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Development and validation of the Generative AI Literacy for Learning Scale (GenAI-LLs)

Muhammed Murat Gümüş
Department of Computer Technology, Amasya University

Mehmet Kara
Department of Educational Sciences, Amasya University

Research on artificial intelligence (AI) in education has mainly focused on the measurement instruments relevant to learning about AI and framing AI literacy as learning about AI. The present study's focus, however, was on developing and validating a scale pertinent to learning with generative artificial intelligence (GenAI) in higher education. Specifically, this study aimed to develop and validate the Generative AI Literacy for Learning Scale (GenAI-LLs). For this purpose, data were collected from three groups of university students at three time points. Exploratory factor analysis was conducted to discover the psychometric structure of the scale. Confirmatory factor analysis was conducted to confirm the explored structure with the data collected from a separate group of participants. Further item and internal consistency analyses were conducted to ensure the validity and reliability of the scale. Test-retest analysis was applied to the data from a different group to ensure the stability of the scale. The findings showed that the GenAI-LLs is a valid and reliable instrument that can be used to measure and evaluate the literacy university students need to learn with GenAI in diverse learning environments, including face-to-face, open, distance and flexible learning. The findings are discussed based on the literature on GenAI, and recommendations for future studies are offered.

Implications for practice or policy:

- Instructors can use GenAI-LLs as a valid and reliable instrument to measure and evaluate university students' GenAI literacy for learning.
- Instructors and curriculum developers may use GenAI-LLs as a framework – covering needs analysis, prompt and language skills, autonomous learning and critical thinking – during curriculum development and instructional design for integrating GenAI into learning environments.
- Higher education stakeholders should develop policies and actionable strategies for integrating GenAI into learning design, based on data from the GenAI-LLs.

Keywords: generative AI literacy, needs analysis, prompt and language skills, autonomous learning, critical thinking

Introduction

Although artificial intelligence (AI) is not a novel concept, it has recently become common in many fields, with the widespread adoption of generative artificial intelligence (GenAI). Specifically, AI tools have been introduced in recent years to improve the quality and efficiency of education, and consequently, the focus of research has been on AI concepts, usage and effects (Huang et al., 2023; Stracke et al., 2023). GenAI and its effects on education have now become a hot topic in education (Cooper, 2023; Ruiz-Rojas et al., 2023) and the spotlight of research efforts. GenAI refers to the systems generating new content such as text, audio, image and video by using deep learning models trained with large data sets (Banh & Strobel, 2023; Bozkurt, 2023). Users can use GenAI tools depending on their educational or learning needs. The examples for educational use include Muse AI for video editing, ChatGPT for accessing and using textual information, Midjourney for image editing, Viesus for design works, CodeGPT for coding tasks, ElevenLabs for audio tasks and Tome AI for presentation.

There are various potential advantages of using GenAI for educational purposes. GenAI tools have the potential to personalise learning experiences and generate content according to learners' individual learning needs and pace (Chan & Hu, 2023; Kuhail et al., 2023; Walter, 2024). Teachers can use these tools to develop course materials, utilise more effective instructional strategies and make learning more efficient and attractive (Salinas-Navarro et al., 2024; Walter, 2024). Despite the advantages, using GenAI in education has some challenges (Bozkurt, 2023; Su et al., 2023). These challenges can include concerns about information trustworthiness, access problems or restrictions due to paid use, potential negative influences on learners' creativity and critical thinking, technical issues during the integration into learning environments and the possible decrease in social learning (Bozkurt, 2023; Su et al., 2023). Therefore, the advantages of GenAI in education depend on the user's competencies in understanding, interpreting and making sense of the generated content (Bozkurt, 2023; Laupichler et al., 2022). In other words, both learners and teachers are required to have the necessary knowledge and skills to benefit effectively from these novel technologies and integrate them into the learning process (Kong et al., 2025; Laupichler et al., 2024). This suggests the need to improve their AI literacy (Cardon et al., 2023; Christ-Brendemühl, 2025; Johnston et al., 2024; Kong et al., 2023; Kong et al., 2025; Walter, 2024). For this reason, GenAI literacy has gained more attention in recent years (Dai et al., 2020; Hermann, 2022; Long & Magerko, 2020; Mikalef & Gupta, 2021; Ng et al., 2021; Steinbauer et al., 2021).

Given the potential of AI in education, improving learners' AI literacy has also become a concern at the higher education level. This is a necessity since harnessing the potential of AI in higher education depends on learners' AI literacy (Alamäki et al., 2024). For this reason, the potential benefits of AI are globally leading the curriculum development efforts in higher education, highlighting the ongoing need for strategy and policy in this regard (Abbasi et al., 2025). There are examples of effective pedagogical approaches at the course level (e.g., Tzirides et al., 2024) and institutional level (e.g., Southworth et al., 2023) to improve learners' AI literacy in higher education. However, a review study on AI in higher and adult education concluded that research in this area is still in the early phases and demands further development for defining AI literacy and delivering the content (Laupichler et al., 2022). A relatively recent study by Salhab (2024) showed that AI literacy is an underemphasised element in the curriculum, suggesting further improvement. Despite efforts at the course and institutional levels, further experimental studies are still needed to reveal the effects of the relevant interventions in diverse populations at the higher education level (Laupichler et al., 2022). As a prerequisite to addressing this and relevant needs for further improvement of AI literacy, the development of appropriate measurement instruments that can determine learners' and teachers' literacy levels and needs is essential (Cetindamar et al., 2024; Laupichler et al., 2022; Ng et al., 2021; B. Wang et al., 2023). This is also a prerequisite for drawing robust conclusions on the educational evaluation of this novel technology. However, many of the relevant studies have adopted GenAI literacy as learning about GenAI or technical competence and addressed ethical issues (Long & Magerko, 2020; B. Wang et al., 2023). This study, on the other hand, adopted the duality of learning about and with GenAI and specifically focused on learning with GenAI in higher education. Based on this standpoint, this study aimed to develop and validate the GenAI Literacy for Learning scale (GenAI-LLs).

GenAI literacy and current measurement instruments

Although GenAI literacy is addressed as a relatively novel concept in the relevant literature, it was defined using similar dimensions to the prior definitions of other digital literacies. The current definitions have the common dimensions of understanding, using, problem-solving, critical thinking and ethical use (Kong et al., 2023; Long & Magerko, 2020; Ng et al., 2021). Based on these dimensions, AI literacy can be defined as the cognitive, affective and sociocultural competencies, including understanding operation principles of AI, problem-solving through the ethical use of AI sources and critical thinking (Kong et al., 2023). In this regard, it can be concluded that GenAI literacy is an essential set of competencies for the effective use of GenAI tools in all fields, including education.

AI literacy is particularly significant for learners to effectively use AI in education. AI-literate learners are expected to effectively use technology (Mikalef & Gupta, 2021; Ng et al., 2021), to comprehend AI technologies (Kong et al., 2023; Ng et al., 2021; Steinbauer et al., 2021) and to be proficient in the ethical concepts of AI (Kong et al., 2023; Ng et al., 2021; B. Wang et al., 2023). They are also expected to demonstrate improved problem-solving and critical thinking skills (Hermann, 2022; Kong et al., 2021; Long & Magerko, 2020). GenAI literacy, based on these AI literacy dimensions, involves the duality of learning about and with GenAI. Whereas the former refers to technical and ethical knowledge and skills to benefit from GenAI for diverse purposes, the latter specifically refers to knowledge and skills required to have an effective learning experience with GenAI.

With the common adoption of GenAI tools, a growing number of diverse measurement instruments have been developed and validated for AI. The existing instruments generally focus on the adoption of AI tools and literacy as a technical competence (Biagini et al., 2024; Laupichler et al., 2023; Ng et al., 2024; Schepman & Rodway, 2020; Y. Wang & Lu, 2023). Some of these studies focused on the development and validation of scales for AI acceptance (Du & Lv, 2024; Karaoglan Yilmaz et al., 2024; Strzelecki, 2024a, 2024b), while others aimed to develop and validate instruments for AI literacy for non-expert users or the general population (Laupichler et al., 2023; Nong et al., 2024; B. Wang et al., 2023), teachers (Ning et al., 2025) and middle school students (Kim & Lee, 2022) and secondary school students (Ng et al., 2024). It is also remarkable that only one scale on AI literacy was developed for university students (Biagini et al., 2024). In the relevant studies, the instruments focused on AI literacy mainly covered the issues of understanding and use of AI tools, critical evaluation and ethics, and generally conceptualised it as learning about AI (Biagini et al., 2024; Laupichler et al., 2023; Ng et al., 2024; Nong et al., 2024; B. Wang et al., 2023). Besides, these scales encompass the umbrella concept of AI rather than specifically covering GenAI. The recently developed scales for learning experience with GenAI focused on learner agency (Xia et al., 2025) and reliance on GenAI in problem-solving (Hou et al., 2025). For this reason, the literature still lacks measurement instruments specifically focused on learning with GenAI, particularly given the crucial need for developing learners' GenAI literacy in higher education (Christ-Brendemühl, 2025). A scale specifically developed for learning with GenAI would enable educational stakeholders to gain insights into the effects of GenAI on learning and how to use and integrate it into education.

The present study

This study is the second phase of a larger research project. In the first phase, the framework for GenAI literacy for learning was proposed using the grounded theory approach (Gümüş, 2025). The study in the first phase was conducted with the participation of professors experienced in AI research and practice from diverse relevant disciplines, including educational technology, computer science and data science. The proposed framework covers readiness factors, core dimensions, potential consequences and potential challenges or negative impacts. In this framework, the core dimensions refer to the competencies for learning with GenAI, while the readiness factors are defined as the prerequisite competencies. The readiness factors are excluded in this study as they are related to learning about GenAI (GenAI technology, digital literacy, ethics and privacy). The present study is based on the core dimensions proposed in the GenAI literacy for learning framework and aimed to validate the relevant part of this framework. Thus, this study aimed to develop and validate a scale that measures GenAI literacy with a specific focus on learning with GenAI by moving beyond technical and ethical issues.

Method

The study aimed to investigate the psychometric characteristics of GenAI-LLs using data from higher education students. For this purpose, the scale development procedure proposed by DeVellis (2012/2014) was followed to ensure its validity and reliability.

Participants

The data were collected from three different groups of university students (see Table 1), selected through convenience sampling. The participants self-reported that they all had previous learning experience with GenAI tools, ensuring that each group met this criterion. They were enrolled in diverse associate and bachelor's degree programmes, which were categorised as social sciences (e.g., psychological counselling, translation and interpreting, history, literature) and natural and applied sciences (e.g., engineering, architecture, construction technology). The data from the first participant group were used to conduct exploratory factor analysis (EFA), while the data from the second group were used to conduct confirmatory factor analysis (CFA). The reliability analyses were conducted separately for each group. Finally, a test-retest analysis was performed using data from the third participant group to ensure the scale's stability.

Table 1
Distribution of the participants in terms of their demographics

Participant group	Gender	Educational level		Total
		Bachelor's degree (*N*)	Associate degree (*N*)	
Group 1	Male	240	52	292
	Female	155	79	234
	Total	395	131	526
Group 2	Male	40	39	79
	Female	49	98	147
	Total	89	137	226
Group 3	Male	8	-	8
	Female	13	-	13
	Total	21	-	21

Group 1 consisted of 395 bachelor's and 131 associate degree students. In this group, 292 of the participants were male, and 234 were female students. A total of 309 participants were enrolled in programmes related to the social sciences, and 217 in programmes related to the natural and applied sciences. Their ages ranged from 18 to 45 (M = 21.26). The highest number of participants were aged 22 and above (N = 203), followed by age 21 (N = 104), 20 (N = 112), 19 (N = 74) and 18 (N = 33). Group 2 covered 89 bachelor's and 137 associate degree students. In this group, 79 of the participants were male, while 147 were female students. Whereas 124 of them were enrolled in the programs of natural and applied sciences, 102 were enrolled in social sciences programmes. Like Group 1, the participants' ages ranged from 18 to 44 (M = 21.98), and most of the participants were aged 22 and above (N = 70), followed by 20 (N = 57), 21 (N = 49), 19 (N = 35), and 18 (N = 15). As for Group 3, a total of 21 participants, eight of whom were males and 13 of whom were females, participated in the study for the test-retest reliability. All participants in this group were enrolled in social sciences programmes. Their ages ranged from 21 to 24 (M = 21.45) and were distributed as 22 and above (N = 7), 20 (N = 8), and 21 (N = 6).

Procedure

The scale development procedure proposed by DeVellis (2012/2014) was followed to develop and validate the GenAI-LLs. The procedure followed is shown in Figure 1. Ethical approval was provided by the Social Sciences Ethics Committee within Amasya University, Türkiye, and an informed consent form was gathered from each participant. In the first stage, a comprehensive literature review was conducted to explore the scale's psychometric structure and to create an item pool accordingly. In addition to the relevant studies, the scale's psychometric structure was developed based on the framework proposed in a previous study conducted using the grounded theory approach (Gümüş, 2025). The item pool was created based on the relevant literature on GenAI competencies (Çelebi et al., 2023; Chan & Colloton, 2024; Hwang et al., 2023; Karaoglan Yilmaz et al., 2024; Kim & Lee, 2022; Laupichler et al., 2022; Ng et al., 2021; Su et al., 2023; B. Wang et al., 2022) and the framework proposed by Gümüş (2025). The GenAI-LLs was structured using a 5-point Likert-type scale from 1 (*strongly disagree*) to 5 (*strongly agree*).

The scale's content validity was ensured through feedback from five professors of educational technology and one professor of computer science, who are experienced in the research and practice of AI. Feedback was additionally obtained from one professor of Turkish language education, because the scale was distributed in Turkish, and from one professor of measurement and evaluation in education. The scale's face validity was also ensured through the feedback gathered from six university students. As a result, the item pool consisted of 44 items.

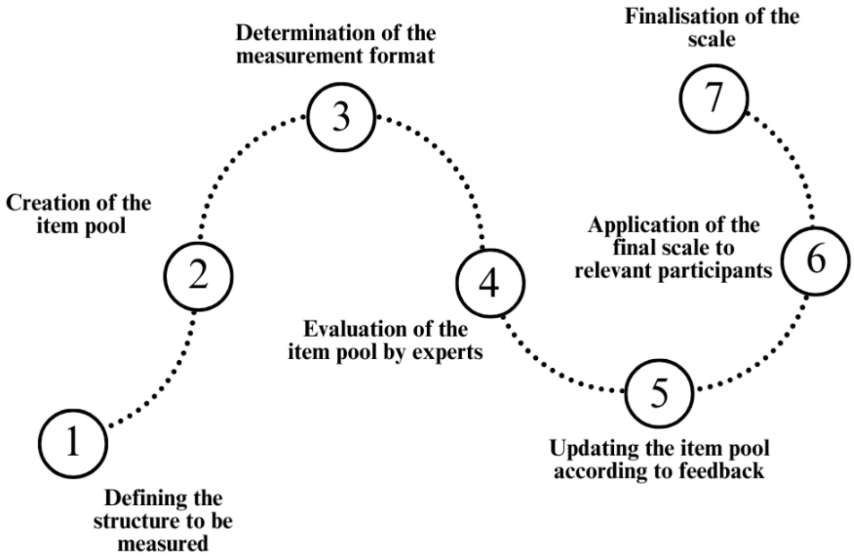


Figure 1. Stages followed in the scale development and validation

Data analysis

The Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were first performed to determine whether the data collected from Group 1 were appropriate for conducting EFA. The obtained KMO value, above .90, showed that the data set is appropriate for performing EFA (Field, 2013). The significant value obtained from Bartlett's test ($p < 0.001$) showed that the collected data are suitable for factor analysis (Büyüköztürk, 2002). Principal component analysis was employed to reveal the factors and factor loadings as recommended by Tabachnick and Fidell (2013). The factor loadings were investigated through the varimax orthogonal rotation method. The varimax method was selected to make factor loadings more explicit and interpretable, assuming that the investigated factors in the EFA are uncorrelated (Field, 2013; Kaiser, 1958; Tabachnick & Fidell, 2013). In addition, items with factor loadings below .40 and cross-loading items with differences in squared loadings of around 0.10 or smaller were considered for exclusion. (Hair et al., 2019). These criteria indicate the statistical fit according to the sample size and are commonly adopted in scale development studies to ensure both the reliability and construct validity of the factors (Stevens & Stevens, 2001). In the final analysis, the factor loadings ranging from .543 to .803 and the explained total variance of 53.674% were assumed to be satisfactory (Büyüköztürk, 2002).

CFA was subsequently conducted for construct validity by confirming the psychometric structure of the theoretical model obtained from the EFA. By this analysis, the hypotheses concerning the relationships between the factors and the items within them were tested (Pohlmann, 2004). The following goodness of fit indices (GFI) were used to determine the model fit (Byrne, 2013; Hu & Bentler, 1999): χ^2/df (chi-square/degree of freedom ratio), comparative fit index (CFI), goodness of fit index (GFI), Adjusted goodness of fit index (AGFI), incremental fit index (IFI), Tucker-Lewis index (TLI), root-mean-square error of approximation (RMSEA) and standardised root-mean-square residual (SRMR). These fit indices must be in the acceptable ranges to ensure the construct validity (Thompson, 2000). The investigated fit indices in this study were mainly observed to be acceptable, indicating a satisfactory model fit (Byrne, 2013; Hu & Bentler, 1999; Kline, 2005; Tabachnick & Fidell, 2013).

Both Cronbach's alpha and McDonald's omega coefficients were computed to reveal the internal consistency of the developed scale. These values are required to be above .70 to ensure the scale's reliability (Büyüköztürk, 2002). Corrected item-total correlations and the independent samples t test, performed between the upper and lower 27% groups in the data, were conducted to investigate item discrimination. The criteria for the item discrimination in the corrected item-total correlation values are that the coefficients above .30 are acceptable, and the coefficients above .40 are perfect items (Tekin, 2019). As for the scale's stability, a test-retest analysis was conducted using the data collected twice from Group 3 (Balcı, 2009). In this regard, it was assumed that the correlations above .70 demonstrated the scale's stability (Büyüköztürk, 2002).

Findings

Validity of the scale

EFA

The KMO analysis was first conducted to determine if the sample size was appropriate for the factor analysis. Bartlett's test of sphericity was conducted to check if the data set is suitable for factor analysis. The KMO value was found to be .908, while Bartlett's test of sphericity provided a significant result ($\chi2(406) = 6896.137$; $p < .001$). These findings suggest that the sample size and the data set are adequate for factor analysis.

The principal components analysis was applied to identify the number of factors, using the varimax orthogonal rotation technique. Based on this analysis, 15 items were removed from the analysis using the following criteria: items with factor loadings less than .40, items demonstrating distribution under multiple factors and items with factor loading differences between them less than .10. Some of the excluded items are as follows: "I can develop my learning strategies through generative AI", "I can use generative AI as a guide" and "I adopt a skeptical approach to the content presented by generative AI". The cross-loading items were evaluated based on the relevant literature. Given the strong factor loadings ranging from .543 to .803, the items were reported under the factor for which they demonstrated a higher factor loading consistent with their content. The analysis was conducted again with the 29 remaining items. Table 2 shows that the scale has four factors and accounts for 53.674% of the variance. The contents of the identified factors were examined, and each of them was labelled based on the qualitative findings and the relevant literature. Thus, the identified factors were labelled as (1) Needs analysis, (2) Prompt and language skills, (3) Autonomous learning and (4) Critical thinking. The scale is available at https://drive.google.com/file/d/1f7Qjz8UbGwuWIAB0yBlMZWlbnaZkporZ/view?usp=sharing.

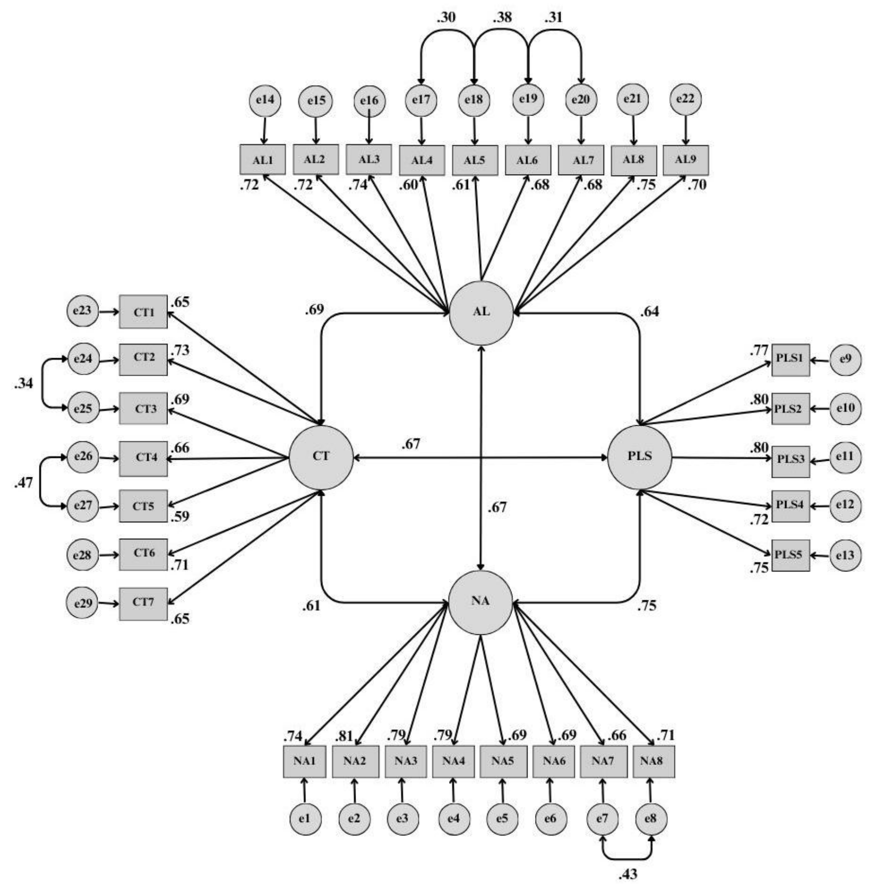
Table 2
Findings from the EFA for GenAI-LLs

Factors	Items	Communality factor	1	2	3	4
1. Needs analysis	1	0.645	0.775			
	2	0.690	0.799			
	3	0.581	0.706			
	4	0.570	0.704			
	5	0.510	0.568			
	6	0.531	0.595			
	7	0.439	0.543			
	8	0.467	0.577			
2. Prompt and language skills	9	0.592		0.720		
	10	0.700		0.803		
	11	0.591		0.715		
	12	0.475		0.592		
	13	0.494		0.579		
3. Autonomous learning	14	0.442			0.559	
	15	0.515			0.680	
	16	0.485			0.636	
	17	0.525			0.721	
	18	0.555			0.743	
	19	0.593			0.748	

Factors	Items	Communality factor	1	2	3	4
	20	0.473			0.603	
	21	0.547			0.654	
	22	0.427			0.552	
4. Critical thinking	23	0.495				0.642
	24	0.583				0.703
	25	0.499				0.638
	26	0.642				0.787
	27	0.580				0.742
	28	0.465				0.613
	29	0.456				0.640
Eigenvalue			9.053	2.772	2.184	1.556
Variance explained		Total = 53.674	31.217	9.559	7.531	5.367

CFA

A separate data set was used to test the psychometric structure revealed by the EFA, consisting of four factors and 29 items. The model obtained from the CFA using maximum likelihood is shown in Figure 2. According to Figure 2, the factor loadings of the items range from .59 to .81, which indicates an adequate level for the model fit. The fit indices gathered from the CFA are presented in Table 3. The fit indices were gathered as $\chi 2$/df = 2.265, CFI = 0.91, GFI = 0.85, AGFI = 0.83, IFI = 0.91, TLI = 0.91, RMSEA = 0.061 and SRMR = 0.054. The obtained values for the fit indices demonstrate an acceptable model fit based on the relevant literature (Kline, 2005; Tabachnick & Fidell, 2013).



Note. CT: critical thinking; AL: autonomous learning; NA: needs analysis; PLS: prompt and language skills
Figure 2. Standardised path diagram produced through the CFA

Table 3
Obtained values for the model fit indices (N = 346)

Fit indices	Obtained values	Acceptance criteria	Decision
χ2/df	2.265	χ2/df ≤ 5	Perfect fit (Kline, 2005)
CFI	0.91	0.90 > CFI	Acceptable fit (Tabachnick & Fidell, 2013)
GFI	0.85	0.90 > GFI	-
AGFI	0.83	0.90 > AGFI	-
IFI	0.91	0.90 > IFI	Acceptable fit (Kline, 2005)
TLI	0.91	0.90 >TLI	Acceptable fit (Kline, 2005)
RMSEA	0.061	RMSEA < 0.08	Acceptable fit (Kline, 2005)
SRMR	0.054	SRMR < 0.10	Perfect fit (Kline, 2005)

Item-factor total and corrected correlations

The correlations between the values from each item and the total scores from each factor, item-factor correlations and corrected item-total correlations were computed to reveal the consistency level of each item with the overall goal of the scale. The item-factor correlations and corrected correlations computed for each item are shown in Table 4. As indicated in the table, correlation coefficients for Factor 1 ranged from .655 to .805, while the correlations for Factor 1 ranged from .713 to .812. As for Factor 3, the correlations ranged from .643 to .756, while the correlations for Factor 4 ranged from .688 to .771. We observed that there are positive and significant correlations between all factors and the items that they cover, suggesting that the items function under the overall goal of the scale.

Table 4
Findings from item-factor correlation and corrected correlation analyses (N = 526)

F1			F2			F3			F4		
Needs analysis			Prompt and language skills			Autonomous learning			Critical thinking		
I	*r*	r^*	I	*R*	r^*	I	*r*	r^*	I	*r*	r^*
1	0.784**	0.694	8	0.760**	0.596	25	0.643**	0.539	35	0.697**	0.569
2	0.805**	0.733	9	0.812**	0.676	26	0.697**	0.604	36	0.745**	0.648
3	0.747**	0.657	10	0.758**	0.600	27	0.693**	0.602	37	0.709**	0.598
4	0.747**	0.662	14	0.713**	0.550	28	0.696**	0.576	38	0.771**	0.662
5	0.696**	0.594	15	0.719**	0.557	29	0.699**	0.585	39	0.736**	0.615
6	0.716**	0.606				30	0.756**	0.669	40	0.693**	0.561
21	0.655**	0.541				31	0.671**	0.578	41	0.688**	0.556
22	0.688**	0.578				32	0.728**	0.644			
						33	0.650**	0.549			

**$p < .001$.
Note. r = item-factor total and corrected correlations r^* = findings from the corrected correlation analyses of the item-factor scores

Table 4 further demonstrates corrected correlations of item-factor scores. The correlations for Factor 1 ranged from .541 to .733, while the correlations for Factor 2 ranged from .550 to .676. The corrected correlations for Factor 3 ranged from .539 to .669, while the ones for Factor 4 ranged from .556 to .662. These correlations are positive and significant, meaning that each item in the scale functions consistently with the overall goal of the scale.

Item discrimination

The upper 27% and lower 27% of the scores obtained from the items were compared by conducting an independent samples *t* test to ensure item discrimination. Table 5 presents the findings from the independent samples t-test and shows that all obtained *t* values for the items are significant ($p < .001$) with a range of *t* values from 6.899 to 16.664. The *t* value for the overall scale was 35.103 and significant

(p <. 001). These findings suggest that all items and the overall scale demonstrate discrimination at a high level.

Table 5
Independent samples t test results for the upper and lower 27% groups

Factor 1 Needs analysis		Factor 2 Prompt and language skills		Factor 3 Autonomous learning		Factor 4 Critical thinking	
I	*t*	I	*t*	I	*t*	I	*t*
1	12.532	8	15.667	25	10.822	35	11.137
2	12.190	9	16.664	26	8.999	36	11.251
3	13.708	10	14.938	27	11.599	37	12.668
4	12.815	14	14.771	28	8.499	38	10.713
5	12.773	15	15.559	29	6.899	39	10.697
6	13.582			30	10.142	40	13.071
21	12.018			31	11.372	41	10.441
22	12.615			32	12.761		
				33	11.952		
F1	20.437	F2	26.451	F3	16.060	F4	17.664
Overall scale							35.103

p < .001.
Note. df: 282.

Reliability of the scale

Internal consistency

Both Cronbach’s alpha and McDonald's omega values were computed to determine the internal consistency of the GenAI-LLs. According to Table 6, the Cronbach alpha and McDonald's omega values obtained for the overall scale are .917 and .912 respectively. As for the factors, the Cronbach alpha values ranged from .809 to .874, while the McDonald's omega values ranged from .805 to .872. These values indicate that the overall scale and the factors demonstrate satisfactory internal consistency.

Table 6
Obtained values for the internal consistency coefficients (N = 526)

Factors	Number of items	Cronbach’s alpha	McDonald's omega
Needs analysis	8	0.874	0.872
Prompt and language skills	5	0.809	0.805
Autonomous learning	9	0.863	0.859
Critical thinking	7	0.844	0.841
Total	29	0.917	0.912

Scale constancy or stability

Test-retest was used to determine the constancy or stability level of the GenAI-LLs. For this purpose, the scale was distributed twice with a 3-week interval to 21 participants. The correlations between the mean scores obtained from the two cycles and the scores from the overall scale and factors were computed to determine how constant or stable the scale is in measuring the GenAI-LL. Table 7 shows that the correlation coefficients obtained from the test-retest ranged from .629 to .858 and were significant. The correlation coefficient obtained for the overall scale was .739, and significant. These findings reveal that the scale provides stable measurements over time.

Table 7
Findings from test-retest analysis (N = 21)

Needs analysis	Prompt and language Skills	Autonomous learning	Critical thinking	GenAI-LLs
r	*R*	*r*	*r*	*r*
0.629**	0.750**	0.858**	0.638**	0.738**

**p <. 001.

Discussion, conclusion and recommendations

The present study aimed to develop and validate the GenAI-LLs. In other words, it aimed to quantitatively confirm a part of the previously proposed framework for GenAI literacy for learning (Gümüş, 2025). The scale was developed and validated by following the scale development procedure proposed by DeVellis (2012/2014). The validated scale consists of four factors and 29 items. The factors covered by the scale are (1) Needs analysis, (2) Prompt and language skills, (3) Autonomous learning and (4) Critical thinking. These factors were consistently explored in the previous qualitative framework development study (Gümüş, 2025). Unlike the prior framework, the items relevant to collaborative learning are included in the autonomous learning factor since learner autonomy in collaborative tasks is covered in this dimension. Besides, the reason collaborative learning is invisible as a standalone factor might be the inadequacy of learners' formal experiences in instructor-guided AI-assisted collaborative learning, although they reported that they have learning experience with GenAI. A recent study by Hou et al. (2025) confirmed this notion by exploring collaborative use as a standalone factor with the participation of learners engaged in instructor-led collaborative problem-solving tasks in class.

The construct validity of the scale was first ensured through the EFA. The findings revealed that the four-factor psychometric structure explains 53.674% of the total variance. Second, the CFA was employed to test how the explored structure fits with the data collected from a separate group of participants. The findings revealed that the measurement model demonstrates a satisfactory model fit. The findings from both the EFA and CFA ensured that the GenAI-LLs demonstrates satisfactory construct validity. Besides, there are positive and significant relationships between item-total correlations, each item and the relevant factor. Item discrimination was also ensured through the independent samples t test conducted to reveal the mean differences between the upper and lower 27% groups. The findings showed that the item discrimination of the GenAI-LLs is satisfactory, as a significant difference was observed for each item. The internal consistency of the scale was checked by computing both Cronbach's alpha and McDonald's omega values for each factor and the overall scale. The GenAI-LLs demonstrated a high level of internal consistency based on the computed values. Test-retest was also employed through the data collected from a separate group of participants in two cycles to ensure the stability of the scale. Thus, we conclude that the GenAI-LLs is a valid and reliable instrument capable of measuring learners' GenAI literacy for learning.

Although the GenAI-LLs has similarities with previously developed and validated scales in the relevant literature, it also has several differences, as the scale specifically focuses on learning with GenAI, rather than learning about it (e.g., technical understanding, application and ethical issues). In this sense, it is essential to elaborate on the distinctions and similarities between the dimensions of the GenAI-LLs and the prior scales on AI literacy and relevant constructs for learning, such as learning agency (Xia et al., 2025) and learner reliance on GenAI in problem-solving (Hou et al., 2025). First, the needs analysis dimension covered in this study refers to how learners select and use the GenAI tools to meet a need or solve a problem, and how they analyse the content generated by these tools. In the same vein, several studies have partially addressed needs analysis by understanding and problem-solving with AI (Kim & Lee, 2022), use (Laupichler et al., 2023; Ma & Chen, 2024) or use and evaluation (Çelebi et al., 2023) and the dimension relevant to information (Biagini et al., 2024). Recently developed scales also partially addressed needs analysis as dimensions such as "goal setting" and "selective action" in learner agency (Xia et al., 2025) or reflective use in the context of problem-solving with GenAI (Hou et al., 2025).

Second, the prompt and language skills dimension covered in this study refers to the learners' interactions with GenAI through prompts and their language knowledge and skills during their learning experience. Although the prompt and language skills are partially covered by the usage dimensions in the relevant studies (Hwang et al., 2023; B. Wang et al., 2023), this study provides specific indicators for how to use language in prompts for learning. The recent scales developed by specifically focusing on learning experience with GenAI likewise covered prompt and language skills such as “self-adjustment” and “selective action” dimensions of learning agency with GenAI (Xia et al., 2025) or “reflective use” dimension of reliance on GenAI in problem-solving (Hou et al., 2025). Given the fundamental role of prompts in GenAI use for learning, the current scale addresses it as a separate factor.

Third, autonomous learning in this study refers to learners’ self-regulation skills for individual and collaborative learning. This dimension also encompasses individualisation of the learning experience, which is distinct from the relevant devised dimensions in the prior studies, such as performance expectancy (e.g. Karaoglan Yilmaz et al., 2024) and planning with AI (Kim & Lee, 2022). Recent scales on learner agency with GenAI consistently encompassed learner autonomy and collaboration with peers, such as “goal setting”, “self-adjustment”, “self-reflection” or “participative action” (Xia et al., 2025) and “reflective use” and “collaborative use” in the GenAI reliance scale (Hou et al., 2025). Thus, the present study indicates that learners’ self-regulation skills in both individual, and collaborative learning play a substantial role in GenAI literacy for learning.

The final dimension of the GenAI-LLs, critical thinking refers to learners’ skills in questioning and evaluating the content generated by GenAI during their learning experiences, such as inaccuracy and bias, which are required to deal with the potential risks of learning with GenAI (Noroozi et al., 2024). Likewise, the critical understanding dimension covered by a relevant study (Hwang et al., 2023) refers to the users’ skills for critically evaluating the content generated by AI. Another study, by Kim and Lee (2022), focused on testing the information or technical aspects of generating information in the dimensions of problem-solving with AI. On the other hand, the GenAI-LLs addresses critical thinking as a factor influencing the learning experience and outputs. Consistently, the recent scales, focusing specifically on learning, also emphasised the role of critical thinking skills for GenAI use for learning by covering “responsible action” dimension of learner agency scale in GenAI context (Xia et al., 2025) and “reflective use” and “cautious use” dimensions of reliance on a GenAI scale in problem-solving (Hou et al., 2025).

The present study makes an original contribution to the relevant literature by moving beyond the technical and ethical aspects of AI literacy in previous studies, which focus more on learning or teaching about AI (e.g. Karaoglan Yilmaz et al., 2024; B. Wang et al., 2023). Unlike previous literacy scales, the present study presents a scale specifically developed and validated for GenAI and the learning experience with it in higher education, consistent with recently developed scales for learning experience with GenAI (Hou et al., 2025; Xia et al., 2025). Given the call for action on improving learners’ GenAI literacy in higher education (Christ-Brendemühl, 2025) and further research on the definition of AI literacy and the content to be taught (Laupichler et al., 2022), the GenAI-LLs contributes to the operational conceptualisation of GenAI literacy for learning and curriculum development in higher education. Additionally, it would make substantial contributions to the integration of GenAI tools into learning environments in higher education contexts by getting actionable insights with data on learning with GenAI. In other words, the scale can be used to gain insights into practices with GenAI, to conduct needs analysis and to evaluate the effectiveness of AI-assisted instruction in higher education in various learning environments, including face-to-face, open, distance and flexible learning.

The current study has several limitations and implications for further studies. First, the study was conducted with convenience sampling in all three data collection cycles, a method that requires replication studies. The GenAI-LLs was also distributed to the participants in Turkish, requiring that the validity and reliability further ensured through the participation of learners from diverse social and cultural contexts. Despite being adequate for this study, the small sample size used in test-retest reliability requires replication studies to enhance the scale’s stability and generalisability. The participants of this study are limited to the undergraduate learners enrolled in face-to-face programmes in higher education. Future studies could use the scale with learners participating in diverse contexts such as K-12 education, open, distance, flexible and adult learning environments, and further provide evidence on the generalisability of the findings. In this sense, the GenAI-LLs can be adapted for the stakeholders of education and corporate training to enhance the external validity. Furthermore, the criterion validity of the scale can be satisfied with further association studies on the theoretically relevant constructs or similar AI literacy scales. Future studies may use the scale as a measurement instrument in associational and experimental studies to reveal related variables and the impact of interventions. Given the call for further experimental studies to demonstrate the impacts of the relevant interventions at the higher education level (Laupichler et al., 2022), the GenAI-LLs can be used to measure and evaluate the effects of the designed interventions in AI-enhanced learning environments. Finally, the scale was developed for the evaluation of learning experience with all GenAI tools. It can be adapted to measure learners' experiences with specific GenAI tools such as ChatGPT or Gemini.

Author contributions

Author 1: Conceptualisation, Investigation, Methodology, Formal analysis, Writing – original draft, **Author 2**: Conceptualisation, Supervision, Investigation, Formal analysis, Writing – review and editing

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Corresponding author: Muhammed Murat Gümüş, muhammedmuratg@gmail.com

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