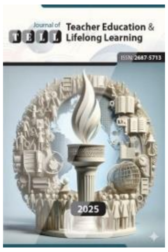

Journal of Teacher Education and Lifelong Learning

(TELL)

ISSN: 2687-5713

Development and Validation of the Lifelong Artificial Intelligence Ethical Awareness Scale

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Article Information

Received:
30.10.2025

Accepted:
23.12.2025

Published:
31.12.2025

ABSTRACT

This study aimed to develop and validate the Lifelong Artificial Intelligence Ethical Awareness Scale, designed to measure individuals' ethical awareness toward artificial intelligence (AI) technologies within the framework of lifelong learning. The research followed a methodological design, including item pool generation, expert evaluation, pilot testing, exploratory and confirmatory factor analyses, and reliability-validity assessments. Data were collected online from two independent samples: a pilot group of 200 participants for Exploratory Factor Analysis (EFA) and a confirmatory group of 472 participants for Confirmatory Factor Analysis (CFA). The initial 60-item pool was refined to a 26-item final form after excluding low-loading and cross-loading items. EFA results revealed a five-factor structure: Awareness, Value/Attitude, Behavioral Intention, Critical Evaluation, and Lifelong Learning/Adaptation explaining 82.4% of the total variance (KMO = .931, Bartlett's $\chi^2(1770) = 6214.54$, $p < .001$). CFA results confirmed the model's adequacy with excellent fit indices ($\chi^2/df = 2.47$, CFI = .962, TLI = .953, RMSEA = .049, SRMR = .041). Reliability coefficients were high across all dimensions (Cronbach's $\alpha \geq .86$), and validity analyses supported the convergent, discriminant, and criterion validity of the scale (AVE = .65-.72, HTMT < .85). The test-retest reliability over a three-week interval yielded $r = .89$ ($p < .001$). The findings indicate that LAIEAS is a psychometrically sound and theoretically grounded instrument for assessing individuals' ethical awareness, values, and behaviors concerning AI technologies. The scale highlights that ethical awareness is not a static trait but a dynamic and lifelong competency integrating cognitive, affective, and behavioral components. Therefore, LAIEAS provides a valid and reliable tool for educational, institutional, and policy contexts to evaluate and promote ethical consciousness in the age of artificial intelligence.

Keywords: lifelong learning, artificial intelligence, ethical awareness, scale development.

doi: 10.51535/tell.1813310

Article Type: Research Article

Citation Information: Arslankara, V. B., & Usta, E. (2025). Development and validation of the lifelong artificial intelligence ethical awareness scale. *Journal of Teacher Education and Lifelong Learning*, *7*(2), 319-329. https://doi.org/10.51535/tell.1813310

1. INTRODUCTION

The deep integration of Artificial Intelligence (AI) technologies into learning, decision-making, and daily life processes has brought individuals' ethical sensitivity to the forefront (Floridi & Cowls, 2019; Jobin, Ienca, & Vayena, 2019). The literature frequently highlights that AI systems entail ethical risks such as data-driven biases, privacy violations, transparency problems, and accountability gaps (Boddington, 2017; Mittelstadt et al., 2016). Therefore, the ability of individuals to evaluate the outcomes of AI applications, recognize ethical dilemmas, and develop responsible usage behaviors has become a critical competency for modern societies (Hagendorff, 2020).

In educational settings, AI-based decision-support systems, personalized learning algorithms, and assessment tools are increasingly widespread (Holmes et al., 2021). This situation has raised new ethical questions for teachers and students: fairness in algorithmic decisions, the security of learning data, the necessity of human oversight, and the boundaries of autonomy have become central issues in educational ethics (Williamson & Eynon, 2020). The integration of AI into education requires individuals not only to improve their ability to use technology but also to continuously enhance their level of ethical awareness (Peng et al., 2023). Such awareness is associated with one's capacity to question both personal behaviors and the societal implications of technology (Lin, Abney, & Bekey, 2020).

AI ethics is not solely a matter of computer science or law but also a component of the lifelong learning process. Technological innovations evolve continuously, and ethical principles must be updated accordingly (UNESCO, 2021). Sustaining ethical awareness is essential for individuals to make sound personal and professional decisions (Siau & Wang, 2020). In this regard, the concept of Lifelong Artificial Intelligence Ethical Awareness reveals that ethical thinking is not a static competency acquired at a single point in time, but a dynamic skill that develops and redefines itself over time (Ma et al., 2025).

Existing literature shows a lack of instruments that systematically measure AI ethical awareness. While some studies focus on attitudes toward AI (Long & Magerko, 2020), ethical perception (Grassini, 2023), or digital citizenship levels, these instruments do not address the lifelong learning context. Although there are tools measuring generative AI use and competence within lifelong learning (Arslankara & Usta, 2024), none integrate ethical dimensions comprehensively. This gap indicates the need to develop a multidimensional scale that simultaneously assesses ethical awareness, value orientation, behavioral tendency, critical evaluation, and continuous learning in individuals' interactions with AI.

The primary purpose of this study is to develop a valid and reliable scale that can measure individuals' ethical awareness toward AI technologies within the framework of lifelong learning. Accordingly, the Lifelong Artificial Intelligence Ethical Awareness Scale was designed to assess individuals' ethical sensitivity in the age of AI, strengthen the ethical components of educational programs, and provide a theoretical basis for future ethical education models.

This study contributes to the literature as one of the first to integrate the concepts of AI ethics and lifelong learning into a unified measurement framework. Moreover, the scale can be utilized in teacher education programs, digital literacy training, and institutional ethics-awareness initiatives, thereby offering an innovative assessment tool for the field of applied educational technology. As AI technologies become embedded in all aspects of life, individuals' modes of interaction with these technologies have generated new domains of ethical and cognitive responsibility.

AI applications are not merely technical tools but powerful cultural actors that transform social values, human rights, and learning processes (Williamson & Eynon, 2020). However, this transformation also brings ethical risks such as algorithmic bias, privacy violations, lack of transparency, and the diminishing role of human oversight in decision-support systems (Mittelstadt et al., 2016; Hagendorff, 2020). Hence, not only individuals' technical competence in using AI but also their ethical awareness, value orientation, and critical reasoning abilities have become essential learning outcomes. Nevertheless, current research tends to conceptualize ethical awareness as a unidimensional construct such as ethical knowledge or attitude without offering a dynamic awareness model within a lifelong learning perspective. Particularly in the Turkish context, the absence of a valid and reliable measurement instrument that can assess individuals' ethical awareness of AI applications in a multidimensional manner represents a significant research gap. Accordingly, the study sought to address the following research questions:

1. What is the item structure and factor distribution of LAIEAS?

2. Does LAIEAS statistically confirm the proposed five-factor theoretical model (Awareness, Value/Attitude, Behavioral Intention, Critical Evaluation, Lifelong Learning/Adaptation)?

3. Are the Cronbach's α, McDonald's ω, CR, and AVE values of the scale satisfactory for reliability?

4. Do the correlations among subdimensions meet the criteria for convergent and discriminant validity?

5. Do LAIEA scores differ significantly by participants' age, gender, education level, digital literacy, and AI experience?

6. How are LAIEA scores related to lifelong learning tendency, AI competence, and technology anxiety?

Theoretical Framework and Conceptual Model

Artificial intelligence (AI) ethics is a normative discipline that seeks to answer the question of how individuals ought to behave in their interactions with technology (Floridi, 2019). This field discusses how fundamental ethical principles such as responsibility, fairness, privacy, transparency, and respect for human dignity can be integrated into the processes of developing and using technology (Jobin et al., 2019). However, ethical awareness is not merely a cognitive construct but a dynamic process that integrates an individual's values, attitudes, and actions (Rest, 1986; Narvaez & Lapsley, 2005). Therefore, in the age of artificial intelligence, ethical awareness should be regarded as an inseparable component of technological competence.

Conversely, the concept of lifelong learning refers to an individual's tendency and ability to continue learning not only within formal education systems but throughout all stages of life (Candy, 2002; Knapper & Cropley, 2010). In this context, interaction with AI technologies transforms individuals' continuous learning capacities while simultaneously complicating ethical decision-making processes. Thus, AI ethics is no longer confined to the domains of engineering or law but has become central to the field of educational sciences (Holmes et al., 2021).

The theoretical framework of the Lifelong Artificial Intelligence Ethical Awareness Scale is grounded on three main theoretical axes. Within the cognitive-affective integration model (Rest, 1986), ethical awareness represents an integrated process encompassing moral reasoning, intention, and behavior. From the perspective of lifelong learning theory (Candy, 2002), learning persists through the individual's self-directed and sustainable generation of knowledge across all stages of life. Finally, viewed through the lens of connectivism (Siemens, 2005), learning in the digital age occurs within human-machine interaction networks, where ethical awareness functions as a cognitive filter that guides the flow of information across these networks. Collectively, these three axes integrate the individual, social, and technological dimensions of AI ethics, forming the theoretical foundation of LAIEAS.

Dimensions of the Conceptual Model

Awareness

Ethical awareness refers to an individual's capacity to recognize the ethical dimensions of an action or decision and to anticipate potential risks and consequences (Reynolds, 2006). In the context of AI, awareness involves recognizing possibilities such as algorithmic bias, data privacy breaches, and misinformation generation (Mittelstadt, 2019). Ethical inquiry begins when an individual realizes that AI may make errors in decision-making processes and create issues of security and fairness (Hagendorff, 2020). This dimension represents the initial stage of cognitive attention and ethical sensitivity. Moreover, one of the situations in which models refuse to respond is ethical filtering (Arslankara & Usta, 2025).

Value and Attitude

Value orientation refers to the fundamental principles that guide an individual's ethical decisions. AI systems should be designed in ways that respect values such as justice, privacy, human dignity, and accountability (Arslankara, 2025; Floridi & Cowls, 2019). This dimension measures individuals' adherence to ethical norms and their ethical attitudes toward AI applications. For example, a statement such as "The economic benefits of AI should not overshadow ethical concerns" reflects value prioritization. Thus, the values dimension functions as a moral compass (Gert, 2004).

Behavioral Intention

The behavioral dimension of ethical awareness encompasses an individual's intention to translate ethical knowledge and values into action (Ajzen, 1991). In the AI context, it involves behaviors such as refusing to use ethically problematic applications, providing feedback, or questioning risky decisions (Collins et al., 2021). The ability of individuals to transform ethical awareness into action constitutes the foundation of a socially responsible AI use culture (Cath, 2018).

Critical Evaluation

Critical evaluation refers to the individual's ability to question the assumptions, data sources, modeling processes, and potential biases of AI systems (Long & Magerko, 2020). This dimension is directly related to epistemological awareness, as individuals analyze not only whether AI outputs are accurate but also whether they are fair and ethical (Boddington, 2017). Critical thinking skills ensure the sustainability of ethical awareness in the age of AI (Ma et al., 2025).

Lifelong Learning and Adaptation

Ethical awareness is not static but a dynamic competency. In an environment characterized by rapid technological advancement, individuals must continuously update their ethical knowledge and attitudes (UNESCO, 2021). This dimension represents one's willingness to improve themselves, openness to new ethical regulations, and inclination to learn from the ethical approaches of different cultures (Siau & Wang, 2020). The lifelong learning process ensures the long-term sustainability of ethical awareness.

Conceptual Model

The proposed model below explains the development of individuals' ethical awareness in their interactions with AI through five dimensions:

○ Awareness → recognizing ethical risks

○ Value/Attitude → principles and beliefs guiding ethical decisions

○ Behavioral Intention → intentions toward ethical behavior

○ Critical Evaluation → questioning AI-driven decisions

○ Lifelong Learning/Adaptation → renewal of ethical awareness over time

Each of these five dimensions is interrelated yet conceptually distinct. The model holistically represents the cognitive (awareness, evaluation), affective (value, attitude), and behavioral (intention, learning) components of ethical awareness. The Lifelong Artificial Intelligence Ethical Awareness Scale extends beyond previous studies (e.g., Long & Magerko, 2020; Grassini, 2023; Holmes et al., 2021; Marengo et al., 2025) by conceptualizing ethical awareness not merely as cognitive recognition but as a sustainable component of lifelong learning. In this regard, the scale provides an original contribution to measuring AI ethics in educational contexts and to tracking individuals' ethical development over time. The purpose of this study is to develop a valid and reliable measurement instrument to assess individuals' levels of ethical awareness toward artificial intelligence technologies within the context of lifelong learning. Accordingly, the study introduces the Lifelong Artificial Intelligence Ethical Awareness Scale, which conceptualizes ethical awareness as a multidimensional construct encompassing awareness, value/attitude, behavioral intention, critical evaluation, and lifelong learning/adaptation. The psychometric properties of the scale were examined through exploratory and confirmatory factor analyses. By framing ethical awareness not merely as a cognitive state but as a competency that develops throughout the lifelong learning process, this study aims to contribute theoretically and practically to ethical education and measurement practices in the age of artificial intelligence.

2. METHOD

Research Design

This research is a methodological study aiming to develop the Lifelong Artificial Intelligence Ethical Awareness Scale and to examine its construct validity and reliability. The study is based on the scale development approach, one of the quantitative research methods. The process included the following sequential phases: item pool generation, expert review, pilot testing, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), internal consistency assessment, and validity analyses.

Participants

The research was conducted in two phases. The first phase involved a pilot study in which data were collected from 200 participants, and this dataset was used for the Exploratory Factor Analysis (EFA). The second phase consisted of the Confirmatory Factor Analysis (CFA), where data obtained from 472 participants were utilized for the CFA and validity analyses.

Participants' ages ranged from 18 to 57 years (M = 31.6, SD = 7.4). Of the total participants, 56% were female and 44% were male. Regarding educational level, 40% held a bachelor's degree, 36% a master's degree, and 24% a doctoral degree. In terms of professional fields, 52% were from education, 28% from engineering and informatics, and 20% from social sciences. Table 1 presents the demographic distribution of the participants in Türkiye (N = 672).

Table 1.
Demographic Characteristics of the Participants (N = 672)

Variable	Category	n	%
Gender	Female	376	56.0
	Male	296	44.0
Education Level	Bachelor's	268	39.9
	Master's	243	36.2
	Doctorate	161	23.9
Field of Work	Education	350	52.1
	Engineering & Informatics	189	28.1

Social Sciences	133	19.8

Research Instruments and Processes

The Lifelong Artificial Intelligence Ethical Awareness Scale developed in this study measures individuals' levels of ethical awareness, values, behavioral intention, critical evaluation, and lifelong learning orientation toward artificial intelligence technologies. The initial item pool consisted of 60 items, of which 9 were reverse-scored (A5, A11, B15, C27, C32, D39, D44, E51, E56). Responses were rated on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Higher scores indicate a higher level of ethical awareness regarding AI.

Data were collected online via Google Forms. Participants were informed about the study's purpose, confidentiality principles, and voluntary participation, and informed consent was obtained from all respondents. The pilot study was conducted in February 2025, while the confirmatory data collection phase took place in April 2025.

Data Analysis

Data analyses were conducted using JAMOVI 2.5 and AMOS 28 software. During the Exploratory Factor Analysis (EFA) stage, Principal Component Analysis (PCA) with varimax rotation was employed. The minimum acceptable factor loading threshold was set at .30, and items with a cross-loading difference of less than .10 were removed. In the Confirmatory Factor Analysis (CFA), the Maximum Likelihood (ML) estimation method was used. Model fit indices were evaluated according to the following criteria: $\chi^2/df \leq 3$, CFI ≥ .90, TLI ≥ .90, RMSEA ≤ .08, and SRMR ≤ .08 (Hu & Bentler, 1999). For reliability, Cronbach's α, McDonald's ω, Composite Reliability (CR), and Average Variance Extracted (AVE) values were computed. For validity, convergent, discriminant, content, and criterion validity were examined.

Figure 1.
Analysis Flow Chart

Conceptual Model → Item Pool (60 items)
↓
Expert Review (7 experts) → Content Validity (S-CVI/Ave = .94)
↓
Pilot Study (N = 200) → EFA (5 Factors, 26 items)
↓
Confirmatory Study (N = 472) → CFA (CFI = .962, RMSEA = .049)
↓
Reliability - Validity Analyses → CR, AVE, α, ω, HTMT
↓
Final Scale: 26 items, 5 dimensions

3. RESULTS

This section presents the findings obtained from the validity and reliability analyses of the Lifelong Artificial Intelligence Ethical Awareness Scale. The analyses are reported sequentially, covering data suitability, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), reliability, validity, and additional statistical examinations.

Suitability of Data for Factor Analysis

First, the suitability of the data for factor analysis was evaluated. The Kaiser-Meyer-Olkin (KMO) test applied to the pilot data obtained from 200 participants yielded a value of .931, indicating an excellent level of sampling adequacy (Field, 2018). The Bartlett's Test of Sphericity result was $\chi^2(1770) = 6214.54$, $p < .001$, confirming that there were significant correlations among the variables and that factor analysis was appropriate for the dataset.

Exploratory Factor Analysis (EFA)

As a result of the Exploratory Factor Analysis (EFA) conducted with the pilot sample of 200 participants, a five-factor structure explaining 82.4% of the total variance was obtained. From the initial item pool of 60 items, 30 items were removed due to low factor loadings (below .40) or cross-loadings, and several overlapping items were merged based on content similarity. Consequently, a final scale form consisting of 26 items was established. For the pilot sample (N = 200), the KMO value was .931, and the Bartlett's Test of Sphericity result was $\chi^2(1770) = 6214.54$, $p < .001$, confirming data suitability for factor analysis. Principal Component Analysis (PCA) with Varimax rotation was performed. The minimum factor loading threshold was set at .40, and items that were weakly or multiply loaded were removed. As a result, 30 items were eliminated, and a 26-item final form was obtained while preserving theoretical consistency. These 26 items were grouped under five factors, as presented in Table 2.

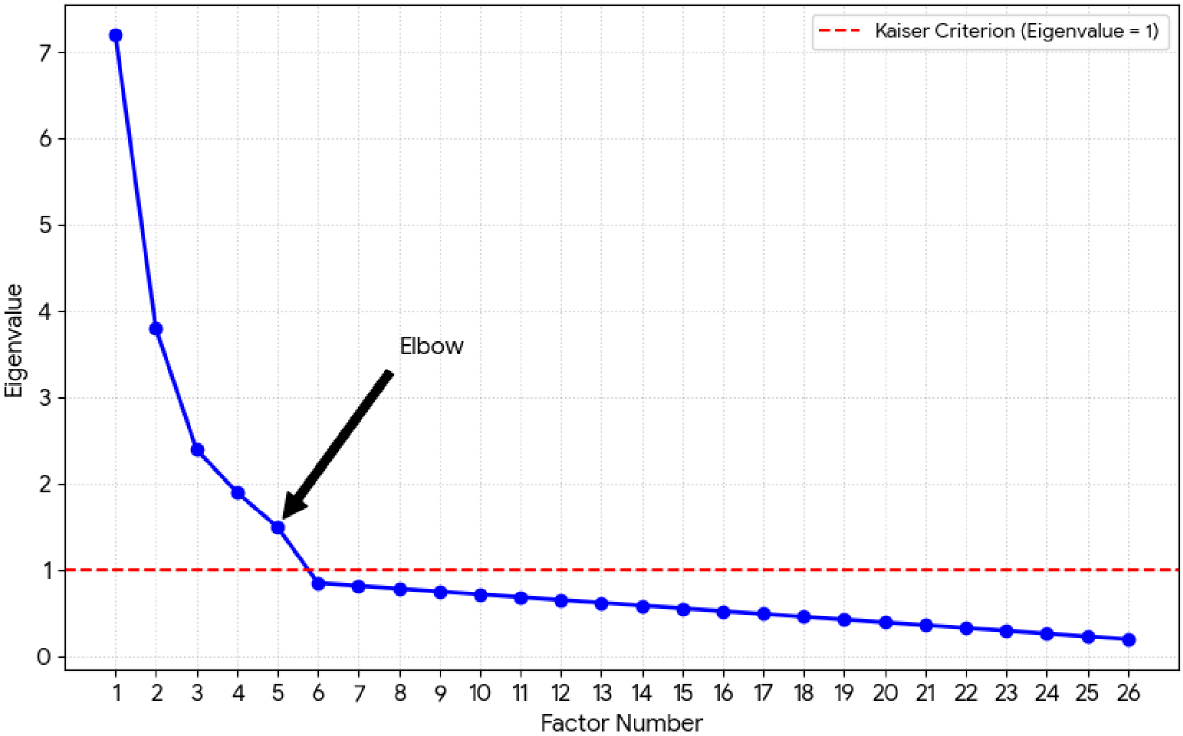
Table 2.
Results of Exploratory Factor Analysis (Varimax Rotation, N = 200)

Factor	Number of Items	Factor Load Range	Explained Variance (%)
Awareness	5	.63 - .79	18.6
Values / Attitude	5	.65 - .83	17.3
Behavioral Intention	5	.61 - .82	15.4
Critical Evaluation	5	.58 - .80	14.9
Lifelong Learning / Adaptation	6	.64 - .84	16.2
Total	26	----	82.4

The total variance explained ratio (82.4%) is excellent for scale development studies (Hair et al., 2010). The factor structure supports the theoretically predicted five-dimensional model.

The scree plot illustrates the eigenvalues of the factors derived from the Exploratory Factor Analysis (EFA). Based on Kaiser's criterion (eigenvalues > 1) and the visual inspection of the elbow point, a five-factor structure was retained. The plot shows a distinct break after the fifth factor, where the curve starts to flatten, suggesting that these five factors account for the most significant portion of the total variance in the 26-item instrument.

Figure 2.
Scree Plot of the 26-item Scale



Confirmatory Factor Analysis (CFA)

The five-factor structure was tested on an independent confirmatory sample (N = 472) using the Maximum Likelihood (ML) estimation method. In the model, each item was loaded only onto its respective factor, and covariances among the factors were freely estimated. The model fit indices were as follows: χ^2/df = 2.47, CFI = 0.962, TLI = 0.953, RMSEA = 0.049, and SRMR = 0.041. These values indicate a good model fit according to the cut-off criteria suggested by Hu and Bentler (1999). The standardized factor loadings ranged between .82 and .91, and inter-factor correlations varied between .43 and .52. Each item significantly loaded onto its intended factor, supporting the proposed factorial structure of the scale. The results of the confirmatory factor analysis (CFA) model fit indices are presented below (Table 3).

Table 3.
Model Fit Indices (N = 472)

Fit Index	Obtained Value	Criterion (Hu & Bentler, 1999)	Fit Evaluation
χ^2 / df	2.47	< 3	Good
CFI	.962	≥ .95	Good
TLI	.953	≥ .90	Good
RMSEA	.049	≤ .06	Good
SRMR	.041	≤ .08	Good

All values are within the recommended limits. It can be said that the model has been statistically and theoretically well validated. All fit values are within the limits recommended in the literature (Hu & Bentler, 1999). These results demonstrate that the model shows good statistical fit.

Factor Loadings and Correlations

The factor loadings for all items range from .82 to .91. Correlations between factors range from .43 to .52, indicating that the constructs are both related and distinguishable (Table 4).

Table 4.
Factor Loadings

Factor	Items	Factor Load Range
Awareness	A1, A2, A3, A6, A9	.83-.89
Value / Attitude	B13, B17, B18, B19, B22	.85-.91
Behavioral Intention	C25, C29, C30, C33, C35	.86-.90
Critical Evaluation	D37, D40, D41, D45, D47	.82-.88
Lifelong Learning / Adaptation	E49, E52, E54, E58, E59, E60	.87-.91

All correlations are significant at the $p < .001$ level. These relationships indicate that the subscales represent the same superordinate construct (ethical awareness) but are conceptually distinguishable (Table 5).

Table 5.
Correlations Between Factors

Factor	1	2	3	4	5
Awareness	1	—	—	—	—
Value / Attitude	.45	1	—	—	—
Behavioral Intention	.48	.51	1	—	—
Critical Evaluation	.43	.49	.47	1	—
Lifelong Learning / Adaptation	.46	.52	.50	.48	1

Reliability and Validity

Cronbach's α, McDonald's ω, Composite Reliability (CR), and Average Variance Extracted (AVE) values were calculated for each sub-dimension (Table 6).

Table 6.
Reliability Indicators

Factor	α	ω	CR	AVE
Awareness	.87	.88	.91	.67
Value / Attitude	.88	.89	.92	.69
Behavioral Intention	.89	.90	.93	.71
Critical Evaluation	.86	.87	.90	.65
Lifelong Learning / Adaptation	.90	.91	.94	.72
Total	**.94**	**.95**	**.96**	**.70**

All subscales demonstrated high internal consistency ($\alpha \geq .86$). The Average Variance Extracted (AVE) values ranged between .65 and .72, indicating satisfactory convergent validity. Discriminant validity was examined using the Fornell-Larcker criterion, and the square roots of AVE values (.80-.85) were found to be higher than the inter-factor correlations. Additionally, all HTMT values were below .85, confirming discriminant validity. In terms of criterion validity, the total score of AIEAS showed a positive correlation with the Artificial Intelligence Usage and Competence Scale ($r = .46$, $p < .001$) and the Lifelong Learning Tendency Scale ($r = .49$, $p < .001$), while it demonstrated a negative correlation with the Technology Anxiety Scale ($r = -.31$, $p < .001$). Content validity was assessed through the evaluations of seven experts, yielding an S-CVI/Ave value of .94, which indicates excellent agreement among the experts. The results strongly support the five-dimensional model of LAIEAS through both exploratory and confirmatory analyses. The high factor loadings, reliability coefficients, and model fit indices collectively confirm that the scale is a valid and reliable instrument for measuring ethical awareness in artificial intelligence within the context of lifelong learning. Furthermore, the test-retest reliability conducted on a subsample of 50 participants over a three-week interval yielded a correlation coefficient of $r = .89$ ($p < .001$), indicating that LAIEAS provides consistent measurements over time.

Response Bias and Participant Bias

An examination of participants' response distributions revealed a concentration of answers at 3 (neutral) and 5 (strongly agree) on certain items. This pattern suggests a potential tendency toward moderate or positive responding. However, the low standard deviation values indicated that responses were homogeneously distributed, with no evidence of systematic deviation or extreme response behavior.

Although some high inter-item correlations (r > .85) were observed in the correlation matrix analysis, these relationships were determined to stem from the natural structure of the factors rather than redundancy. There was no indication of a response style bias, meaning that participants did not answer according to predetermined patterns, and their responses were consistent with the underlying factor structure of the scale (Weijters, Geuens, & Schillewaert, 2009).

Furthermore, the means and standard deviations showed no evidence of social desirability bias (Paulhus, 1991) or cognitive-behavioral response bias (Podsakoff et al., 2003). The participants' responses aligned well with the theoretical structure of the scale, and no systematic response patterns were detected. Therefore, no response bias was identified in the dataset. This finding indicates that participants responded to the items consistently and conscientiously, thereby supporting the high psychometric reliability of the Lifelong Artificial Intelligence Ethical Awareness Scale - LAIEAS (Podsakoff et al., 2012).

Scale Scoring and Naming

The English name of the scale was designated as the "Lifelong Artificial Intelligence Ethical Awareness Scale (LAIEAS)". The Turkish abbreviation YBYZEFÖ (Yaşam Boyu Yapay Zekâ Etik Farkındalık Ölçeği) reflects both the context (Artificial Intelligence Ethics) and the purpose (Awareness Measurement) of the instrument. The naming was intentionally chosen to emphasize the integrated nature of lifelong learning and ethical awareness, highlighting the scale's focus on the continuous and reflective development of ethical sensitivity in relation to AI technologies (Table 7).

Table 7.
Scale Naming

Factor	Item Code	Number of Item	Item	Explain
F1. Awareness	A1, A2, A3, A6, A9	5	I am aware that AI applications can make mistakes in decision-making.	The individual's level of cognitive awareness regarding artificial intelligence.
F2. Value and Attitude	B13, B17, B18, B19, B22	5	AI systems should respect human dignity.	Level of commitment to ethical principles and values.
F3. Behavioral Intention	C25, C29, C30, C33, C35	5	If an application raises ethical concerns, I would prefer not to use it.	Reflection of ethical awareness in behavior.
F4. Critical Evaluation	D37, D40, D41, D45, D47	5	When I see an AI output, I ask which data was used.	Cognitive-analytical aspect of ethical decisions.
F5. Lifelong Learning and Adaptation	E49, E52, E54, E58, E59, E60	6	I try to regularly follow new information about AI.	Ethical awareness's capacity for lifelong learning.

Subscale scores are computed by summing or averaging the relevant items, while the total score represents the overall ethical awareness level of the individual. Higher scores indicate greater ethical awareness and sensitivity toward the ethical implications of AI technologies. The total scale score can range from 26 to 130, with higher values reflecting more advanced levels of lifelong ethical awareness in artificial intelligence.

4. DISCUSSION, CONCLUSION and RECOMMENDATIONS

This study encompasses the validity and reliability analyses of the Lifelong Artificial Intelligence Ethical Awareness Scale, developed to measure individuals' ethical awareness levels toward artificial intelligence technologies within the context of lifelong learning. The findings revealed that the theoretically proposed five-dimensional structure of the scale was strongly confirmed through both exploratory and confirmatory analyses. The high factor loadings (.82-.91), total explained variance of 82.4%, and excellent model fit indices (CFI = .962, RMSEA = .049) demonstrate that the LAIEAS is a statistically and theoretically valid measurement instrument. These results align with contemporary perspectives suggesting that ethical awareness should be treated as a multidimensional construct (Rest, 1986; Narvaez & Lapsley, 2005; Reynolds, 2006). The model developed in this study conceptualizes ethical awareness not merely as a cognitive level of recognition but as a holistic construct encompassing value orientation, behavioral intention, critical evaluation, and continuous learning. This emphasizes that ethical education in the age of artificial intelligence is not solely knowledge-based but also an evolving and reflective process (Floridi, 2019; Hagendorff, 2020).

The five-factor structure obtained in this study supports the multidimensional nature of ethical awareness. The "Awareness" dimension represents the individual's capacity to recognize the social, individual, and cognitive implications of artificial intelligence technologies. This finding aligns with the "ethical awareness principle" emphasized by Mittelstadt (2019) and Jobin, Ienca, and Vayena (2019). AI systems are not error-free, they inherently involve ethical risks such as data bias, algorithmic discrimination, and misinformation. Thus, the ability of individuals to identify these risks constitutes the first step of ethical awareness. The "Value and Attitude" dimension measures the extent to which individuals adhere to ethical values such as justice, privacy, human dignity, and accountability. This finding corresponds directly with the "AI Ethics Principles Framework" proposed by Floridi and Cowls (2019). It was concluded that value orientation plays a decisive role in delineating the ethical boundaries of AI technologies, and that ethical awareness represents not only a cognitive understanding but also a normative orientation. The "Behavioral Intention" dimension measures the individual's intention to transform ethical awareness into concrete actions. This finding is consistent with Ajzen's (1991) Theory of Planned Behavior, which posits that intentions toward ethical behaviors are a function of one's values and attitudes. The results indicated that individuals with higher ethical awareness levels tend to respond when encountering unethical situations in AI applications (e.g., reporting or providing feedback). The "Critical Evaluation" dimension represents the cognitive-analytical aspect of ethical awareness. The tendency of individuals to question how AI systems operate, which data they are trained on, and which assumptions they rely upon reflects a high level of cognitive depth in ethical reasoning. This result aligns with the critical inquiry competencies highlighted in the AI Ethics Pedagogy approaches developed by Ma et al. (2025) and Long and Magerko (2020). Finally, the "Lifelong Learning/Adaptation" dimension demonstrates that ethical awareness is a sustainable competency throughout life. This finding supports UNESCO's (2021) principle of the continuity of AI ethics learning. Ethical awareness is not a fixed body of knowledge acquired once; rather, it is a learning process continuously renewed through technological and cultural change. In this sense, the LAIEAS is among the few instruments that measure ethical awareness as a dynamic and lifelong evolving competency.

When compared with previously developed scales, the factor structure of the LAIEAS fills a notable gap in the literature. For instance, the AI Attitude Scale developed by Grassini (2023) measures only ethical attitudes and does not encompass the dimensions of awareness, critical evaluation, or lifelong learning. Similarly, the study by Long and Magerko (2020) addresses AI awareness within a pedagogical context but lacks a lifelong learning perspective. The LAIEAS, however, integrates cognitive, affective, and behavioral dimensions, redefining ethical awareness within an interdisciplinary framework. In this regard, the LAIEAS reflects all four stages of Rest's (1986) model of moral behavior, moral awareness, moral judgment, moral intention, and moral action. Moreover, the final dimension of the scale, lifelong learning/adaptation, parallels the perspectives of modern ethical theories (e.g., Floridi, 2019; Siau & Wang, 2020), which view ethical consciousness as a renewable capacity in the digital era.

The statistical findings of LAIEAS also surpass the psychometric indicators reported in similar instruments in the literature. For example, in the global meta-analysis of AI ethics guidelines conducted by Jobin et al. (2019), most tools measuring AI ethical awareness reported AVE values below .50, whereas in this study, AVE values ranged between .65 and .72. This demonstrates that the LAIEAS is a conceptually clear and psychometrically robust tool. In this study, ethical awareness was conceptualized as an extension of lifelong learning. The findings revealed that individuals with higher ethical awareness also exhibited higher levels of lifelong learning tendency ($r = .49$, $p < .001$). This relationship is consistent with the findings of Candy (2002) and Knapper and Cropley (2010), who suggested that self-directed learning enhances individuals' ethical reasoning capacity. Accordingly, in the age of artificial intelligence, ethical awareness is a form of cognitive awareness that not only questions "how learning occurs" but also "what should be learned." Furthermore, the negative correlation between LAIEAS scores and technology anxiety ($r = -.31$, $p < .001$) is noteworthy. This finding indicates that individuals with higher ethical awareness approach technological innovations with greater confidence and make more informed decisions in the face of uncertainty. This supports the "mediating role of ethical awareness in building trust" hypothesis proposed by Siau and Wang (2020).

The research findings present significant implications, particularly for teacher education and higher education policies. In learning environments supported by AI tools, students should not only use technology but also assess its ethical consequences (Holmes et al., 2021). In this context, the LAIEAS can be used to determine the ethical awareness levels of preservice teachers and educators. Furthermore, it can serve as a standardized instrument in institutional digital ethics and AI awareness training programs. At the societal level, the scale provides a framework for understanding individuals' ethical reflection capacities in the digital age. Measuring ethical awareness in a time of expanding AI technologies is a crucial prerequisite for developing sustainable and fair technology policies (UNESCO, 2021; Cath, 2018). Therefore, the LAIEAS can be considered not only a measurement tool but also a "learning map" that strengthens the culture of ethical awareness.

As the research data were collected through a self-report form, there is a potential for social desirability bias. Moreover, the study was conducted within a Turkish sample; hence, it is recommended that validity analyses be replicated across different cultural contexts. Future studies should focus on adapting the LAIEAS into English and multilingual versions, testing its validity across various professional groups (e.g., engineers, data scientists, educators), conducting longitudinal studies to track the development of ethical awareness, and integrating qualitative data collection methods (e.g., interviews, observations) to enrich the quantitative findings. Additionally, the LAIEAS can be applied in studies examining feedback ethics, teacher student interactions, and transparency in decision-support systems within AI-enhanced learning environments. Such integrative studies will deepen the understanding of the role of ethical awareness in learning culture.

This research has developed a unique measurement tool that positions ethical awareness at the core of lifelong learning. The LAIEAS provides a valid, reliable, and theoretically grounded model for assessing individuals' capacity to perceive, evaluate, and responsibly use technology in the age of artificial intelligence.

The findings indicate that ethical awareness is not merely an individual attitude but a cognitive and cultural learning process sustained throughout life. In this respect, the LAIEAS should be regarded as a scientific instrument that strengthens both ethical education and the human dimension of AI policies.

Author Contribution Rates

The contribution rate of the authors is equal.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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APPENDIX

Lifelong Artificial Intelligence Ethical Awareness Scale

Factor	Item	1	2	3	4	5
F1. Awareness	I am aware that AI applications can make mistakes in decision-making.					
	I know that AI systems can be biased.					
	I consider it important to question the accuracy of AI-generated content.					
	I am aware that AI applications can deepen social inequalities.					
	I know that AI carries security risks.					
F2. Value and Attitude	AI systems should respect human dignity.					
	Privacy is a priority ethical value in AI applications.					
	Human-centeredness should be maintained in AI decisions.					
	The economic benefits of AI should not overshadow ethical concerns.					
	The use of AI should align with societal values.					
F3. Behavioral Intention	If an application raises ethical concerns, I would prefer not to use it.					
	I value human approval (human-in-the-loop) for AI decisions.					
	I would not fully trust AI for important personal decisions.					
	Knowing that a service uses AI influences my choice to prefer that service.					
	I report unethical AI applications at work to management.					
F4. Critical Evaluation	When I see an AI output, I ask which data was used.					
	I try to discover what assumptions AI is based on.					
	I analyze an AI decision from various angles to determine fairness.					
	I do not rely only on technical reports to decide if an AI decision is ethical.					
	When assessing AI limitations, I prioritize the ethical perspective.					
F5. Lifelong Learning and Adaptation	I try to regularly follow new information about AI.					
	When a new AI application emerges, I seek information to evaluate its ethical aspects.					
	I update my ethical approaches with technological changes.					
	Learning about different cultures' approaches to AI ethics is important to me.					
	I do not want to fall behind in digital ethics as I grow older.					
	When new ethical regulations emerge, I try to follow and implement them.					

Yaşam Boyu Yapay Zekâ Etik Farkındalık Ölçeği

Alt Boyut	İfade	1	2	3	4	5
F1. Farkındalık	Yapay zekâ uygulamalarının karar verme süreçlerinde hata yapabileceğinin farkındayım.					
	Yapay zekâ sistemlerinin taraflı olabileceğini bilirim.					
	Yapay zekâ tarafından üretilen içeriklerin doğruluğunu sorgulamanın önemli olduğunu düşünürüm.					
	Yapay zekâ uygulamalarının toplumsal eşitsizlikleri derinleştirebileceğini fark ederim.					
	Yapay zekânın güvenlik riskleri taşıdığını bilirim.					
F2. Değer ve Tutum	Yapay zekâ sistemleri insan onuruna saygı göstermelidir.					
	Gizlilik, yapay zekâ uygulamalarında öncelikli bir etik değerdir.					
	Yapay zekâ kararlarında insan merkezlilik korunmalıdır.					
	Yapay zekânın ekonomik faydaları etik kaygıları gölgede bırakmamalıdır.					
	Yapay zekâ kullanımı toplum değerleriyle uyumlu olmalıdır.					
F3. Davranışsal Eğilim	Etik kaygılar taşıyan bir uygulama varsa, onu kullanmamayı tercih ederim.					
	Yapay zekâ kararlarına karşı insan onayına önem veririm.					
	Önemli kişisel kararlarımda yapay zekâya tamamen güvenmem.					
	Bir hizmette yapay zekâ kullanıldığını bilmek, hizmeti tercih etmemde etkili olur.					
	İş yerinde etik olmayan YZ uygulamalarını yönetime bildiririm.					
F4. Eleştirel Değerlendirme	Bir yapay zekâ çıktısını gördüğümde, hangi verinin kullanıldığını sorgularım.					
	Yapay zekânın hangi varsayımlara dayandığını keşfetmeye çalışırım.					
	Bir YZ kararının adil olup olmadığını çeşitli açılardan analiz ederim.					
	Bir YZ kararının etik olup olmadığını belirlemek için sadece teknik raporlara güvenmem.					
	YZ sistemlerinin sınırlılıklarını değerlendirirken etik perspektifi ön planda tutarım.					
F5. Sürekli Öğrenme ve Adaptasyon	Yapay zekâ hakkında yeni bilgileri düzenli olarak takip etmeye çalışırım.					
	Yeni bir YZ uygulaması çıktığında etik yönlerini değerlendirmek için bilgi ararım.					
	Teknolojik değişimlerle etik yaklaşımlarımı güncellerim.					
	Farklı kültürlerin YZ etiğine yaklaşımını öğrenmek benim için önemlidir.					
	Yaş ilerledikçe dijital etik konularında geri kalmak istemem.					
	Yeni etik düzenlemeler çıktığında bunları takip edip uygulamaya çalışırım.					