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Construction and Validation of the Artificial Intelligence Disclaimer Literacy Scale Instrument (AI-DLS)

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ABSTRACT

The use of Generative Artificial Intelligence (GenAI) in higher education poses epistemic risks, including information hallucinations, limited accuracy, and content bias. Although AI developers include disclaimers as a risk mitigation measure, the effectiveness of this mechanism is often hampered by the phenomenon of warning fatigue, so it does not always encourage user evaluative behavior. This study aims to develop and validate the Artificial Intelligence Disclaimer Literacy Scale as a psychometric instrument to measure students' awareness, understanding, attitudes, and critical evaluation of AI disclaimers. The study employed a quantitative psychometric development design divided into five stages: literature review, indicator formulation, instrument item development, empirical testing, and statistical validation. The instrument was tested on 165 students at the Faculty of Teacher Training and Education. Data analysis included item validity testing using corrected item–total correlation, reliability testing using Cronbach's Alpha, and Exploratory Factor Analysis (EFA) using the Principal Component Analysis (PCA) method with Varimax rotation to test construct validity. The results showed that the AI-DLS instrument, consisting of 30 statement items, was proven valid and reliable. All items had a correlation value ≥ 0.30, with excellent reliability across all four dimensions (Cronbach's Alpha = 0.828 - 0.937). The EFA results showed a Kaiser–Meyer–Olkin (KMO) value of 0.932 and a factor structure capable of explaining 66.89% of the total variance. These findings indicate that the AI-DLS has strong psychometric qualities and is suitable for use as a diagnostic instrument to map students' epistemic readiness to interact with Artificial Intelligence systems critically and responsibly.

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A. INTRODUCTION

The use of Generative Artificial Intelligence (GenAI) in higher education is growing rapidly and transforming the way students interact with academic assignments. Large language models (LLMs) such as ChatGPT, Gemini, and Claude enable students to quickly and efficiently summarize literature, draft papers, and explore ideas (Dwivedi et al., 2023). While offering significant benefits, the use of GenAI also carries epistemic risks, as these systems can generate information that appears linguistically convincing but is factually incorrect, a phenomenon known as hallucination (Ji et al., 2023).

This risk is exacerbated by the tendency toward automation bias, a condition where users place excessive trust in automated systems and reduce critical evaluation of the information they generate (Miao et al., 2023; Parasuraman & Manzey, 2010). Although automated assessment technology offers high efficiency, the validity of learning evaluations still requires human intervention to assess judgmental aspects such as the depth of arguments and ethical context, which machines cannot fully perform (Rahman & Dewantara, 2025). Recent studies have shown that excessive use of AI dialogue systems can reduce students' ability to assess source reliability and think independently, especially when the AI's clear and convincing language is perceived as a sign of truth or intelligence (Mollick, 2024; Zhai et al., 2024).

In an effort to mitigate these risks, AI developers include disclaimers that explain the system's limitations and remind users to double-check the information provided. Theoretically, disclaimers serve as an incentive for users to be more vigilant in using and evaluating AI output. However, research in Human–Computer Interaction shows that digital warnings are often ignored because users become accustomed to seeing them repeatedly, so their presence does not always translate into behavioral changes (Carroll, 2024; Wogalter, 2018).

Current AI literacy studies generally focus on technology acceptance, ease of use, and perceived benefits (Gimpel et al., 2023). Existing AI literacy instruments primarily focus on general AI knowledge, ethical awareness, technical competencies, or attitudes toward AI technologies. For example, the AI Literacy Questionnaire developed by Ng et al. (2024) measures affective, behavioral, cognitive, and ethical dimensions of AI literacy, while the GenAI Literacy for Learning Scale developed by Gümüş and Kara (2025) emphasizes learning-related competencies associated with generative AI. Similarly, Nong et al. (2024) developed an AI Literacy Scale that focuses on general AI understanding and responsible use. However, none of these instruments specifically measures users' literacy regarding AI disclaimers as a mechanism designed to communicate epistemic limitations and encourage critical evaluation of AI-generated information. Therefore, the AI-DLS addresses a distinct measurement gap by focusing on disclaimer literacy as a component of epistemic vigilance in AI use.

Furthermore, although the present validation study was conducted with university students, the conceptual structure of AI-DLS is not restricted to academic contexts. The instrument may also be applied to teachers, lecturers, educational administrators, professionals, and other users of generative AI systems whose decisions may be influenced by AI-generated outputs. This broader applicability increases the potential utility of the AI-DLS as a diagnostic tool for assessing responsible AI use across educational and professional settings. Based on this gap, this study aims to develop and validate the AI Disclaimer Literacy Scale (AI-DLS) as a psychometric instrument to measure students' literacy regarding AI disclaimers. This instrument is designed to encompass four main constructs: awareness, understanding, attitude, and critical evaluation, representing the cognitive, affective, and behavioral dimensions of AI literacy.

The main novelty of this study lies in the shift in focus of AI literacy studies from a predominantly technical skills-based approach to an epistemic vigilance approach to AI safety mechanisms, particularly disclaimers. Most previous AI literacy research has focused on operational capabilities, technology acceptance, and the functional use of AI in learning. Instead, this research specifically explores how AI users perceive, understand, respond to, and evaluate disclaimers as signals of the epistemic limitations of AI systems. Until now, disclaimers have generally been treated as interface elements assumed to be effective without systematic empirical testing. By developing and validating the Artificial Intelligence Disclaimer Literacy Scale (AI-DLS), this research fills a crucial gap in educational technology research by providing a psychometric instrument that explicitly measures the cognitive awareness and epistemic responsibility of AI users.

B. METHODS

Research Design

This study employed a quantitative psychometric instrument development design to produce a valid and reliable measurement tool for educational research (Agustina & Ahman, 2024). The focus of this study was to evaluate the validity and reliability of the Artificial Intelligence Disclaimer Literacy Scale (AI-DLS).

Participants

The study participants were 165 students from the Faculty of Teacher Training and Education (FKIP). The student teachers were selected because of their strategic role as future educators who will be responsible for integrating and teaching AI technologies in educational settings.

Instrument Item Development Procedure

The AI-DLS development was conducted through five main stages.

Stage 1: Literature Review

The researchers examined current literature (2021–2025) on AI literacy, automation bias, epistemic vigilance, and the role of disclaimers in AI systems.

Stage 2: Construct and Indicator Formulation

Based on the research theoretical framework, four main constructs were established: awareness, understanding, attitude, and critical evaluation. Each construct was operationalized into measurable indicators for empirical assessment.

Stage 3: Instrument Item Development

The instrument was structured in a five-level Likert scale with a total of 30 statements, all formulated in a positive form to minimize ambiguity and response bias.

Stage 4: Instrument Testing

The instrument was administered to 165 FKIP students, and the resulting data were used for validity and reliability analyses.

Stage 5: Statistical Analysis

Data analysis was conducted using SPSS, which included item validity testing (Corrected Item-Total Correlation), reliability testing (Cronbach's Alpha), and exploratory factor analysis to support construct validity (Ng et al., 2024).

The selected statistical procedures were aligned with established psychometric instrument development practices. Corrected Item–Total Correlation was employed to evaluate the contribution of each item to its corresponding construct and to identify potentially weak items. Cronbach’s Alpha was used to assess the internal consistency reliability of each dimension because it remains one of the most widely accepted indicators of scale reliability in educational and psychological measurement. Exploratory Factor Analysis (EFA) was selected because the AI-DLS represents a newly developed instrument whose underlying factor structure had not been empirically established. Following recommendations in psychometric research, Principal Component Analysis with Varimax rotation was applied to explore latent dimensions and improve factor interpretability during the initial validation stage (Costello & Osborne, 2005).

Table 1. AI Disclaimer Literacy Grid Scale

Variables	Dimension	Indicator	Number of Items	Number of Items
Awareness (X1)	Awareness	Attention to and recognition of AI disclaimers	X1.1–X1.5	5
Understanding (X2)	Understanding	Understanding the meaning of the content and implications of the disclaimer	X2.1–X2.5	5
Attitude (Z)	Attitude	Affective caution toward AI use	Z.1–Z.5	5
Critical Evaluation (Y)	Critical Evaluation	Verification, cross-checking, and epistemic responsibility in evaluating AI-generated information	Y.1–Y.15	15
			Total	30

Awareness (X1) measures attention and recognition of AI disclaimers; Understanding (X2) measures the cognitive ability to interpret their meaning and implications; Attitude (Z) measures affective caution toward AI use; and Critical Evaluation (Y) measures verification behavior and epistemic responsibility in evaluating AI-generated information.

C. RESULT AND DISCUSSION

1. Item Validity Test Results

Item validity was evaluated using Corrected Item – Total Correlation and significance testing. Items with corrected item – total correlation values ⩾ 0.30 and statistically significant correlations ($p < 0.05$) were considered valid. All items satisfied these criteria, with significance values below 0.001.

1) Construct Awareness (X1)

Table 2. Item Validity Test Results for Construct Awareness (X1)

Item	Statement	r item–total (Pearson)	Sig. (2-tailed)	Corrected Item–Total Correlation	Decision
X1.1	I am aware that the generative AI tools I use usually include a disclaimer, which is a statement/warning about its limitations.	0.774**	.000	0.636	Valid
X1.2	I always pay attention to the disclaimer statements displayed by generative AI tools (e.g., ChatGPT, Gemini, Claude, Perplexity, etc.).	0.820**	.000	0.703	Valid
X1.3	I know where information about limitations/disclaimers on the AI tools I frequently use is located.	0.871**	.000	0.775	Valid
X1.4	I think AI disclaimers are standard information found in many Artificial Intelligence (AI) products.	0.704**	.000	0.564	Valid

X1.5	I have an active way to search for or read more about the disclaimer on at least one AI product I use.	0.694**	.000	0.482	Valid

Source: Primary Data Processed by SPSS (2025)

2) Construct Understanding (X2)

Table 3. Item Validity Test Results for Construct Understanding (X2)

Item	Statement	r item–total (Pearson)	Sig. (2-tailed)	Corrected Item–Total Correlation	Decision
X2.1	I understand that AI disclaimers are intended to inform users that AI output is not always accurate.	0.847**	.000	0.745	Valid
X2.2	I understand that AI disclaimers indicate that information from AI needs to be checked, repeated, or further verified by humans.	0.861**	.000	0.774	Valid
X2.3	I understand that AI disclaimers often mention that AI can generate biased content.	0.810**	.000	0.696	Valid
X2.4	I understand that AI disclaimers remind users that decision-making does not rely entirely on AI output.	0.839**	.000	0.739	Valid
X2.5	I understand that the objective AI disclaimer is to protect developers while providing guidance for users.	0.783**	.000	0.664	Valid

Source: Primary Data Processed by SPSS (2025)

3) Construct Attitude (Z)

Table 4. Item Validity Test Results for Attitude Construct (Z)

Item	Statement	r item–total (Pearson)	Sig. (2-tailed)	Corrected Item–Total Correlation	Decision
Z.1	I think the disclaimer in AI is an important thing for users to pay attention to.	0.861**	.000	0.777	Valid
Z.2	I tend to be more cautious in using AI output after learning about the limitations of the AI disclaimer.	0.855**	.000	0.770	Valid
Z.3	The AI disclaimer increases my awareness of the potential negative risks of using AI.	0.837**	.000	0.733	Valid

Z.4	I find the AI disclaimer to be a useful guide for the responsible use of AI responses.	0.876**	.000	0.805	Valid
Z.5	There is a disclaimer that makes me more critical in assessing the output produced by AI.	0.855**	.000	0.768	Valid

Source: Primary Data Processed by SPSS (2025)

4) Construct Critical Evaluation (Y)

Table 5. Results of the Critical Evaluation Construct (Y) Validity Test

Item	**Statement**	**r item–total (Pearson)**	**Sig. (2-tailed)**	**Corrected Item–Total Correlation**	**Decision**
Y.1	When I receive output from AI, I always consider the possibility that the information is inaccurate.	0.747**	.000	0.700	Valid
Y.2	I try to identify potential information bias in the AI output.	0.729**	.000	0.681	Valid
Y.3	I feel the need to conduct a thorough evaluation of the reliability of the information provided by the AI.	0.727**	.000	0.681	Valid
Y.4	I consider the limitations of current AI knowledge when evaluating the accuracy of information	0.754**	.000	0.710	Valid
Y.5	I recognize that the quality of AI output can vary significantly depending on the type of command.	0.751**	.000	0.707	Valid
Y.6	If I use information from AI for academic work, I will verify it with credible sources.	0.742**	.000	0.696	Valid
Y.7	I try to find alternative perspectives to compare with the AI output.	0.781**	.000	0.742	Valid
Y.8	I think cross-verification is an important step in using AI in academia.	0.716**	.000	0.666	Valid
Y.9	I feel more confident using AI output after comparing it with other sources.	0.563**	.000	0.486	Valid
Y.10	I actively seek out sources with different perspectives than the AI output.	0.729**	.000	0.679	Valid
Y.11	I am cautious about making academic decisions based solely on AI.	0.664**	.000	0.607	Valid

Y.12	I evaluate AI output before using it as a basis for argumentation.	0.762**	.000	0.719	Valid
Y.13	I consider the implications of using AI in academic decision-making.	0.774**	.000	0.736	Valid
Y.14	I feel responsible for answering questions based entirely on accurate information from the AI.	0.786**	.000	0.751	Valid
Y.15	I believe the final decision rests with me, not with the AI.	0.749**	.000	0.706	Valid

Source: Primary Data Processed by SPSS (2025). *The ** symbol indicates significance at p < 0.01 (SPSS format).*

The validity test results indicate that all 30 AI-DLS items are empirically valid, with a Corrected Item-Total Correlation value of ≥ 0.30 and a significance value of $p < 0.001$. These findings confirm the validity of all four constructs: Awareness (X1), Understanding (X2), Attitude (Z), and Critical Evaluation (Y).

2. Reliability Test Results

Table 6. Reliability of the AI-DLS Instrument

Construct	Number of Items	Cronbach's Alpha
Awareness (X1)	5	0.828
Understanding (X2)	5	0.886
Attitude (Z)	5	0.909
Critical Evaluation (Y)	15	0.937

Source: Primary Data Processed by SPSS (2025)

The reliability test yielded the following Cronbach's Alpha values: Awareness (X1) = 0.828; Understanding (X2) = 0.886; Attitude (Z) = 0.909; and Critical Evaluation (Y) = 0.937. All values were above the 0.80 threshold, indicating excellent internal consistency (Hair et al., 2017).

3. Data Adequacy Test for Factor Analysis

Before conducting factor analysis, data adequacy was tested using the Kaiser–Meyer–Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test of Sphericity.

Table 7. KMO and Bartlett Test Results

Indicator	Mark
KMO Measure of Sampling Adequacy	0.932
Bartlett's Test of Sphericity (χ^2)	3564.197
df	435
Sig.	0.000

Source: Primary Data Processed by SPSS (2025)

Interpretation of Table 7

The KMO value of 0.932 indicates a very high level of sample adequacy (≥ 0.90), making the data highly suitable for factor analysis. The Bartlett's Sphericity Test results showed a significance level of $p < 0.001$, indicating that the correlation matrix between items does not form an identity matrix. Therefore, all items in the AI-DLS instrument meet the requirements for analysis using exploratory factor analysis.

4. Summary of Exploratory Factor Analysis Results for the AI-DLS Instrument

Table 8. Summary of Exploratory Factor Analysis Results for the AI-DLS Instrument

Aspect	Results
Number of Items	30
Extraction Method	Principal Component Analysis
Rotation Method	Varimax with Kaiser Normalization
KMO	0.932 (Very Good)
Bartlett's Test	$\chi^2 = 3564.197$; $p < 0.001$
Number of Empirical Factors	5
Number of Conceptual Factors	4
Total Variance Explained	66.897%
Factor Loading Range	0.502 – 0.819
Items Eliminated	None

Source: Primary Data Processed by SPSS (2025)

The EFA results indicated a robust factor structure with very high sample adequacy. All items had adequate factor loadings and were retained. The empirical structure was consistent with the four-construct conceptual framework of the AI-DLS, supporting its theoretical coherence.

Construct Validity Based on Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) was conducted to test the construct validity of the Artificial Intelligence Disclaimer Literacy Scale (AI-DLS) Instrument. The Kaiser–Meyer–Olkin (KMO) test showed a value of 0.932, indicating very good sample adequacy, while the Bartlett's Sphericity Test was significant at $p < 0.001$. These findings indicate that the dataset met the assumptions required for exploratory factor analysis. Analysis using the Principal Component Analysis method and Varimax rotation resulted in five empirical factors with eigenvalues greater than one, which cumulatively explained 66.897% of the total variance. All items had communality values and factor loadings above the minimum required threshold, so no items were eliminated from the instrument. Although five factors were empirically formed, the structure was then simplified into four conceptual factors in accordance with the theoretical framework of the initial instrument: awareness, understanding, attitude, and critical evaluation. This simplification was carried out based on the similarity of meaning and psychological function between items, particularly in the critical evaluation dimension, which includes verification behaviors, reliability assessment practices, and epistemic responsibility in evaluating AI-generated information. Thus, the EFA results support the construct validity of the AI-DLS instrument and indicate that this instrument has a strong and theoretically consistent factor structure.

DISCUSSION

The AI-DLS demonstrated strong psychometric quality, supported by excellent sampling adequacy (KMO = 0.932) and a significant Bartlett's Test ($p < 0.001$), confirming the suitability of the data for latent construct analysis. The EFA findings further confirmed strong construct validity and supported the multidimensional nature of AI disclaimer literacy, indicating substantial explanatory power for an educational measurement instrument. All items demonstrated communality and factor loadings above the minimum required threshold, thus requiring no item elimination. These findings indicate that all items contributed meaningfully to the underlying construct measured by the AI-DLS. Although five factors were empirically formed, this structure was then simplified into four conceptual factors: awareness, understanding, attitude, and critical evaluation, consistent with the initial theoretical framework for instrument development. This simplification was theoretically driven by considering the similarities in meaning and psychological functions among items, particularly within the fragmented dimension of in-depth critical evaluation.

The fifth empirical factor did not represent a theoretically distinct construct but rather reflected a subdivision of items within the broader critical evaluation domain. These items shared common epistemic functions related to verification, judgment, and responsible evaluation of AI-generated information. Therefore, the four-factor conceptual model was retained to preserve theoretical coherence, parsimony, and interpretability while remaining consistent with the original framework used in instrument development without compromising empirical validity.

This finding aligns with recent literature confirming that AI literacy, particularly in the context of generative AI, cannot be reduced to declarative knowledge alone but encompasses multiple dimensions of attitude and critical evaluation (Ng et al., 2024; Nong et al., 2024). The presence of multiple empirical factors strengthens the argument that AI disclaimer literacy is a complex construct involving awareness, risk understanding, affective readiness, and independent evaluative judgment.

From a theoretical perspective, the four dimensions of AI-DLS can be understood as an interconnected process of epistemic literacy. Awareness represents the initial stage in which users recognize the presence of AI disclaimers and become conscious of the limitations of AI systems. Such awareness facilitates understanding, enabling users to interpret the meaning and implications communicated through disclaimers. Greater understanding is expected to shape users' attitudes by fostering caution and encouraging more responsible perceptions regarding AI-generated outputs. These attitudes subsequently support critical evaluation behaviors, including verification, cross-checking, and independent judgment of AI-generated information. In this sense, the dimensions may operate sequentially, progressing from awareness and understanding toward evaluative action. Although the current study did not empirically test causal relationships among the constructs, the proposed framework provides a theoretical explanation of how disclaimer literacy may contribute to responsible and critical AI use.

This theoretical progression is consistent with educational and psychological models of literacy development and aligns with previous AI literacy studies, which emphasize that cognitive understanding of AI systems contributes to more responsible attitudes and critical engagement with AI-generated content (Ng et al., 2024; Nong et al., 2024). Consistent with the novelty proposed in this study, AI-DLS extends AI literacy research by focusing on disclaimer literacy as an epistemic safety mechanism that has received limited empirical attention. By integrating EFA results into an epistemic literacy framework, this instrument bridges the acceptance approach to AI-based literacy with approaches that emphasize vigilance, verification, and reflection, which are essential for AI-based knowledge sources (Nong et al., 2024). In an educational context, these findings have important implications because they demonstrate that students' readiness to use generative AI responsibly is determined not only by technical understanding but also by systematically measurable attitudinal structures and evaluative skills (Bittle & El-Gayar, 2025; Cotton et al., 2024). Such skills are essential to ensure that technology integration continues to position humans as the primary decision makers within a human-in-the-loop framework, where developers are advised to design AI as a transparent and ethical co-designer (Rahman et al., 2025).

Practically, the Artificial Intelligence Disclaimer Literacy Scale (AI-DLS) provides a standardized measurement tool for educators and higher education administrators to map students' literacy levels in response to the limitations of generative AI. This instrument can be used as an initial assessment to identify student groups that may be vulnerable to uncritical use of AI and as a basis for designing more targeted, preventative, and needs-based AI literacy programs. From a policy perspective, the findings of this study emphasize the need for a shift in digital literacy policy in higher education, from an operational approach focused on skills to strengthening epistemic literacy and critical vigilance towards AI systems. The AI-DLS instrument may serve as a reference in formulating institutional policies related to the use of generative AI, including the development of academic ethics guidelines, AI literacy curricula, and system evaluations that explicitly consider the role of AI. Thus, the resulting policies are not only normative but also supported by empirical data on the readiness and attitudes of AI users, thereby encouraging more responsible and safe use of technology in higher education. While the Artificial Intelligence Disclaimer Literacy Scale (AI-DLS) has demonstrated excellent validity and reliability, this study has several limitations. The research sample was limited to 165 education students; therefore, the findings cannot yet be generalized to broader populations of generative AI users.

D. CONCLUSION AND SUGGESTIONS

This study successfully developed and validated the Artificial Intelligence Disclaimer Literacy Scale (AI-DLS) instrument as a tool to measure generative AI user literacy. The developed instrument consists of 30 items covering four main constructs: awareness, understanding, attitude, and critical evaluation. The results of the validity test indicate that all items are empirically valid, while the reliability test shows excellent internal consistency across constructs. The feasibility of the instrument structure is also supported by a very high Kaiser–Meyer–Olkin (KMO) value (0.932), indicating excellent sampling adequacy. Furthermore, the results of Exploratory Factor Analysis confirm the construct validity of the instrument with a strong factor structure that aligns with the underlying theoretical framework. Thus, the AI-DLS can be considered suitable for use in educational contexts to measure users' readiness and awareness in responding to the limitations of artificial intelligence systems. These findings confirm that AI literacy is not simply a matter of reading warnings but rather a complex process involving cognitive and epistemic awareness among GenAI users.

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