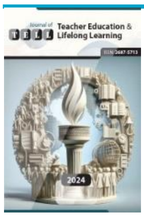

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Generative Artificial Intelligence as a Lifelong Learning Self Efficacy: Usage and Competence Scale

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ABSTRACT

The aim of this study is to develop a scale to measure the usage and competence levels of generative artificial intelligence as a lifelong learning self-efficacy among young and adult lifelong learners. Research data were collected from 248 individuals aged between 18 and 55. After a thorough review of the literature and theoretical frameworks such as the Technology Acceptance Model, Self-Efficacy Theory and Connectivism, an item pool for the scale was created. Similar scales in the related field were examined, and the item pool was developed accordingly. The items were reviewed by experts in educational technology, lifelong learning, and scale development. After making the necessary revisions, the trial form of the scale was presented to the participants. To determine the construct validity of the scale, exploratory factor analysis was conducted. The results of the exploratory factor analysis indicated that the scale consisted of two factors. The first factor comprises 10 items, while the second factor consists of 9 items. Confirmatory factor analysis was performed to reveal the relationships within the factors, the relationships between the variables and the factors, and the explanatory power of the factors on the model. The internal consistency coefficient, Cronbach's alpha reliability value, was determined to be .833, and the Spearman-Brown coefficient was found to be .711, both of which indicate acceptable reliability. In conclusion, the Generative Artificial Intelligence Usage and Competence (GAIUC) Scale is expected to fill a gap in the literature by providing a validated tool to measure both the usage and competence of lifelong learners in using AI. This scale can serve as a foundation for future studies exploring AI-supported learning in various educational contexts.

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INTRODUCTION

Despite rapid advancements in the field of artificial intelligence, practical research on artificial intelligence, especially in the field of education and lifelong learning, is still in its early stages. In this context, the utilization of available innovative tools and associated research efforts becomes significantly important. However, questions surrounding innovations such as artificial intelligence -like whether AI will take over our jobs- arouse curiosity but also raise concerns among individuals (Ersöz, 2020). Such concerns may lead to avoidance of the subject, indecision, and even foster antipathy. It is evident that there is a notable gap in scale studies related to artificial intelligence. The primary objective of this study is to develop a scale that evaluates the level of usage and competence in artificial intelligence among lifelong learners, aiming to facilitate steps to enhance this level for rapid adaptation to the future world. This study aims to fill the gap in scale development related to artificial intelligence usage and competence among lifelong learners -specifically focusing on educators, students, teachers, and professionals in various sectors- and to make a significant contribution to the academic literature.

Artificial intelligence has become an integral part of our lives in many fields (Aslan, 2019). Artificial intelligence (AI) has indeed become a significant part of daily life and numerous industries, driving advancements and improvements across various fields. AI is used to improve diagnostic accuracy, personalize treatment plans, and speed up drug discovery processes (Semenov, Baranova & Yagya, 2022; Bohr & Memarzadeh, 2020; Bhattad & Jain, 2020). AI systems analyze vast amounts of financial data in real-time to optimize trading decisions and detect unusual patterns that may indicate fraud (Singh, Garg & Tiwari, 2019; Xie, 2019; Baranidharan, 2023). Smart factories use AI to adjust production schedules and inventory levels in real-time (Staš, Tolnay & Magdolen, 2009; Hrnjica & Softic, 2020; Li, Hou, Yu, Lu & Yang, 2017). AI systems are also used for traffic management, reducing congestion, and optimizing the flow of vehicles on busy streets (Duan et al., 2021). And especially AI is reshaping education by offering personalized learning experiences, automating grading systems, and providing virtual tutoring through intelligent chatbots (Shen, 2020; Li et al., 2021; Qin & Wang, 2022; Medvedev, Golovyatenko & Podymova, 2022). However, this integration has led to the disappearance of many professions and changes in the job descriptions of others. According to Facebook artificial intelligence experts, artificial intelligence is expected to take on new roles in human activities in many areas, ranging from production to education, sales to maintenance and repair, and even the management of smart robots. Additionally, artificial intelligence and robots will enable the emergence of new service sectors. This increasing digitization of industries is also transforming the field of education, particularly through the integration of artificial intelligence technologies, hence artificial intelligence awareness holds significant importance for educators. Aslan (2019) states, “If advanced technologies usher in more effective and constructive educational models, then qualified and productive individuals can be nurtured for the future.” It is evident that artificial intelligence, by integrating theories and technologies, brings about significant changes in the educational process and will continue to do so (Arslan, 2020). For example, AI-driven personalized learning systems are already enabling teachers to tailor educational experiences to individual student needs, while AI-powered analytics are helping educators track and improve student performance (Fan, Wu, Zheng, Zhang & Jiao, 2023; Zhu, 2019; Maseleno et al., 2018; Azcona, 2019). In this process, educators especially need to develop professional awareness to effectively adapt to a digitized society and meet the evolving needs of students. Tools such as ‘Generative Artificial Intelligence as a Lifelong Learning Self Efficacy: Usage and Competence Scale’ can provide data on how educators adapt to AI technologies and their professional competence, offering guidance for future studies.

Machines began to take over tasks that required human physical strength, and humanity, by adapting to this transformation, created opportunities for gains from this new situation with the onset of the Industrial Revolution. However, by the 21st century, the question arose of how tasks achievable with human intelligence could be performed by machines (Tegmark, 2019).

Examining the origins of artificial intelligence, it is evident that the scientist Alan Turing played a significant role. In his 1950 paper "Computing Machinery and Intelligence," Turing posed the question "Can machines think?" and refuted objections to this idea (Pirim, 2006). Additionally, Turing is renowned for deciphering the Enigma code used by the German military and for his involvement in the construction of the first electronic computers in London. Turing investigated whether machines could perform decision-making and problem-solving tasks, similar to humans, and developed the Turing test for this purpose (Say, 2018; Arslan, 2020).

While humans can access information through their five senses, artificial intelligence can access information more quickly and extensively through internet connectivity (Tunç & Sanduvaç, 2020). This advantage has enabled AI to play a role in various industries such as healthcare, banking, communication, commerce, video games, the military, automotive, and robotics (Gunkel, 2012; Safadi, Fonteneau & Ernst, 2015; Stanciu & Rindașu, 2021).

Bandura's Self-Efficacy Theory (Bandura, 1977) suggests that individuals' beliefs in their capabilities to perform tasks are critical for motivation and persistence in learning. This theory provides the framework for assessing how lifelong learners view their competence and confidence in using artificial intelligence tools. According to the Technology Acceptance Model (TAM) (Davis, 1989), individuals' perceived ease of use and perceived usefulness significantly influence their acceptance of new technologies. In the context of artificial intelligence, this model provides a foundation for understanding how lifelong learners perceive and develop competence in using AI technologies. Siemens' Connectivism Theory (2005) posits that learning occurs through networks and connections facilitated by digital technologies. This theory underpins the concept of AI-supported lifelong learning, where learners continuously adapt to new technologies and information through their engagement with AI systems.

The rapid development and proliferation of artificial intelligence technology necessitate the identification of appropriate competencies to enable individuals and societies to use this technology effectively and safely. The use of artificial intelligence and machine learning techniques is increasingly prevalent across many professions, making the ability to effectively use AI technologies crucial for professional success. AI technologies also play a significant role in education and training, and an AI usage and competence scale can be an important tool for assessing the knowledge and skills of students, teachers, and educators in the field of AI. There is growing societal awareness of the impacts and potential risks of AI technologies; hence, an AI usage and competence scale can help individuals use AI systems more consciously and better understand potential risks. For these reasons, the study of AI usage and competence as a lifelong learning self-efficacy is considered significant.

As a result, this study aims to investigate individuals' usage and competence levels in artificial intelligence. In line with this objective, the following sub-objectives have been pursued:

➔ What is the construct validity status of the Generative Artificial Intelligence Usage and Competence (GAIUC) Scale?

➔ What is the reliability status of the Generative Artificial Intelligence Usage and Competence (GAIUC) Scale?

METHOD

This study is research on scale development. Below, the process of validity and reliability testing of the scale for usage and competence in artificial intelligence, along with the characteristics of the study group, are presented.

Research design

Our study, aiming to develop a valid and reliable scale to assess the usage and competence of artificial intelligence tools by lifelong learners, adopts a descriptive survey model. The descriptive survey model allows for the direct depiction of current or ongoing situations and summarizes the characteristics of the collected data (Karasar, 2007). Therefore, in this study, a descriptive survey model has been employed.

The scale was developed based on a multi-theoretical framework. The ‘AI Usage Competence’ dimension is grounded in the Technology Acceptance Model (Davis, 1989), which emphasizes the importance of perceived ease of use and usefulness in technology adoption. The ‘Self-Efficacy in AI Usage’ dimension is rooted in Bandura’s (1977) Self-Efficacy Theory, reflecting the confidence individuals feel in their ability to use AI tools effectively. Finally, the ‘AI-Supported Lifelong Learning’ dimension is informed by Siemens’ (2005) Connectivism Theory, which highlights the role of digital networks in ongoing learning processes.

Research Universe and Sample

In the initial stage of item pool development, there were 76 items. Following eliminations due to redundancy, divergence from conceptual boundaries, and factors loading below certain thresholds, a decision was made to start working with 33 items as draft items. After review by educational technology experts, counseling psychologists, and language specialists, 22 items were selected for implementation. The research data were obtained from 248 participants in the first half of the year 2024. Basic information regarding the participants is provided in the table below.

Table 1. *Participant Data*

Gender	Male	Female	Total
18-25 years	23	26	49
26-35 years	28	44	72
36-45 years	49	35	84
46-55 years	25	18	43
Total	**125**	**123**	**248**

Participants were selected based on their engagement in lifelong learning activities, with age ranges reflecting the end of compulsory education up to the pre-retirement period. This selection was made to capture a broad spectrum of AI usage and competence levels in various stages of adult learning. Accordingly, the number of male and female participants in the study was balanced. In terms of age distribution, the majority of the participants were middle-aged individuals.

Data Analysis

In this process, JAMOVI software was used for data analysis. Principal component analysis was conducted to determine the construct validity of the scale developed to measure lifelong learners’ usage and competence in artificial intelligence (Büyüköztürk, 2002). The suitability of the data for factor analysis was examined based on the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett’s Test of Sphericity. Following exploratory factor analysis, 3 negative items out of 19 were recoded, and a minimum factor loading criterion of 0.40 was considered for model fit (Büyüköztürk, 2002; Hair, Hult, Ringle & Sarstedt, 2021; Hair, Risher, Sarstedt & Ringle; 2019; Wieland, Durach, Kembro & Treiblmaier, 2017; Ali, Rasoolimanesh, Sarstedt, Ringle & Ryu, 2018). The number of factors was determined using eigenvalues and a scree plot. The discriminant validity of the 19 items was examined through the independent samples t-test. Additionally, the significance of the lower and upper 27% group item scores was investigated to observe how lifelong learners’ usage and competence in artificial intelligence were influenced through the scale items. The validity of the scale consisting of 19 items was established. Following exploratory factor analysis, confirmatory factor analysis was performed. In confirming the acceptability of the entire scale, RMSEA, S-RMR, GFI, AGFI, CFI, NFI, and IFI values were considered (Byrne, 2011; Çokluk, Şekercioğlu & Büyüköztürk, 2010). To determine the reliability of the scale, internal consistency coefficients Cronbach's alpha and Spearman-Brown values were examined.

FINDINGS / RESULTS

Findings Related to Validity

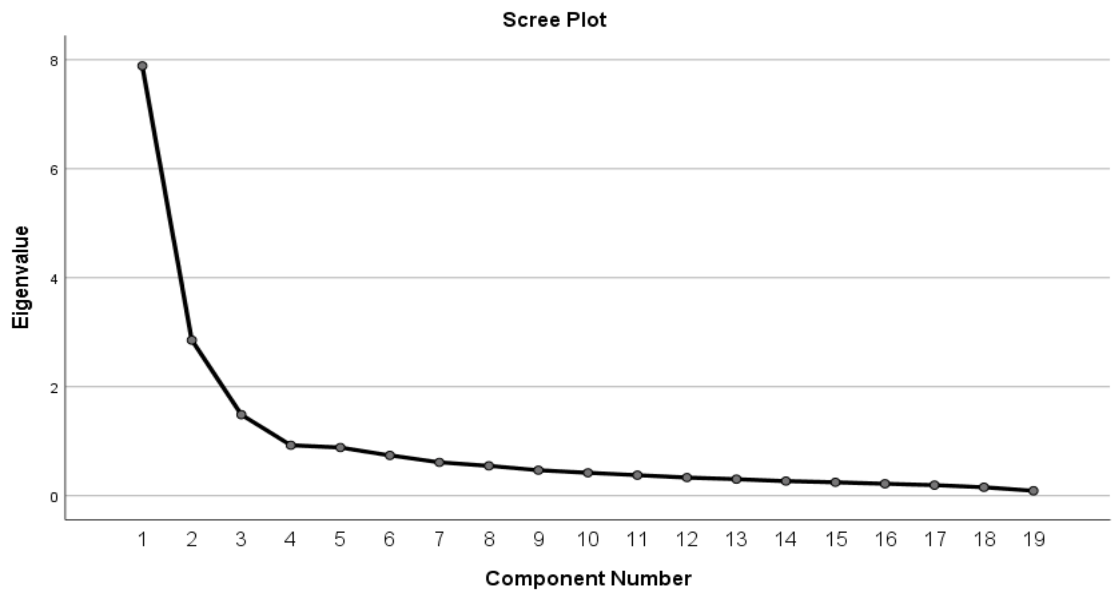
The construct validity of the Artificial Intelligence Usage and Competence Scale was evaluated through item-factor correlations and item discriminant validity values. The results are as follows:

Construct Validity

Findings Regarding Exploratory Factor Analysis (EFA)

The items in the scale were initially developed based on the theoretical frameworks of the Technology Acceptance Model (Davis, 1989), Self-Efficacy Theory (Bandura, 1977), and Connectivism (Siemens, 2005). These frameworks provided the foundation for understanding how lifelong learners engage with AI tools and how AI supports their learning processes. During the exploratory factor analysis, items with low factor loadings (below 0.40) were systematically removed to ensure content validity. Items that exhibited collinearity or redundancy were also excluded based on a thorough re-examination of the data.

For exploratory factor analysis, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test are examined. A KMO value greater than 0.60 and a significant Bartlett's test ($p < 0.05$) indicate suitability for factor analysis (Büyüköztürk, 2002). In this analysis, KMO = 0.825 and the Bartlett test yielded a significant result with $p = 0.000$. As a result, a structure consisting of two components was obtained. The factor loadings were examined, and items with loadings below 0.40 were excluded from the analysis. To ensure that content validity was not compromised, a re-examination was conducted based on a difference of 0.1 between factor loadings for collinearity control. Ultimately, it was determined that the items were grouped under 2 factors, explaining 61.43% of the total variance. The distribution of factor eigenvalues is provided in Graph 1.



Graph 1. *Scree Plot*

Exploratory factor analysis is presented in Table 2. As shown in the table, a two-factor structure has been analyzed. The factor loadings and the amount of variance explained by each factor are displayed in the table.

Table 2. *Factor loading distribution table for exploratory factor analysis*

Number	Items	Factor 1	Factor 2
I7	I can use AI-assisted learning tools effectively.	-0.70	
I3	I have no trouble coping with difficulties in my learning process by using AI tools.	-0.68	
I5	I can customize/personalize my learning process by using AI tools.	-0.66	
I8	I can organize my learning process by using AI-assisted learning tools.	-0.66	
I19	I think the use of AI-based learning applications helps me use my time more efficiently.	-0.60	
I27	I believe that AI-assisted learning processes increase my access to learning resources.	-0.52	
I18	I think AI-assisted learning processes restrict my freedom (-).	-0.51	
I12	I can manage AI-based learning materials efficiently.	-0.50	
I25	I find the accuracy of the learning content suggested by AI sufficient.	-0.48	
I1	I can understand the algorithm of AI tools.	-0.46	
I11	I can comprehend complex subjects by using AI-based learning tools.		-0.60
I15	I find AI-assisted personalized learning experiences effective.		-0.58
I23	I believe that AI-assisted learning processes increase my learning speed.		-0.54
I10	I can keep up with current developments in my learning process by using AI.		-0.50
I24	I believe that the use of AI-based learning applications reduces my stress in the learning process.		-0.50
I26	I think the use of AI reduces learning barriers in my learning process.		-0.49
I21	I believe that the use of AI-based learning applications decreases my motivation in the learning process (-).		-0.47
I22	I think the use of AI-based learning applications reduces my social interactions (-).		-0.44
I13	I have the competence to evaluate and select the learning content provided by AI.		-0.41
	Varience explained	20.614	40.186
	Eigenvalue	1.741	1.465

As seen in Table 2, the first factor of the scale consists of 10 items, with factor loadings ranging from 0.46 to 0.70. The eigenvalue of this factor is observed to be 1.741. It is noted that this factor accounts for 20.614% of the total variance. The second factor of the scale comprises 9 items, with factor loadings ranging from 0.41 to 0.60 and an eigenvalue of 1.465, explaining a variance of 40.816%.

The development of the scale items was guided by established theoretical frameworks. The AI Usage Competence dimension is grounded in the Technology Acceptance Model (Davis, 1989), which posits that perceived ease of use and usefulness are key factors in determining individuals' competence in using technology. The items in this dimension were crafted to assess how lifelong learners perceive and engage with AI tools. Similarly, the AI-Supported Learning Motivation dimension draws from Bandura's Self-Efficacy Theory (1977), emphasizing the role of confidence in one's ability to use AI tools, and Siemens' Connectivism Theory (2005), which highlights the importance of networked learning environments supported by AI technologies.

Findings Regarding Confirmatory Factor Analysis (CFA)

Following exploratory factor analysis, a scale comprising 19 items distributed across 2 factors was derived. Subsequently, confirmatory factor analysis was performed utilizing the obtained data. Confirmatory factor analysis serves to ascertain the interrelation between factors, the association between variables and factors, and the degree to which the factors elucidate the model (Brown, 2015). Findings in the literature suggest that both EFA and CFA cannot be conducted using the same dataset. However, in this study, due to the unavailability of a different dataset, both EFA and CFA were performed using the same dataset, with EFA solely employed to strengthen the CFA results.

Table 3. *Standard fit goodness criteria and obtained values*

Fit Dimensions	Perfect Fit	Acceptable Compliance	Research Data
$\chi 2$/sd	$0 \leq \chi 2/sd \leq 2$	$2 \leq \chi 2/d<5$	1.762
RMSEA	$0 \leq$ RMSEA $\leq .05$	$.05 \leq$ RMSEA $\leq .08$	0.047
S-RMR	$0 \leq$ S-RMR $\leq .05$	$.05 \leq$ S-RMR $\leq .10$	0.076
GFI	$.95 \leq$ GFI ≤ 1	$.90 \leq$ GFI $\leq .95$	0.921
AGFI	$.95 \leq$ AGFI ≤ 1	$.90 \leq$ AGFI $\leq .95$	0.951
CFI	$.97 \leq$ CFI ≤ 1	$.95 \leq$ CFI $\leq .97$	0.954
NFI	$.95 \leq$ NFI ≤ 1	$.90 \leq$ NFI $\leq .95$	0.896
IFI	$.95 \leq$ IFI ≤ 1	$.90 \leq$ IFI $\leq .95$	0.927

Table 3 presents the results of confirmatory factor analysis. Upon examination of the goodness-of-fit indices of the CFA model established with 248 data points, it can be inferred that the model exhibits excellent fit as indicated by a chi-square value of 1.762 (Byrne, 2013). Additionally, both RMSEA and AGFI values meet the criteria for excellent fit. Further scrutiny of the remaining indices including S-RMR, GFI, CFI, NFI, and IFI reveals acceptable fit according to critical thresholds (Marsh, Balla & McDonald, 1988; Schermelleh-Engel, Moosbrugger & Müller, 2003; Byrne, 2013).

Item Factor Correlations and Item Discrimination

The correlation between the items within each factor and the scores obtained from these items was calculated using the item-factor correlation method. This analysis aimed to determine the extent to which the items in the scale serve the overall purposes, the relationship between the presence or absence of each item in the scale, and consequently, the contribution of each item to the scale. The calculated item-factor correlation values are presented in Table 4.

Table 4. *Item-factor correlation values*

Factor 1	r	Factor 2	r
I1	0.61	I10	0.70
I3	0.42	I11	0.58
I5	0.68	I13	0.72
I7	0.72	I15	0.60
I8	0.69	I21	0.76
I12	0.73	I22	0.73
I18	0.43	I23	0.75
I19	0.62	I24	0.69
I25	0.49	I26	0.78
I27	0.42		

The values provided in the table represent the Pearson correlation coefficients between each item and each factor. These coefficients quantitatively express the relationship between each item and each factor. Accordingly, the item-factor correlations for the items in the first factor range from .42 to .73, while those for the items in the second factor range from .58 to .78. It is observed that the relationship between the items in the scale and their respective factors is positive and significant ($p < .000$). Based on these results, it can be stated that the items contribute to the purpose of their respective factors and the scale.

To assess the discriminant power of the scale items, the results obtained from each item were sorted in descending order, and groups consisting of the bottom 27% and top 27% of participants (124 individuals each) were identified. Subsequently, independent samples t-test analysis was conducted between the bottom and top groups, and the t-values indicating the discriminant power and significance levels were presented in Table 5.

Table 5. *Item discriminant validity powers*

Factor 1	t	p	Factor 2	t	p
I1	9.56	<0.001	I10	6.70	<0.001
I3	8.12	<0.001	I11	7.80	<0.001
I5	7.89	<0.001	I13	7.55	<0.001
I7	6.34	<0.001	I15	8.10	<0.001
I8	8.21	<0.001	I21	7.35	<0.001
I12	7.65	<0.001	I22	6.90	<0.001
I18	7.30	<0.001	I23	8.00	<0.001
I19	6.75	<0.001	I24	7.45	<0.001
I25	8.50	<0.001	I26	8.25	<0.001
I27	7.90	<0.001			

An examination of Table 5 reveals that the values obtained from the independent samples t-test regarding the 17 items, factors, and total score in the scale range from 6.34 to 9.56. The differences identified in the analysis are found to be significant (p<.001). Thus, it can be said that both the items and the overall scale demonstrate a high level of discriminant validity.

Scale Reliability

To determine the reliability of the scale, the results of the following analyses were examined. Spearman Brown and Cronbach's Alpha coefficients were examined for the two factors and the whole. Table 6 shows the reliability coefficients.

Table 6. *Reliability coefficients*

Factors	Item Number	Spearman Brown	Cronbach's Alpha
Artificial Intelligence Usage Competence	10	.734	.846
Artificial Intelligence Learning Motivation	9	.715	.870
The Whole Scale	**19**	**.711**	**.833**

Table 6 reveals that the Spearman–Brown coefficient of the scale comprising 19 items and two factors is 0.711, while the Cronbach alpha value is 0.833. The reliability coefficients of both individual items and the scale as a whole fall within the acceptable range (Eroğlu, 2008; Kline, 1994), indicating that both the items and the overall scale demonstrate reliability and consistency.

DISCUSSION, CONCLUSION, RECOMMENDATIONS

In this research, a scale was created and validated to assess usage and competence of lifelong learning self-efficacy in artificial intelligence (AI). The outcome of this study led to the development of the Generative Artificial Intelligence Usage and Competence Scale, which includes 2 factors and 19 items. The first factor encompasses 10 items, whereas the second factor comprises 9 items.

The scale reflects positive items completely (5), significantly (4), moderately (3), slightly (2), and not at all (1) based on Likert-type responses. For negative items, the coding is reversed. Following exploratory factor analysis, a two-factor scale was identified. Several scales in the related field were examined for factor naming, and original names were assigned (Kaya et al., 2022; Çelebi, Yılmaz, Demir & Karakuş, 2023; Polatgil & Güler, 2023; Karaoğlan Yılmaz, Yılmaz & Ceylan, 2023; Karaoğlan Yılmaz & Yılmaz, 2023). In this context, Factor 1 was labeled as AI Usage Competence, and Factor 2 was named AI-Supported Learning Motivation.

In the distribution of factors, items with factor loadings less than 0.40 were excluded from the analysis, along with redundant items. In the stage of construct validity analysis, factor loadings, variance explained, and eigenvalues were considered, indicating that the scale's construct validity is at an appropriate level. After the exploratory factor analysis revealed a two-factor structure of the scale, confirmatory factor analysis was conducted to confirm the factor structures. The results of confirmatory factor analysis showed that the scale model was supported by the data. The validity and reliability studies of the scale were conducted with 248 individuals aged between 18 and 50. The reliability analysis of the scale was examined using Spearman Brown and Cronbach's alpha values, which indicated that the scale could provide reliable measurements. Independent samples t-test was conducted to determine the difference between the top and bottom 27% groups in item discrimination. The results showed that the discriminative power of both the scale items and the scale as a whole was high. This scale is considered to provide a measurement tool for assessing levels of generative artificial intelligence usage and competence as a lifelong learning self-efficacy in the literature. Lifelong learning is one of the attitudes expected from students in primary, secondary, and tertiary education today. We can say that our education system is shaped based on this phenomenon to some extent. However, for this process to shed light on all learning activities, it is necessary to examine it more thoroughly in terms of generative artificial intelligence.

Following exploratory factor analysis, confirmatory factor analysis was conducted on the scale data to confirm the factor structures of the scale, which was divided into two factors. The results of the applied confirmatory factor analysis indicated that the generated scale model was supported by the data. Item-factor correlations were examined to determine the extent to which items composing the scale could measure the characteristic they intended to measure with their respective factors. The values obtained from the examined item-factor correlations suggest that the items and factors in the scale significantly serve the purpose of measuring the desired characteristic of the scale as a whole.

Reviewing the literature, several scale studies related to artificial intelligence (AI) can be observed. For instance, the study by Ferikoğlu and Akgün (2022) developed the Artificial Intelligence Awareness Level Scale for Teachers to analyze teachers' awareness of AI integration in education and to determine their tendencies in developing the concept of AI and its sub-branches. This scale consists of 4 dimensions and 27 items, namely Theoretical Knowledge, Practical Knowledge, Associative Ability, and Belief-Attitude. The Artificial Intelligence Anxiety Scale developed by Akkaya, Özkan, and Özkan (2021) is an adaptation of the scale developed by Wang and Wang (2019) into Turkish. This scale, comprising 16 items, is composed of 4 factors: Learning, Job Change, Sociotechnical Blindness, and AI Structuring. On the other hand, the Generative Artificial Intelligence Acceptance Scale developed by Karaoğlan Yılmaz et al. (2023) consists of 4 factors and 20 items, named Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Impact. Additionally, Çelebi et al. (2023) conducted the adaptation of the Artificial Intelligence Literacy Scale, developed by Wang, Rau and Yuan (2023), into Turkish. This scale, designed for non-expert adult individuals in AI, comprises four dimensions: Awareness, Usage, Evaluation, and Ethics, with a total of 12 items. These scales in the literature have been examined in terms of their specific subject area, target audience, and the number of factors and items. As seen, these scales developed in the literature have focused on dimensions such as AI literacy, AI anxiety, acceptance of generative AI, and awareness. In contrast, in this study, the scale developed aims to explain the dimensions of AI usage and competence, conceptualized as a lifelong learning self-efficacy, with two factors: AI Usage Competence and AI-Supported Learning Motivation. This attempt aims to provide a more comprehensive and inclusive framework. Hence, it can be argued that this scale differs from others in the literature and contributes to the existing body of knowledge.

The advancement of AI technology has profoundly impacted our lives. With the widespread adoption of smart devices and AI-based applications, even ordinary users have found themselves using AI and becoming aware of its implications. This technology has found extensive use in various fields such as education, healthcare, and finance, making it challenging for individuals to fully grasp its integral role in their lives (Wang et al., 2023). The number of AI tools developed today is rapidly increasing, making it increasingly difficult to precisely determine their exact numbers. This surge indicates the beginning of a new era; in other words, the current state of technology symbolizes the onset of a new age known as the AI era, necessitating individuals to adapt to the changes it brings, becoming an inevitable necessity for people. Although specific foundational competencies have been identified for using AI, evaluating these competencies is also crucial. In the information age, technology undergoes continuous and irreversible change and transformation. The rapid adoption and use of digital technologies in our daily lives have brought about significant changes in our learning, time management, communication, and work methods, significantly influencing the skills individuals need to acquire. Particularly, with the increasing prominence of generative AI applications in various fields such as healthcare, finance, education, transportation, and production, AI literacy has become a crucial literacy skill that individuals need to acquire across all sectors (Mertala, Fagerlund & Calderon, 2020). Considering lifelong learning as an aspect that students need to develop throughout their educational journey (Usta, 2023), it is essential to recognize the close association between generative AI and lifelong learning. Formal education alone will not suffice to acquire this competency. Therefore, the philosophy of lifelong learning should be adopted at every level of education, starting from preschool, with a focus on learning to learn. Additionally, values such as effective and efficient use of learning resources, setting, and achieving learning goals, and valuing knowledge and personal development should be integral parts of educational practices and learning experiences. Since the philosophy of lifelong learning underpins all educational environments, the use of generative AI should also be seen within this context. However, while supporting lifelong learning, it is important to bear in mind that every virtual world harbors both threats and opportunities, as evidenced in previous studies (Arslankara & Usta, 2018; Arslankara, Demir, Öztaş & Usta, 2022; Korkmaz, Vergili & Karadaş, 2021; Şahin, Asal Özkan & Turan, 2022).

The AI Usage Competence dimension is directly influenced by Davis's (1989) Technology Acceptance Model, which suggests that individuals' perceived usefulness and ease of use determine their engagement with new technologies. This model helps explain why participants with higher perceptions of AI's usefulness and ease of use showed higher competence in AI tools. Meanwhile, the AI-Supported Learning Motivation dimension is grounded in Bandura's (1977) Self-Efficacy Theory, which posits that individuals with higher confidence in their abilities are more likely to succeed in using AI tools effectively. Participants who expressed greater self-efficacy also demonstrated stronger motivation to engage in AI-supported learning, supporting this theoretical connection.

Author Contribution Rates: The contribution rate of the authors is equal.

Conflict of Interest: The peer review and editorial decision-making process for this manuscript were exclusively managed by an independent member of the journal's editorial board to maintain impartiality. A rigorous double-blind peer review protocol was employed, ensuring that the author's editorial affiliation remained undisclosed to the reviewers. Moreover, every stage of this process was meticulously aligned with the journal's ethical policies and internationally recognized standards, including those established by the Committee on Publication Ethics (COPE).

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APPENDIX:

Num	**GENERATIVE ARTIFICIAL INTELLIGENCE USAGE AND COMPETENCE (GAIUC) SCALE (ENGLISH)**	Doesn' t reflect at all	Less reflective	Moderately reflective	Very reflective	Fully reflective
Factor 1: AI Usage Competence						
1	I can use AI-assisted learning tools effectively.	1	2	3	4	5
2	I have no trouble coping with difficulties in my learning process by using AI tools.	1	2	3	4	5
3	I can customize/personalize my learning process by using AI tools.	1	2	3	4	5
4	I can organize my learning process by using AI-assisted learning tools.	1	2	3	4	5
5	I think the use of AI-based learning applications helps me use my time more efficiently.	1	2	3	4	5
6	I believe that AI-assisted learning processes increase my access to learning resources.	1	2	3	4	5
7	I think AI-assisted learning processes restrict my freedom (-).	1	2	3	4	5
8	I can manage AI-based learning materials efficiently.	1	2	3	4	5
9	I find the accuracy of the learning content suggested by AI sufficient.	1	2	3	4	5
10	I can understand the algorithm of AI tools.	1	2	3	4	5
Factor 2: AI-Supported Learning Motivation						
11	I can comprehend complex subjects by using AI-based learning tools.	1	2	3	4	5
12	I find AI-assisted personalized learning experiences effective.	1	2	3	4	5
13	I believe that AI-assisted learning processes increase my learning speed.	1	2	3	4	5
14	I can keep up with current developments in my learning process by using AI.	1	2	3	4	5
15	I believe that the use of AI-based learning applications reduces my stress in the learning process.	1	2	3	4	5
16	I think the use of AI reduces learning barriers in my learning process.	1	2	3	4	5
17	I believe that the use of AI-based learning applications decreases my motivation in the learning process (-).	1	2	3	4	5
18	I think the use of AI-based learning applications reduces my social interactions (-).	1	2	3	4	5
19	I have the competence to evaluate and select the learning content provided by AI.	1	2	3	4	5

No	ÜRETKEN YAPAY ZEKA KULLANIM VE YETERLİK (ÜYZKY) ÖLÇEĞİ (TÜRKÇE)	Hiç yansıtmıyor	Az yansıtıyor	Orta düzeyde	Çok yansıtıyor	Tamamen yansıtıyor
Faktör 1: Yapay Zeka Kullanım Yeterliği						
1	Yapay zeka destekli öğrenme araçlarını etkili bir şekilde kullanabilirim	1	2	3	4	5
2	Yapay zeka araçlarını kullanarak öğrenme sürecimdeki zorluklarla başa çıkmada sorunum yoktur	1	2	3	4	5
3	Yapay zeka araçlarını kullanarak öğrenme sürecimi özelleştirebilirim / kişiselleştirebilirim	1	2	3	4	5
4	Yapay zeka destekli öğrenme araçlarını kullanarak öğrenme sürecimi düzenleyebilirim	1	2	3	4	5
5	Yapay zeka tabanlı öğrenme uygulamalarının kullanımının zamanımı daha etkin kullanmama yardımcı olduğunu düşünüyorum	1	2	3	4	5
6	Yapay zeka destekli öğrenme sürecinin öğrenme kaynaklarına erişimimi artırdığını düşünüyorum	1	2	3	4	5
7	Yapay zeka destekli öğrenme sürecinin özgürlüğümü kısıtladığını düşünüyorum (-)	1	2	3	4	5
8	Yapay zeka tabanlı öğrenme materyallerini verimli bir şekilde yönetebilirim	1	2	3	4	5
9	Yapay zeka tarafından önerilen öğrenme içeriklerinin doğruluğunu yeterli buluyorum	1	2	3	4	5
10	Yapay zeka araçlarının algoritmasını anlayabilirim.	1	2	3	4	5
Faktör 2: Yapay Zeka Destekli Öğrenme Motivasyonu						
11	Yapay zeka tabanlı öğrenme araçlarını kullanarak karmaşık konuları anlayabilirim	1	2	3	4	5
12	Yapay zeka destekli kişiselleştirilmiş öğrenme deneyimlerini etkili buluyorum	1	2	3	4	5
13	Yapay zeka destekli öğrenme sürecinin öğrenme hızımı artırdığını düşünüyorum	1	2	3	4	5
14	Yapay zeka kullanarak öğrenme sürecimdeki güncel gelişmeleri takip edebilirim	1	2	3	4	5
15	Yapay zeka tabanlı öğrenme uygulamalarının kullanımının öğrenme sürecimdeki stresimi azalttığını düşünüyorum	1	2	3	4	5
16	Yapay zeka kullanımının öğrenme sürecimdeki öğrenme engellerini azalttığını düşünüyorum	1	2	3	4	5
17	Yapay zeka tabanlı öğrenme uygulamalarının kullanımının öğrenme sürecimdeki motivasyonumu azalttığını düşünüyorum (-)	1	2	3	4	5
18	Yapay zeka tabanlı öğrenme uygulamalarının kullanımının sosyal etkileşimlerimi azalttığını düşünüyorum (-)	1	2	3	4	5
19	Yapay zeka tarafından sağlanan öğrenme içeriklerini değerlendirme ve seçme yeterliğine sahibim	1	2	3	4	5