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Pilot Adaptation and Preliminary Validation of the Generative AI Literacy for Learning Scale (GenAI-LLs) in Engineering Education

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Abstract: *The widespread adoption of Generative Artificial Intelligence (GenAI) in higher education has increased the need for valid instruments capable of assessing the competencies required for effective and responsible AI-supported learning. This pilot study aims to linguistically and contextually adapt and preliminarily validate the Generative AI Literacy for Learning Scale (GenAI-LLs) developed by Gümüş and Kara (2025) for engineering Project-Based Learning (PBL). The sample comprised 138 engineering students from the Technical University of Cluj-Napoca, Romania. Data were analysed using Exploratory Factor Analysis (EFA), descriptive statistics, Cronbach's alpha, Pearson correlation analysis, independent-samples t-tests, and one-way ANOVA. The EFA retained a four-factor solution explaining 61.30% of the total variance, characterised by the integration of Needs analysis and Prompting and language skills into a single factor and the differentiation of Autonomous learning into collaborative and autonomous components. The empirically derived GenAI literacy factors demonstrated good to excellent internal consistency. Correlation analyses indicated predominantly positive relationships among the four factors. No significant gender differences were identified, whereas students with more positive attitudes towards GenAI reported significantly higher levels of several GenAI literacy dimensions. The findings provide preliminary evidence supporting the psychometric adequacy of the Romanian adaptation of the GenAI-LLs and establish a foundation for future confirmatory validation studies in engineering higher education.*

Keywords: *Generative AI literacy; Project-Based Learning; engineering education; psychometric validation; exploratory factor analysis.*

1. Introduction

The rapid expansion of Generative Artificial Intelligence (GenAI) technologies is transforming in contemporary educational systems, making AI literacy an essential educational competency for preventing superficial forms of cognitive automation (European Commission, 2026). Although AI literacy has traditionally been conceptualised as a predominantly technical construct, focused on the use and understanding of algorithmic systems, this perspective increasingly overlooks the role of AI as an active partner in learning processes (Gümüş & Kara, 2025).

Recent literature highlights a structural shift from learning *about* AI to learning *with* AI, whereby AI systems are integrated as resources supporting educational processes (Holmes & Tuomi, 2022; UNESCO, 2023, 2024). This transition is accompanied by an emerging conceptualisation of GenAI literacy, which views GenAI as a collaborative cognitive partner rather than merely an information retrieval tool (Ng et al., 2025). Within this perspective, GenAI supports inquiry, problem-solving, feedback, and knowledge construction (Holmes & Tuomi, 2022; Kong et al., 2024). Within engineering education, these developments are particularly relevant to Project-Based Learning (PBL), where students engage in authentic, collaborative, and complex problem-solving activities that can be enhanced through AI-supported learning environments (Prince & Felder, 2006; Kong et al., 2024).

As GenAI becomes increasingly embedded in higher education, the ability to assess students' preparedness to use these technologies effectively and responsibly has become equally important. Reliable and valid instruments are therefore needed to evaluate the knowledge, skills, and critical competencies that underpin GenAI literacy and to support evidence-based educational practice. One of the first instruments specifically developed for this purpose is the Generative AI Literacy for Learning Scale (GenAI-LLs) proposed by Gümüş and Kara (2025), which conceptualises GenAI literacy through four complementary dimensions: Needs analysis, Prompting and language skills, Autonomous learning, and Critical thinking. Although the scale demonstrated promising psychometric properties in its original validation, its applicability in other educational, linguistic, and cultural contexts remains to be established.

Against this background, the present pilot study aimed to linguistically and contextually adapt the GenAI-LLs for Romanian engineering higher education and to provide preliminary evidence regarding its factorial structure, internal consistency, and construct relationships. By extending the validation of the instrument to the context of engineering PBL, the study contributes to the development of reliable tools for assessing GenAI literacy in AI-supported higher education.

2. Conceptual framework for GenAI literacy in higher education

2.1. Transformation of higher education in the GenAI era

While artificial intelligence has demonstrated transformative impact in industrial and commercial sectors (Dwivedi et al., 2023), its potential in higher education continues to evolve as universities integrate AI into teaching and learning (Luckin et al., 2016). The emergence of GenAI is accelerating the shift towards student-centred learning, where knowledge is actively co-constructed through interactions with teachers, peers, and intelligent systems, consistent with constructivist perspectives on learning (Vygotsky, 1978). Beyond supporting learning activities, GenAI is reshaping the relationship between information access and knowledge construction, requiring learners to develop higher levels of critical judgement, interpretation, and conceptual understanding in digitally mediated environments (Popenici, 2022).

GenAI is therefore redefining the roles of teachers and students. Instead of acting primarily as knowledge providers, teachers increasingly serve as facilitators of learning, while students are expected to become active, self-regulated learners capable of critically interacting with AI-generated content (Kasneci et al., 2023; Holmes et al., 2022). At the same time, the widespread adoption of GenAI requires universities to expand digital competency frameworks by incorporating AI literacy, moving beyond technical skills to competencies related to critical evaluation, responsible use, and effective collaboration between humans and AI (Gümüş & Kara, 2025).

These changes are particularly relevant in project-based engineering education, where UNESCO emphasises that AI should augment, not replace, human judgment, agency and learning processes (UNESCO, 2023, 2025). Consequently, future engineers are expected to develop the skills needed to collaborate effectively with intelligent systems, using GenAI to support creativity, innovation, critical thinking and complex problem-solving, while maintaining responsibility for evaluating AI-generated solutions (UNESCO, 2023, 2024).

2.2. *From AI literacy to GenAI literacy*

Existing conceptual frameworks of AI literacy generally describe it as a multidimensional construct that encompasses awareness and understanding, practical application, critical evaluation, and ethical responsibility (Long & Magerko, 2020; Ng et al., 2021). From a developmental perspective, these frameworks conceptualize AI literacy as a continuum that progresses from understanding fundamental AI concepts to their effective, critical, and responsible application in authentic problem-solving and decision-making contexts. Building on these perspectives, Kong et al. (2024) extend the conceptualization by incorporating cognitive, metacognitive, affective, and ethical dimensions, reflecting the increasingly human-centred nature of AI literacy in educational settings.

The emergence of GenAI represents a qualitative shift in this conceptualization. Unlike conventional AI systems, GenAI actively generates text, code, images, and technical solutions, requiring learners to not only understand AI, but also to interact effectively with it. GenAI literacy therefore extends beyond traditional AI literacy to incorporate skills related to needs analysis, prompt engineering, self-regulated human-AI collaboration, and critical evaluation of AI-generated outcomes.

At the same time, the increasing autonomy of generative systems introduces challenges related to information accuracy, bias, and epistemic overreliance (Dwivedi et al., 2023). These risks reinforce the importance of maintaining human oversight through the *"human-in-the-loop"* principle (European Commission, 2026), making critical evaluation a core competency for the responsible use of AI (UNESCO, 2024; Swiecki et al., 2022). This perspective is particularly relevant to the present study, which examines critical thinking as a distinct dimension of GenAI literacy within engineering PBL. Conversely, when pedagogically integrated, GenAI has the potential to enhance higher-order thinking, personalised feedback, problem-solving, and student engagement, especially in project-based engineering education (Mayasari et al., 2024; Zhang et al., 2024). Consequently, students are expected not only to use GenAI tools, but also to develop the skills necessary to collaborate with them effectively, critically, and responsibly. These developments have also created the need for valid instruments capable of assessing the competencies required for effective and responsible GenAI-supported learning in higher education.

2.3. Theoretical framework of GenAI-LLs: dimensional structure of GenAI literacy

Drawing on contemporary perspectives of AI literacy, Gümüş and Kara (2025) conceptualise GenAI literacy as a multidimensional construct of self-regulated learning mediated by large language models (LLMs). The GenAI-LLs framework comprises four complementary and interconnected dimensions that describe the competencies required for effective and responsible collaboration with GenAI.

1. **Needs analysis** refers to the metacognitive ability of learners to identify knowledge gaps and determine how GenAI can support the initial stages of learning and problem-solving, based on the principles of self-regulated learning (Zimmerman, 2002; Kasneci et al., 2023).
2. **Prompting and language skills** encompass the iterative formulation and refinement of prompts that enable effective communication with AI systems and optimise problem-solving outcomes (White et al., 2023; Shneiderman, 2020).
3. **Autonomous learning** reflects the ability of learners to regulate their own learning processes and exercise agency, using GenAI as a learning partner, consistent with

theories of self-determination and self-regulated learning (Ryan & Deci, 2000; Kasneci et al., 2023).

4. **Critical thinking** involves the reflective evaluation of AI-generated content, including the identification of inaccuracies, limitations, bias and ethical implications associated with AI-supported learning (Zawacki-Richter et al., 2019; Kasneci et al., 2023).

Together, these dimensions provide an integrated framework for understanding GenAI literacy as a form of self-regulated and human-centred interaction with GenAI, encompassing metacognitive, behavioural, and evaluative competencies. Although these dimensions were conceptualised as distinct components, their theoretical interconnectedness motivated the use of oblique factor rotation in the present exploratory analysis.

Collectively, the GenAI-LLs represents one of the first instruments specifically designed to assess GenAI literacy in educational settings and therefore provides a suitable framework for examining how students interact with GenAI in learning contexts (Gümüş & Kara, 2025).

2.4. Project-Based Learning as a context for developing GenAI literacy

Project-Based Learning (PBL) provides an authentic educational context in which GenAI can evolve from a passive source of information to an active partner in problem-solving and knowledge construction (Kong et al., 2024; Gümüş & Kara, 2025). In engineering education, the integration of LLMs supports iterative processes of design, analysis, collaboration, and solution refinement, making PBL particularly well-suited for promoting and observing GenAI literacy competencies (Kasneci et al., 2023; Zawacki-Richter et al., 2019).

Accordingly, PBL represents a natural context for the manifestation of the four dimensions of the GenAI-LLs framework, as each stage of project development corresponds to a specific competency: Needs analysis (problem definition), Prompting and language skills (information seeking and AI interaction), Autonomous learning (self-regulated solution development), and Critical thinking (solution validation and evaluation). This alignment suggests that GenAI literacy should be understood not as an abstract digital competency, but as a situated capability that emerges through authentic learning experiences, in which students strategically and responsibly integrate AI throughout the engineering design process.

Despite the growing body of research on AI literacy, technology acceptance, and the ethical implications of AI use (Ng et al., 2024; Venkatesh et al., 2012), the pedagogical integration of GenAI as an active learning partner remains insufficiently theorised and empirically validated in higher education (Zawacki-Richter et al., 2019; Kasneci et al., 2023). This gap is particularly evident in engineering education, where validated instruments capable of assessing GenAI-specific competencies are still limited.

In this context, the present pilot study addresses this gap by adapting and preliminarily validating the GenAI-LLs scale (Gümüş & Kara, 2025) with a sample of engineering students. According to the Standards for Educational and Psychological Testing, validity refers to the extent to which evidence and theory support the interpretation and intended use of test scores rather than being an intrinsic property of the instrument itself (AERA, APA, & NCME, 2014). Against this background, the present pilot study aimed to linguistically and contextually adapt the GenAI-LLs for Romanian engineering higher education and to provide preliminary evidence regarding its psychometric properties. Specifically, the study examined the factorial structure and internal consistency of the adapted instrument, explored the relationships among the empirically derived GenAI literacy factors, and investigated potential differences associated with gender and attitudes towards GenAI.

3. Research methodology

This pilot study aimed to linguistically and contextually adapt the GenAI-LLs for Romanian engineering higher education and to provide a preliminary psychometric evaluation of the adapted instrument. Given the exploratory nature of the research and the absence of previous applications of the instrument in the Romanian educational context, the validation focused on examining the factorial structure, internal consistency, and the relationships between the four factors. Accordingly, the findings should be interpreted as preliminary evidence supporting the structural validity and reliability of the adapted instrument, providing a foundation for subsequent validation studies using larger and independent samples.

3.1. Research objectives and hypotheses

To achieve this goal, the study pursued three research objectives:

- RO1: To examine the factorial structure of the Romanian adaptation of the GenAI-LLs in the context of engineering higher education.
- RO2: To investigate the relationships among the four factors.
- RO3: To examine whether the four factors differ according to students' gender and attitudes towards GenAI.

Based on the theoretical framework, the following hypotheses were formulated:

- H1: Positive relationships are expected among the four factors.
- H2: There are no statistically significant gender differences across the four factors.
- H3: Students with more positive attitudes towards GenAI report higher levels of the four factors.

3.2. Participants

A total of 138 second-year engineering students from the Technical University of Cluj-Napoca, Romania, participated in this pilot study. All participants were enrolled in PBL courses at the time of data collection. The gender distribution was relatively balanced, comprising 57 male students (41.3%) and 81 female students (58.7%). Overall attitudes towards GenAI were assessed using a single global item and categorised into three attitude groups for comparative analyses. Most participants reported a high level of positive attitude towards GenAI (61.6%, n = 85), followed by a moderate attitude (26.1%, n = 36), whereas only 12.3% (n = 17) reported a low level of positive attitude. The participant-to-item ratio was approximately 4.8:1 (138 participants for 29 items), which is considered acceptable for an exploratory pilot validation study, although larger samples are recommended for subsequent confirmatory validation (Hair et al., 2022).

3.3. Data collection instrument

The present study involved the linguistic translation and contextual adaptation of the original instrument rather than a formal cross-cultural adaptation involving procedures such as forward–back translation and expert committee review. The original English version of the GenAI-LLs (Gümüş & Kara, 2025) was translated into Romanian by the researcher, with particular attention to preserving the conceptual meaning of each item. To enhance its relevance for engineering education, several contextual references were adapted to the PBL environment while maintaining the underlying theoretical constructs. Permission to translate, linguistically and contextually adapt, and preliminarily validate the GenAI-LLs was obtained from the original authors. Accordingly, no forward–back translation, expert committee review, or separate pilot testing was undertaken prior to this pilot validation study.

Data were collected using a structured questionnaire comprising two sections (Appendix). The first section collected participant characteristics, including gender and their overall attitudes towards GenAI. Attitudes towards GenAI were assessed using a single global item: “Overall, I have a favourable attitude towards the use of GenAI in higher education"), rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The item was included as an exploratory indicator of students' overall perceptions rather than as a validated multidimensional measure of attitudes towards GenAI. Because the attitude measure consisted of a single global item, responses were grouped into three ordered categories (low, moderate, and high) to facilitate exploratory comparisons between students with different levels of overall attitudes towards GenAI. This categorisation was intended solely for exploratory group comparisons and should not be interpreted as representing a validated multidimensional measure of attitudes.

The second section included the translated and contextually adapted version of the Generative AI Literacy for Learning Scale (GenAI-LLs) (Gümüş & Kara, 2025). The original instrument consists of 29 items rated on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree) and is organised into four theoretical dimensions of GenAI literacy:

1. Needs analysis (8 items): identifying learning needs and selecting appropriate GenAI resources (e.g., "I can select the right GenAI tool for the content I need.").
2. Prompting and language skills (5 items): formulating and refining prompts to achieve relevant and accurate outputs.
3. Autonomous learning (9 items): using GenAI to support self-regulated, individual and collaborative learning processes.
4. Critical thinking (7 items): critically evaluating AI-generated information and identifying potential errors, limitations or bias (e.g., "I can question the content generated by GenAI.").

3.4. Procedure and data analysis plan

Data were collected at the beginning of the second semester of the 2025–2026 academic year via Microsoft Forms. The questionnaire link was distributed through institutional communication channels. Statistical analyses were primarily conducted using IBM SPSS Statistics 22, whereas JASP (version 0.19.3) was used to perform Horn's Parallel Analysis. Consistent with the exploratory aim of the study, data analysis followed a sequential procedure. First, the distribution of the data was examined using Skewness and Kurtosis indices together with the Kolmogorov-Smirnov and Shapiro-Wilk tests. Exploratory Factor Analysis (EFA), based on Principal Axis Factoring with Promax rotation, was then conducted to examine the factorial structure of the adapted GenAI-LLs. The number of factors to retain was determined using the Kaiser criterion (eigenvalues > 1), Horn's Parallel Analysis, visual inspection of the scree plot, and theoretical interpretability (Hair et al., 2022). Internal consistency was subsequently evaluated using Cronbach's alpha coefficients for both the original theoretical dimensions and the four factors identified through EFA. Following the identification of the empirical factor structure, composite factor scores were computed as the mean of the items loading on each factor. Pearson correlation analysis was then used to examine relationships among the four factors. Gender differences were analysed using independent-samples t-tests, whereas differences according to students' attitudes towards GenAI were examined using one-way analysis of variance (ANOVA). When significant omnibus effects were identified, Games-Howell post hoc comparisons were performed. Effect sizes were estimated using Cohen's d for the t-tests and eta squared (η^2) for the ANOVA.

This analytical strategy enabled a preliminary evaluation of the structural validity and internal consistency of the adapted instrument, while also examining relationships among the four factors and their associations with selected participant characteristics.

Participation in the study was voluntary and anonymous. Before completing the questionnaire, participants were informed about the purpose of the study, the anonymous processing of the data, and the exclusive use of the responses for research purposes. Completion of the questionnaire was considered to constitute informed consent.

4. Results

4.1. Assessment of data distribution

To assess the assumptions underlying the subsequent parametric analyses, data distribution was examined using the Kolmogorov-Smirnov test (with Lilliefors correction), the Shapiro-Wilk test, and the Skewness and Kurtosis indices (Table 1).

Table 1. Distribution shape and normality tests for the GenAI-LLs dimensions

Variable / Dimension	Skewness	Kurtosis	Kolmogorov-Smirnov	df	p	Shapiro-Wilk	df	p
1. Needs analysis	0.009	-0.716	.196	138	< .001	.937	138	< .001
2. Prompting and language skills	-0.394	0.055	.163	138	< .001	.923	138	< .001
3. Autonomous learning	-0.324	-0.116	.095	138	.004	.973	138	.007
4. Critical thinking	-0.257	-0.687	.123	138	< .001	.927	138	< .001

a. Lilliefors significance correction

Although both normality tests indicated statistically significant deviations from normality for all dimensions ($p < .05$), these tests are known to be highly sensitive to sample size, often identifying trivial departures from normality in medium and large samples (Hair et al., 2022; Kline, 2023). Therefore, the interpretation was complemented by the examination of Skewness and Kurtosis values. All coefficients fell within the recommended range of −1 to +1, indicating only minor deviations from normality and supporting the assumption of approximately normal distributions. Accordingly, the use of parametric statistical procedures in the subsequent analyses was considered appropriate.

4.2. Exploratory Factor Analysis (EFA) of the GenAI-LLs

Given the pilot nature of the study and the contextual adaptation of the instrument to engineering education, the factorial structure of the Romanian GenAI-LLs was examined using Exploratory Factor Analysis (EFA). As this represents an initial psychometric evaluation, Confirmatory Factor Analysis (CFA) is planned for future research using an independent sample. EFA is recommended when adapting an instrument to a new linguistic or educational context, as it allows the underlying dimensional structure to emerge empirically before confirmatory testing (Worthington & Whittaker, 2006).

The suitability of the data for factor analysis was confirmed by a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.895, indicating very good sampling adequacy, and a statistically significant Bartlett's test of sphericity, $\chi^2(406) = 2978.799$, $p < .001$, demonstrating sufficient intercorrelations among the items for factor extraction. Principal Axis Factoring with Promax rotation and Kaiser normalisation was selected because the dimensions of GenAI literacy were theoretically expected to be correlated (Hair et al., 2022; Kline, 2023).

The EFA identified a four-factor solution with initial eigenvalues greater than 1 (11.516, 4.184, 2.108, and 1.398). The decision to retain four factors was based on the Kaiser criterion (eigenvalues > 1), Horn's Parallel Analysis, visual inspection of the scree plot, and the theoretical interpretability of the factor solution (Hair et al., 2022).

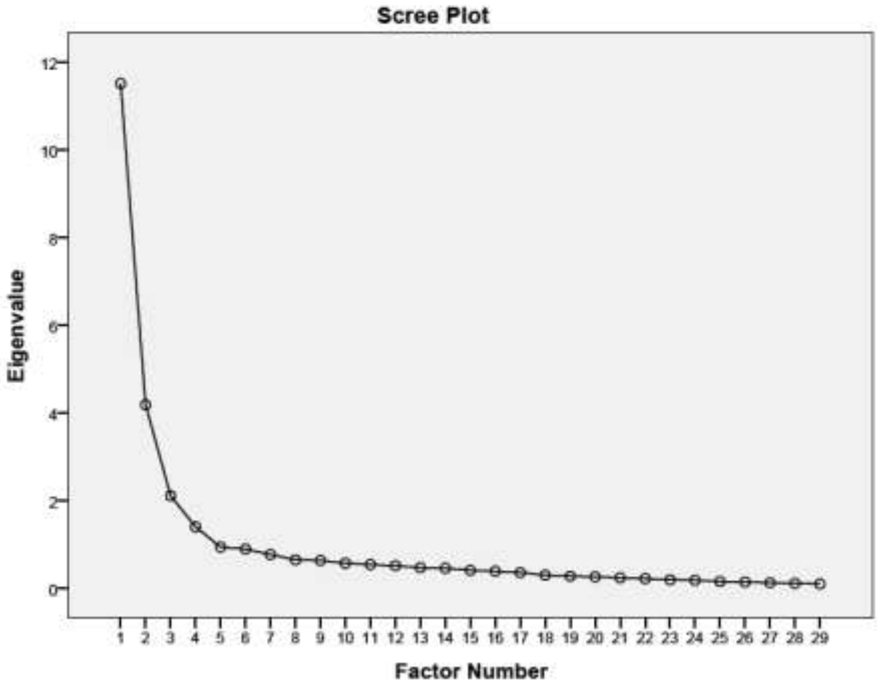

Fig. 1. Scree plot supporting the four-factor solution of the Romanian GenAI-LLs

The factor extraction statistics are presented in Table 2. Based on the Extraction Sums of Squared Loadings, the retained four-factor solution explained 61.30% of the total variance. In accordance with recommendations for oblique rotations, only the Extraction Sums of Squared Loadings were used to report the explained variance, whereas the Rotated Sums of Squared Loadings were considered solely to facilitate interpretation of the rotated solution and were not interpreted as additive proportions of explained variance (Hair et al., 2022).

Table 2. Initial Eigenvalues, Extraction Sums of Squared Loadings, and Rotation Sums of Squared Loadings for the Four-Factor Solution

Factor	Initial Eigenvalues	% of Variance	Extraction SS Loadings	% of Variance	Cumulative %	Rotation SS Loadings
1	11.516	39.710	11.123	38.355	38.355	9.758
2	4.184	14.429	3.851	13.279	51.634	5.553
3	2.108	7.267	1.739	5.997	57.630	7.162
4	1.398	4.819	1.063	3.664	61.295	7.894

Note. Extraction method: Principal Axis Factoring. Rotation method: Promax with Kaiser normalisation.

Horn's Parallel Analysis (based on factor analysis) further supported the retention of four factors. The observed eigenvalues for the first four factors exceeded the corresponding eigenvalues generated from random data, whereas the fifth observed eigenvalue fell below the simulated value, providing additional empirical support for the four-factor solution.

Communality estimates were generally satisfactory, indicating that the extracted factors adequately represented the retained items. Although several items exhibited comparatively lower communality values, all exceeded commonly recommended minimum thresholds for exploratory research, supporting the retention of all 29 items (Hair et al., 2022). The Pattern Matrix and communality estimates are presented in Table 3.

Table 3. Pattern Matrix and Communality Estimates for the Four-Factor Solution of the Romanian GenAI-LLs

Items	F1	F2	F3	F4	Communalities (h^2)
prom2	0.946				0.722
prom5	0.891				0.607
prom3	0.833				0.615
prom4	0.807				0.645
need2	0.807				0.578
prom1	0.770				0.637
need4	0.662				0.504
need1	0.599			0.333	0.571
need3	0.567				0.579
need5	0.530				0.453
need6	0.382			0.327	0.550
need7	0.336			0.318	0.498
auto7		0.962			0.818
auto5		0.841			0.699
auto6		0.802			0.731
auto9		0.797			0.634
auto4		0.770			0.555
auto8		0.483			0.619
crit7			0.891		0.675
crit5			0.873		0.642
crit4			0.868		0.637
crit6			0.663		0.655
crit2			0.614		0.551
crit1			0.517		0.438
crit3	0.410		0.491		0.558
auto2				0.933	0.757
auto1				0.891	0.789
auto3				0.777	0.616
need8				0.544	0.441

Note. Extraction method: Principal Axis Factoring. Rotation method: Promax with Kaiser Normalization. Only factor loadings ≥ .30 are displayed. h^2 = communality.

Inspection of the Pattern Matrix supported a clear and interpretable four-factor solution. Factor 1 combined all Prompting and language skills items with most Needs analysis items, with primary factor loadings ranging from .336 to .946. Because Factor 1 integrated the original Needs analysis and Prompting and language skills dimensions, it is referred to hereafter as Needs analysis and Prompting skills for readability. Factor 2 comprised six items originally belonging to the Autonomous learning dimension, representing *Collaborative learning*, with factor loadings ranging from .483 to .962. Factor 3 retained all Critical thinking items with loadings between .491 and .891. Factor 4 comprised the remaining three Autonomous learning items together with one Needs analysis item, representing *Autonomous learning*, with loadings ranging from .544 to .933.

Most items demonstrated moderate to high primary factor loadings and satisfactory communality estimates (range = .438-.818), supporting the adequacy of the four-factor solution (Hair et al., 2022). Four items (need1, need6, need7, and crit3) exhibited moderate secondary loadings on additional factors. Specifically, need1, need6, and need7 showed secondary loadings on Factor 4, whereas crit3 also loaded moderately on Factor 1. Although need6 and need7 exhibited relatively similar primary and secondary loadings, their primary loadings remained slightly higher, communalities were satisfactory, and their conceptual content was consistent with the retained factor. The remaining cross-loading items (need1 and crit3) showed clearer differences between their primary and secondary loadings. Given the use of Promax oblique rotation, such cross-loadings were considered acceptable because theoretically related latent constructs were expected to correlate (Hair et al., 2022; Kline, 2023). Nevertheless, the factorial assignment of need6 and need7 should be considered provisional until confirmed through CFA using an independent sample.

Taken together, the four-factor solution was consistently supported by the Kaiser criterion, Horn's Parallel Analysis, scree plot inspection, and theoretical interpretability, providing convergent evidence for the factorial structure of the Romanian adaptation of the GenAI-LLs. Although several items were redistributed across factors compared with the original validation study, the adapted instrument retained a coherent multidimensional structure.

The inter-factor correlation matrix is presented in Table 4. As expected, following Promax oblique rotation, the extracted factors were positively correlated, with coefficients ranging from 0.129 to 0.608.

Table 4. Factor Correlation Matrix

Factor	F1	F2	F3	F4
F1	1.000			
F2	0.287	1.000		
F3	0.602	0.129	1.000	
F4	0.608	0.550	0.456	1.000

Note. F1-F4 correspond to the four factors identified by the EFA.

The strongest associations were observed between Factor 1 and Factor 4 (r = .608) and between Factor 1 and Factor 3 (r = .602), whereas the weakest relationship was found between Factor 2 and Factor 3 (r = .129). The magnitude of the inter-factor correlations indicates that the four factors are conceptually related while remaining empirically distinguishable. These findings support the use of an oblique rotation and provide additional evidence that the adapted GenAI-LLs captures distinct, yet interrelated, dimensions of GenAI literacy (Hair et al., 2022; Kline, 2023).

To ensure methodological consistency, all subsequent reliability and inferential analyses were conducted using the four factors identified through the EFA.

4.3. Descriptive statistics and internal consistency reliability for the four factors

Table 5 presents the descriptive statistics and internal consistency coefficients for the four factors identified through the EFA. All factors demonstrated good to excellent internal consistency, with Cronbach's alpha coefficients ranging from .875 to .934, exceeding the recommended threshold for exploratory research (Hair et al., 2022). Taken together, the mean scores indicated relatively high levels of GenAI literacy across the four factors.

Table 5. Descriptive statistics and internal consistency of the four factors

Factor	No. of items	M	SD	Cronbach's α
F1. Needs analysis and Prompting skills	12	4.140	0.552	0.934
F2. Collaborative learning	6	3.51	0.888	0.907
F3. Critical thinking	7	4.19	0.597	0.895
F4. Autonomous learning	4	4.02	0.738	0.875

Note. M = mean; SD = standard deviation.

The highest mean score was observed for Critical thinking (M = 4.19, SD = 0.597), followed by Needs analysis and Prompting skills (M = 4.14, SD = 0.552) and Autonomous learning (M = 4.02, SD = 0.738). Collaborative learning showed the lowest mean score (M = 3.51, SD = 0.888), suggesting that students reported lower confidence in using GenAI to support collaborative learning activities than in other aspects of GenAI literacy.

Cronbach's alpha coefficients indicated good to excellent internal consistency across all four factors, supporting the reliability of the factor structure identified through EFA. The overall scale demonstrated excellent internal consistency (α = .936). At the factor level, Cronbach's alpha coefficients were: 0.934 for Needs analysis and Prompting skills (F1), 0.907 for Collaborative learning (F2), 0.895 for Critical thinking (F3) and 0.875 for Autonomous learning (F4). All coefficients exceeded the recommended threshold of .70 for exploratory research (Hair et al., 2022), indicating satisfactory to excellent internal consistency.

Collectively, these findings provide preliminary evidence that the four-factor structure is internally consistent and suitable for assessing GenAI literacy in engineering PBL contexts.

Nevertheless, further validation using larger and independent samples is required to confirm the stability of the identified structure.

4.4. Relationships among the four factors

To examine the relationships among the four factors, Pearson correlation coefficients were calculated (Table 6). Taken together, the analyses showed predominantly positive associations among the four factors.

Table 6. Pearson correlations among the four factors

Factor	F1	F2	F3	F4
F1	-	.315**	.610**	.615**
F2		-	.120**	.522**
F3			-	.416**
F4				-

***The correlation is significant at the $p < .01$ level (2-tailed).*

Factor 1 (Needs analysis and Prompting skills) showed positive correlations with Factor 2 (Collaborative learning) ($r = .315$, $p < .001$), Factor 3 (Critical thinking) ($r = .610$, $p < .001$), and Factor 4 (Autonomous learning) ($r = .615$, $p < .001$). Collaborative learning was also positively associated with Autonomous learning ($r = .522$, $p < .001$). By contrast, the association between Collaborative learning and Critical thinking was weak and not statistically significant ($r = .120$, $p = .161$). Critical thinking demonstrated a moderate positive correlation with Autonomous learning ($r = .416$, $p < .001$). Collectively, these findings provide partial support for H1. Most of the four factors were positively and significantly correlated, whereas the association between Collaborative learning and Critical thinking did not reach statistical significance. The observed pattern indicates that the factors represent related, yet empirically distinguishable, dimensions of GenAI literacy.

4.5. Group differences

To examine gender differences in the four factors (H2), independent-samples t-tests were performed (Table 7). Levene's test indicated that the assumption of homogeneity of variances was satisfied for all four factors (all $p > .05$), supporting the use of the standard independent-samples t-test.

Table 7. Results of the independent samples t-test by gender

Factor	Male (N = 57) M ± SD	Female (N = 81) M ± SD	t(136)	p (2-tailed)	Cohen's d
F1	4.12 ± 0.547	4.15 ± 0.558	-0.375	.708	0.054

F2	3.48 ± 0.930	3.53 ± 0.863	-0.306	.760	0.056
F3	4.21 ± 0.614	4.17 ± 0.588	0.299	.766	0.067
F4	4.05 ± 0.725	3.99 ± 0.749	0.484	.629	0.081

Note. M = mean; SD = standard deviation; t = independent-samples t-test statistic.

As shown in Table 7, independent-samples t-tests indicated no statistically significant gender differences across any of the four factors. Specifically, no significant differences were observed for Needs analysis and Prompting skills ($t(136) = -0.375$, $p = .708$), Collaborative learning ($t(136) = -0.306$, $p = .760$), Critical thinking ($t(136) = 0.299$, $p = .766$), or Autonomous learning ($t(136) = 0.484$, $p = .629$). Effect sizes (Cohen's d) were negligible across all four factors (d = .054-.081), indicating minimal practical differences in GenAI literacy between male and female students. Therefore, H2 was not rejected.

A one-way analysis of variance (ANOVA) was conducted to examine differences in the four factors according to students' attitudes towards GenAI (Table 8). Although attitudes towards GenAI were measured using a single ordinal item, the three response categories – low (n = 17), moderate (n = 36), and high (n = 85) – were treated as independent groups for exploratory comparisons of mean differences across the four factors. Given the exploratory purpose of the study and the approximately normal distribution of the dependent variables, one-way ANOVA was considered appropriate. Levene's test confirmed that the assumption of homogeneity of variances was satisfied for all four factors (all $p > .05$).

Table 8. One-way ANOVA comparing the four factors across attitude categories

Factor	Low M ± SD	Moderate M ± SD	High M ± SD	F(2,135)	p	η2	Effect size
F1	3.88 ± 0.500	3.95 ± 0.620	4.27 ± 0.492	7.105	.001	0.095	Medium
F2	2.95 ± 0.811	3.20 ± 0.690	3.75 ± 0.896	9.604	<.001	0.125	Medium
F3	4.08 ± 0.749	4.12 ± 0.629	4.24 ± 0.550	0.735	.481	0.011	Small
F4	3.22 ± 0.927	3.80 ± 0.589	4.27 ± 0.606	21.243	<.001	0.239	Large

Note. M = mean; SD = standard deviation; η^2 = eta squared. Levene's test indicated that the assumption of homogeneity of variances was satisfied for all four factors (all p > .05). According to Cohen (1988), η^2 values of .01, .06, and .14 indicate small, medium, and large effect sizes, respectively.

Significant group differences were identified for Factor 1 (Needs analysis and Prompting skills), $F(2, 135) = 7.105$, $p = .001$, Factor 2 (Collaborative learning), $F(2, 135) = 9.604$, $p < .001$, and Factor 4 (Autonomous learning), $F(2, 135) = 21.243$, $p < .001$. However, no statistically significant differences were observed for Factor 3 (Critical thinking), $F(2, 135) = 0.735$, $p = .481$.

Games-Howell post hoc comparisons showed that students in the high-attitude category scored significantly higher than those in both the low- and moderate-attitude categories on Factors 1, 2, and 4 (all $p < .05$). No significant differences were observed between the low- and moderate-attitude categories. Likewise, none of the pairwise comparisons for Critical thinking reached statistical significance. Consequently, H3 was partially supported.

Effect size estimates (η^2) indicated that students' attitudes towards GenAI had the strongest association with Autonomous learning ($\eta^2 = .239$), representing a large effect. Medium effect sizes were observed for Collaborative learning ($\eta^2 = .125$) and Needs analysis and Prompting skills ($\eta^2 = .095$), whereas the effect for Critical thinking was negligible ($\eta^2 = .011$). Taken together, these findings suggest that more positive attitudes towards GenAI are predominantly associated with competencies related to the active use and educational integration of AI into learning, whereas Critical thinking appears comparatively independent of students' attitudinal profile.

5. Discussion

The present pilot study aimed to linguistically and contextually adapt the GenAI-LLs (Gümüş & Kara, 2025) for Romanian engineering education and to provide a preliminary psychometric evaluation of the adapted instrument.

5.1. Discussion of the psychometric validation

Regarding RO1, the EFA provided evidence supporting the structural validity of the Romanian adaptation of the GenAI-LLs in the context of engineering PBL. Although the four-factor solution differed partially from that reported in the original validation study by Gümüş and Kara (2025), the same number of latent dimensions was retained, supporting the multidimensional conceptualisation of GenAI literacy. The observed differences in item allocation suggest that contextual adaptation to engineering PBL influenced the empirical organisation of the factors while preserving the multidimensional conceptual framework proposed by Gümüş and Kara (2025).

One notable finding was the integration of the original Needs analysis dimension and Prompting and language skills dimension within the first factor. Unlike the original study, Romanian engineering students appeared to perceive identifying learning needs, selecting appropriate GenAI tools, and formulating effective prompts as interconnected stages of the same learning process. Recent perspectives further emphasise that effective prompting represents not only a technical skill, but also an integral component of AI literacy, a pedagogical competency through which learners guide, refine, and regulate AI-supported learning processes (UNESCO, 2024; Holmes et al., 2024; Ng et al., 2025).

A second important finding concerned the differentiation of the original Autonomous learning dimension into two related, yet distinct, factors representing Collaborative learning and Autonomous learning. Interestingly, inspection of the original validation study also suggests conceptual overlap within this dimension, although the authors retained a single factor (Gümüş & Kara, 2025). In the Romanian engineering sample, this distinction emerged more clearly, indicating that students differentiate between collaborative AI-supported learning and individually regulated learning when engaging in project-based activities. This distinction is consistent with contemporary AI literacy frameworks, which recognise that effective AI-supported learning requires both collaborative engagement and autonomous regulation of learning (Long & Magerko, 2020; UNESCO, 2024; Holmes et al., 2024). The observed separation therefore suggests that engineering students in PBL differentiate more clearly between collaborative and individual modes of AI-supported learning than was reported in the original validation study.

In contrast, the Critical thinking dimension remained conceptually coherent, with all corresponding items loading on a single factor. This finding reinforces the role of critical evaluation as a core component of GenAI literacy and is consistent with frameworks that identify the evaluation of AI-generated information, including its accuracy, reliability, bias, and ethical implications, as essential for responsible AI use (Long & Magerko, 2020; Ng et al., 2021; UNESCO, 2024).

Finally, four items (need1, need6, need7, and crit3) exhibited moderate secondary loadings on additional factors. Whereas need1, need6, and need7 reflected the conceptual proximity between Needs analysis and Autonomous learning, crit3 showed a moderate secondary loading on the integrated Needs analysis and Prompting skills factor. The relatively similar primary and secondary loadings observed for need6 and need7 suggest that these items may capture competencies located at the interface between identifying learning needs and regulating AI-supported learning. This overlap is theoretically plausible, as recognising learning needs and selecting appropriate AI support are closely intertwined with self-regulated learning processes in engineering PBL. Their retention within the Needs analysis factor was supported by their slightly higher primary loadings, satisfactory communalities, and conceptual consistency with the construct. Nevertheless, their factorial allocation should be interpreted cautiously and verified through CFA in an independent sample. Similarly, the cross-loading observed for crit3 is theoretically plausible because identifying potential bias in AI-generated content requires not only critical evaluation but also the ability to formulate appropriate prompts and obtain information that can subsequently be critically examined. In AI-assisted learning, prompt formulation and critical evaluation operate as complementary and iterative processes rather than as independent competencies (UNESCO, 2024). The primary loading of crit3 remained higher than its secondary loading, its communality was satisfactory, and its conceptual content supported its retention within the Critical thinking factor.

The descriptive statistics suggest that engineering students reported relatively high levels of GenAI literacy across most of the four factors. Critical thinking obtained the highest mean score, indicating that students perceived themselves as relatively confident in evaluating the accuracy, bias, and reliability of AI-generated content. This finding aligns with contemporary AI literacy frameworks, which identify critical evaluation as a core competency for the responsible use of GenAI in higher education (Long & Magerko, 2020; UNESCO, 2024; Ng et al., 2021). Similarly, the high mean observed for Needs analysis and Prompting skills suggest that students were generally able to identify learning needs and formulate effective prompts when interacting with GenAI tools. Conversely, Collaborative learning received the lowest mean score and exhibited the greatest variability, indicating that students perceived collaborative AI-supported learning as less developed than individual AI-supported competencies. A similar tendency has been noted in studies showing that students adopt GenAI more readily for individual learning than for collaborative knowledge construction, unless collaborative AI use is explicitly scaffolded by instructional design. This pattern may reflect the fact that collaborative use of GenAI within PBL requires additional pedagogical support and structured opportunities for peer interaction, rather than depending solely on students' individual use of AI tools (Holmes et al., 2024; UNESCO, 2024).

The high internal consistency coefficients further indicate that the four factors represent internally consistent constructs despite the partial redistribution of several items identified through EFA. The excellent reliability observed for Factor 1 further supports the empirical integration of Needs analysis and Prompting skills within the adapted instrument.

Collectively, the findings provide preliminary evidence that the Romanian adaptation of the GenAI-LLs preserves the multidimensional nature of GenAI literacy while reflecting the specific characteristics of engineering PBL. The four-factor structure and the high levels of internal consistency support the suitability of the adapted instrument for further psychometric evaluation. Nevertheless, confirmation of the identified structure through CFA and measurement invariance testing in larger and independent samples is needed before the instrument can be recommended for broader application.

5.2. Discussion of relationships and group differences

Regarding RO2, Pearson correlation analysis showed that most of the four factors were positively associated, providing substantial, although not complete, support for H1. The strongest relationships involved Factor 1 (Needs analysis and Prompting skills), which demonstrated strong positive correlations with both Critical thinking and Autonomous learning. These findings suggest that students who are more capable of identifying learning needs and formulating effective prompts also tend to engage more actively in self-regulated learning and to demonstrate stronger critical evaluation of AI-generated information. This pattern is consistent with contemporary frameworks describing prompt engineering, critical evaluation, and self-regulated learning as complementary competencies underpinning effective and responsible use of GenAI (UNESCO, 2024; Holmes et al., 2024; Ng et al., 2021). Although the original validation study primarily focused on the factorial structure of the GenAI-LLs, the present findings extend this evidence by demonstrating that the four factors remain positively associated, while preserving sufficient distinctiveness to represent complementary aspects of GenAI literacy.

Interestingly, Collaborative learning was moderately associated with Autonomous learning but was not significantly correlated with Critical thinking. This finding suggests that AI-supported collaboration and the critical evaluation of AI-generated information represent complementary, but relatively independent aspects of GenAI literacy within engineering PBL. While collaborative activities primarily involve communication, coordination, and shared problem-solving, critical evaluation requires individual epistemic judgement, which may develop independently of collaborative engagement.

Regarding RO3, no statistically significant gender differences were identified across any of the four factors. Therefore, H2 was not rejected. This finding is consistent with recent studies reporting that gender plays only a limited role in explaining AI literacy among university students (Mansoor et al., 2024). The findings therefore suggest that the competencies represented by the four factors develop similarly among male and female engineering students participating in PBL.

Regarding H3, students with more positive attitudes towards GenAI reported significantly higher levels of Needs analysis and Prompting skills, Collaborative learning, and Autonomous learning, whereas no significant differences were observed for Critical thinking. These findings indicate that positive attitudes towards GenAI are predominantly associated with competencies related to the active educational use and integration of AI rather than with evaluative competencies. Students who expressed more favourable attitudes towards GenAI also reported greater confidence in identifying learning needs, formulating effective prompts, collaborating with peers through AI-supported activities, and regulating their own learning with the support of GenAI. Similar patterns have been reported in engineering education, where positive perceptions of AI are associated with greater engagement in AI-assisted learning and problem-solving (Zhang et al., 2024).

However, Critical thinking did not differ significantly across attitude categories, suggesting that the ability to critically evaluate AI-generated information represents a relatively stable academic competency that is less closely associated with students' general attitudes towards GenAI. This finding is consistent with contemporary AI literacy frameworks, which conceptualise critical evaluation as an essential competency for responsible AI use regardless of users' levels of technological acceptance (Long & Magerko, 2020; Ng et al., 2021; UNESCO, 2024).

The effect size estimates further strengthen this interpretation. Students' attitudes towards GenAI showed the strongest association with Autonomous learning (large effect), followed by Collaborative learning and Needs analysis and Prompting skills (medium effects), whereas the association with Critical thinking was negligible. These findings suggest that favourable attitudes towards GenAI are more closely related to behavioural and self-regulatory aspects of AI-supported learning than to students' critical evaluation of AI-generated information.

Taken together, the findings support the conceptualisation of GenAI literacy as a multidimensional construct integrating technical, metacognitive, collaborative, and critical competencies. Within engineering PBL, identifying learning needs, formulating effective prompts, collaborating with peers, regulating learning, and critically evaluating AI-generated information appear to function as complementary processes that support effective and responsible use of GenAI in complex learning tasks (Long & Magerko, 2020; UNESCO, 2024; Ng et al., 2025).

From an educational perspective, these findings highlight the need to rethink the role of GenAI within PBL, shifting the emphasis from the technical use of AI tools towards their pedagogically meaningful integration in self-regulated and collaborative learning. Rather than viewing GenAI primarily as a source of information, educators should encourage students to engage critically with AI-generated outputs, refine prompts iteratively, and reflect on how AI supports learning and problem-solving. Human-in-the-loop approaches, in which students remain responsible for evaluating, validating, and improving AI-generated content, may provide an effective pedagogical framework for achieving these goals (UNESCO, 2024; Holmes et al., 2024). Practical strategies could include the use of reflective AI learning journals documenting prompt formulation and refinement, critical evaluation of AI-generated responses, integration of AI-mediated feedback, and the contribution of GenAI to both individual and collaborative project work. Such practices may help transform AI use from a predominantly instrumental activity into a transparent, reflective, and educationally meaningful learning process.

6. Limitations and directions for future research

This pilot validation study has several limitations that should be considered when interpreting the findings and when generalising the results.

First, the Romanian version of the GenAI-LLs was developed through linguistic translation and contextual adaptation for engineering PBL rather than a formal cross-cultural adaptation procedure involving forward–back translation and expert committee review. Although permission to translate, adapt, and preliminarily validate the instrument was granted by the original authors and the conceptual meaning of the original items was preserved, the present findings should be interpreted as preliminary. Future studies should undertake a comprehensive cross-cultural adaptation in accordance with established international guidelines.

Second, as a pilot validation study, the sample was obtained from a single technical university and consisted of 138 participants, representing a participant-to-item ratio of approximately 4.8:1. Although adequate for an exploratory EFA, larger and more heterogeneous samples are required to improve the generalisability and stability of the findings. Moreover, psychometric validation is an iterative process that requires the accumulation of evidence across different samples and contexts before an instrument can be considered well established (DeVellis & Thorpe, 2022).

Third, the psychometric evaluation relied exclusively on EFA. Consequently, the proposed four-factor structure should be regarded as preliminary until confirmed through CFA. Future validation studies should also examine measurement invariance across relevant groups (e.g., gender, academic disciplines or study year) to determine whether the instrument operates equivalently across different populations.

Fourth, both GenAI literacy and attitude towards GenAI were assessed using self-report measures, which may have increased the risk of common-method bias. In addition, attitudes towards GenAI were measured using a single global item and subsequently grouped into three categories. Although this approach facilitated exploratory group comparisons using ANOVA, it does not capture the multidimensional nature of attitudes towards GenAI and resulted in unequal category sizes, particularly for the low-attitude category. Consequently, these findings should be interpreted with caution. Future studies should employ validated multi-item attitude scales and more appropriate analytical approaches, such as ordinal regression or structural equation modelling.

Finally, although all items were retained because their primary factor loadings exceeded their secondary loadings and were conceptually consistent with the identified factors, need6 and need7 exhibited relatively similar primary and secondary loadings. This pattern may reflect the conceptual overlap between Needs analysis and Autonomous learning rather than a psychometric limitation. Nevertheless, the factorial allocation of these items should be regarded as preliminary and verified through CFA and cross-validation using larger, independent samples.

Future research should extend the validation of the Romanian GenAI-LLs using larger and more diverse samples from different higher education contexts. Beyond CFA, future studies should examine additional sources of validity evidence, including convergent, discriminant, criterion-related validity, longitudinal stability, and measurement invariance. Combining quantitative validation with qualitative approaches (e.g., interviews, focus groups, or learning diaries) may also provide deeper insights into how engineering students integrate GenAI into autonomous, collaborative, and critically reflective learning within PBL environments.

7. Conclusion

This pilot study provided preliminary evidence supporting the proposed internal structure of the Romanian adaptation of the GenAI-LLs for assessing GenAI literacy for use in engineering PBL. Although the EFA retained the original four-factor conceptualisation of GenAI literacy, it also revealed a partial reorganisation of several dimensions, reflecting the specific characteristics of AI-supported learning in engineering education. These findings provide preliminary support for the multidimensional conceptualisation of GenAI literacy, while highlighting the close relationships between identifying learning needs, prompt formulation, self-regulated learning, collaborative learning, and critical evaluation of AI-generated information.

The study further demonstrated that more positive attitudes towards GenAI were associated with higher levels of several GenAI literacy dimensions, particularly those related to the active educational use of AI, whereas no statistically significant gender differences were identified. Together, these findings suggest that GenAI literacy represents a complex educational competency integrating technical, metacognitive, collaborative, and critical dimensions that are essential for the effective and responsible use of AI in higher education.

Given the exploratory nature of this pilot validation, the findings should be interpreted as preliminary. Further psychometric evaluation using larger and independent samples is required to confirm the proposed factor structure through CFA, examine measurement invariance, and provide additional evidence of validity and reliability. Consistent with Kane's (2013) argument-based approach to validation, the present study provides preliminary evidence supporting the interpretation and intended use of scores obtained with the Romanian version of the GenAI-LLs in engineering higher education. Nevertheless, the adapted Romanian version of the GenAI-LLs represents a promising instrument for future research and for assessing students' GenAI literacy in engineering higher education, while also supporting the design and evaluation of AI-enhanced PBL environments.

Ethics statement

In accordance with the institutional guidance of the Technical University of Cluj-Napoca, formal ethical approval was not required because this study involved an anonymous voluntary questionnaire completed by adult university students and did not involve the collection of sensitive personal data. Participation was voluntary, informed consent was obtained before completion of the questionnaire, and all responses were collected anonymously.

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Appendix

The Generative AI Literacy for Learning Scale (GenAI-LLs)

(adapted from Gümüş & Kara, 2025)

Instructions: The purpose of this questionnaire is to explore students' experiences and perceptions regarding the use of Generative Artificial Intelligence (GenAI) in project-based learning within engineering education and to support the validation of a research instrument designed to assess GenAI literacy.

When responding to the statements below, please consider your experiences of using GenAI tools in engineering-related project activities. Using the scale provided (1 = strongly disagree to 5 = strongly agree), indicate the extent to which each statement reflects your experiences or opinions.

There are no right or wrong answers. We are interested in your honest responses. All responses are anonymous, will be treated confidentially, and will be used solely for research purposes.

SECTION I:

1. Gender:

- □ Female
- □ Male

2. Attitude level: Overall, I have a favourable attitude towards the use of GenAI in higher education.

- □ Strongly disagree
- □ Disagree
- □ Neutral
- □ Agree
- □ Strongly agree

SECTION II:

No. item	**Dimension**	**Code**	**Items**	**1-strongly disagree, 2-disagree, 3-neutral, 4-agree, 5-strongly agree**
1.	Needs analysis	need1	I can select the right GenAI tool for the content I need.	1 2 3 4 5
2.		need2	I can use GenAI tools to carry out a project.	1 2 3 4 5
3.		need3	I can determine the content type I need through GenAI tools.	1 2 3 4 5
4.		need4	I can decide whether I need GenAI tools at any stage of solving a project.	1 2 3 4 5
5.		need5	I can determine whether the content I will get from the GenAI tools is the knowledge I need to carry out a current project.	1 2 3 4 5
6.		need6	I know how to benefit from the GenAI tools to achieve my learning goals.	1 2 3 4 5
7.		need7	I can use GenAI tools to simplify a topic.	1 2 3 4 5
8.		need8	I can use GenAI tools to detail a topic.	1 2 3 4 5
9.	Prompt and language skills	prom1	I can enter detailed prompts into the GenAI tools to get access to the content I need.	1 2 3 4 5
10.		prom2	I can improve the prompts I enter into the GenAI tools to reach the content I need.	1 2 3 4 5
11.		prom3	I can detect the deficiencies in my prompts depending on the content generated by GenAI.	1 2 3 4 5
12.		prom4	I can create prompts to make the content generated by GenAI more meaningful.	1 2 3 4 5
13.		prom5	I can create prompts appropriate to diverse GenAI tools to reach the content I need.	1 2 3 4 5
14.		auto1	I can use GenAI to get feedback on what I learn.	1 2 3 4 5

15.	Autonomous learning	auto2	I can use GenAI to evaluate my performance on a specific issue.	1 2 3 4 5
16.		auto3	I can gain awareness through GenAI for my general learning progress in a field.	1 2 3 4 5
17.		auto4	I can use GenAI as a classmate role.	1 2 3 4 5
18.		auto5	I can use GenAI to improve my dialogue with my teammates in group work.	1 2 3 4 5
19.		auto6	I can use GenAI to collaborate with my teammates to complete a project.	1 2 3 4 5
20.		auto7	I can use GenAI to facilitate group activities for a project.	1 2 3 4 5
21.		auto8	I can evaluate the quality of the tasks I have completed by using GenAI tools.	1 2 3 4 5
22.		auto9	I can complete my tasks in group work by using diverse GenAI tools.	1 2 3 4 5
23.	Critical thinking	crit1	I can question the content generated by GenAI.	1 2 3 4 5
24.		crit2	I can reason about the accuracy of the content presented by GenAI.	1 2 3 4 5
25.		crit3	I can draw a logical conclusion about the bias in the content presented by GenAI.	1 2 3 4 5
26.		crit4	I reference other sources to decide on the accuracy of the content presented by GenAI.	1 2 3 4 5
27.		crit5	I reference other sources to decide on the objectivity of the content presented by GenAI.	1 2 3 4 5
28.		crit6	I can decide whether the content presented by GenAI is scientific knowledge or a subjective view.	1 2 3 4 5
29.		crit7	I verify the accuracy of the content presented by GenAI before using it.	1 2 3 4 5