore the need to treat critical and responsible orientation as a partly distinct educational outcome that requires explicit pedagogical attention, rather than assuming it will emerge automatically from increased usage or confidence.

4.4. Instructional and Institutional Context

The regression model for RQ4, which included instructional and institutional support, perceived GenAI literacy, and critical and responsible orientation as predictors, explained a small but statistically significant portion of variance in the outcome variable, with perceived GenAI literacy as the only significant predictor. Perceived instructional and institutional support, as well as critical-responsible orientation, did not add substantial explanatory power once literacy was included, suggesting that students' self-assessed competence is more closely linked to the focal outcome than their perceptions of the support climate. This finding should be interpreted cautiously, given the modest R^2 and the single-country, four-faculty context, but it aligns with recent reviews that describe institutional responses to GenAI in higher education as fragmented and often lagging behind students' own experimentation (Ogunleye et al., 2024). Systematic analyses of GenAI integration across higher education emphasize that policy signals and teaching guidelines remain inconsistent, which may explain why students' perceptions of institutional support are not yet a strong driver of their actual GenAI-related behaviors or literacy. From a practical perspective, this suggests that simply issuing policy documents or generic warnings is unlikely to be sufficient; support structures need to be visible, concrete, and closely tied to students' day-to-day learning practices to meaningfully shape behavior.

4.5. Implications for AI Literacy Development in Higher Education

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Across the research questions, the results indicate a clear need for AI literacy initiatives that integrate practical skill development with explicit attention to the critical and ethical dimensions of GenAI use. Students who feel less literate understandably request basic guidance, while more literate students express additional support needs that reflect a growing awareness of GenAI's complexity. Both groups, however, identify responsible use as a key area where they need help. Designing AI literacy curricula that scaffold this progression – from basic operational competence to reflective, context-sensitive use – would align well with emerging frameworks that treat GenAI literacy as a multi-layered construct encompassing knowledge, skills, and attitudes (O'Dea et al., 2026; Zhang et al., 2024). Given the modest effect sizes and the stronger influence of age on critical-responsible orientation, universities may need to adopt differentiated strategies for different student groups. For first-cycle students, embedding GenAI-related activities into core courses and explicitly modeling processes such as verifying outputs, citing AI use, and negotiating assessment rules may be especially important. For older or more advanced students, greater emphasis could be placed on designing discipline-specific GenAI workflows and engaging them in co-creating guidelines, which recent reviews identify as a promising approach for making AI policies meaningful in practice (Kasneci et al., 2023; Ogunleye et al., 2024).

4.6. Limitations and Directions for Future Research

Several limitations must be acknowledged when interpreting these findings. First, the cross-sectional, self-report design precludes causal conclusions and may be affected by social desirability or recall biases in students' reports of GenAI use and literacy. This limitation is common in the emerging GenAI literature and has been repeatedly noted in systematic reviews, which call for more longitudinal and experimental designs to capture how GenAI-related competencies and practices evolve over time (Deng et al., 2025; Zhang et al., 2024). Second, the sample comes from four faculties in Slovenia and is heavily skewed toward female students, which limits the generalizability of the demographic patterns and may inflate or mask gender differences in critical-responsible orientation. Third, the constructs of perceived GenAI literacy, support needs, and critical-responsible orientation were measured with relatively brief scales; although internal consistency was acceptable, future work should further validate these measures and, where possible, triangulate them with behavioral indicators such as actual GenAI use logs or performance in AI-supported tasks. Finally, the modest variance explained in all regression models underscores that important determinants of GenAI use and literacy, such as disciplinary culture, prior AI training, or macro-level policy environments, remain to be integrated more systematically into empirical models (O'Dea et al., 2026; Zhang et al., 2024).

Despite these limitations, the study contributes to a growing body of work mapping how higher education students perceive their GenAI literacy, what kinds of support they need, and how these perceptions relate to responsible use. It reinforces recent claims that GenAI literacy should be treated as a central learning outcome in higher education (Kasneci et al., 2023; Zhang et al., 2024) and points to concrete leverage points, especially targeted support for responsible use and clearer institutional signaling, through which universities can move beyond ad hoc reactions to more thoughtful integration of GenAI into teaching and learning.

5. Conclusions

This study found that perceived GenAI literacy is linked to broader and more varied learning-related use of GenAI, but this association is modest and does not automatically extend to a critical and responsible orientation. Students at all literacy levels reported significant support needs, especially regarding responsible use. The finding that higher perceived literacy sometimes coincided with greater awareness of knowledge gaps suggests that competence and uncertainty can develop together. The results also show that age, rather than perceived literacy, was a stronger predictor of a critical-responsible orientation, while perceived instructional and institutional support added little explanatory power in the tested models. The findings support the view that GenAI literacy in higher

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education should not be limited to operational familiarity or frequency of use. Instead, effective educational responses should combine practical skill development with explicit attention to ethical judgment, critical evaluation, and contextualized use. Universities should move beyond generic encouragement or prohibition and provide structured, visible, and discipline-sensitive support for responsible GenAI engagement. Future research should examine these relationships longitudinally, use more robust measures of actual competence and behavior, and test how institutional policies and pedagogical designs influence both learning-related use and critical orientation over time.

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Abbreviations

The following abbreviations are used in this manuscript:

GenAI	Generative Artificial Intelligence

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