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Development and Validation of an AI Literacy Scale

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ABSTRACT

Amidst rapid advancements in artificial intelligence (AI), acquiring AI-related skills has become essential for societal development. Assessing the public's AI literacy is thus critical for enhancing overall societal competitiveness. This study aimed to develop an evaluation index system for measuring public AI literacy, encompassing five dimensions with 15 specific indicators: application ability, cognitive ability, morality, critical thinking, and self-efficacy. Data were collected through surveys, and quantitative analysis validated the system's rationality. The constructed AI literacy measurement tool provides a reliable foundation for evaluating core competencies in the AI era, filling a research gap with practical and theoretical significance.

1. Introduction

With the rapid advancements and profound transformation in human-machine interactive technology, the importance of updating and adjusting the current technical literacy framework has become increasingly apparent and urgent. In particular, the rise of artificial intelligence (AI) applications, such as ChatGPT and other generative AI models, highlights the dual nature of technological development: immense opportunities on the one hand and significant risks and challenges on the other. These challenges include concerns about data privacy and security, which arise from the vast amounts of sensitive information processed by AI systems. Unauthorized access to or misuse of this data can lead to potential harm for users and organizations alike, raising the stakes for robust data protection mechanisms. Similarly, legal and ethical considerations surrounding the deployment of AI have become pressing topics, as the rapid pace of innovation outstrips regulatory frameworks, leaving policymakers struggling to establish effective guidelines. Issues such as bias in algorithmic decision-making, lack of transparency in AI processes, and ethical dilemmas in automated systems all demand urgent attention from researchers and practitioners. Moreover, the sustainability and reliability of AI systems have sparked debates about whether these technologies can adapt and scale to meet long-term societal needs, particularly as they face challenges related to energy consumption, environmental impact, and technical robustness [11].

Against this complex backdrop, AI literacy has emerged as a critical area of focus in academic discourse [12]. As an extension and deepening of the foundational concepts of information and digital literacy, AI literacy reflects the evolving demands of a technology-driven era [14]. It incorporates traditional literacy requirements, such as the ability to search for, evaluate, and use digital information effectively, while simultaneously expanding to address the unique features of AI technologies. These features include understanding machine learning algorithms, interpreting AI-driven outputs, and critically assessing the ethical implications of AI applications [18]. Unlike its predecessors, AI literacy also emphasizes the need for individuals to anticipate and adapt to future technological developments, ensuring that they remain informed and capable of engaging with emerging tools and systems [6].

Existing research has provided valuable insights into the broader concept of digital literacy, often focusing on its intersection with intelligent systems, education, and technical frameworks. For example, Ai explored the human-technology relationship in intelligent systems, shedding light on how users interact with and perceive AI-driven tools [1]. Yang et al. examined the role of digital literacy in educational settings, emphasizing its importance for equipping students and teachers with the skills needed to navigate a technology-rich environment [17]. Similarly, the China Central Educational Technology Center investigated the technical and engineering dimensions of digital literacy, highlighting the need for a strong technical foundation to support effective engagement with digital tools [4]. Despite these contributions, research on AI-specific contexts, particularly regarding perceived usefulness and perceived ease of use, remains scarce. Perceived usefulness, as defined by Davis [5], refers to the degree to which a user believes that a particular technology will enhance their performance, while perceived ease of use captures the extent to which users perceive a technology as being free of effort. Both constructs are crucial for understanding user acceptance and adoption of new technologies, as they directly influence attitudes and behaviors.

Although the components and cultivation strategies for AI literacy measurement frameworks have been explored to some extent, there remains a significant gap between theoretical development and practical application. Much of the existing research is limited to theoretical discussions or framework proposals, with few empirical studies providing the data needed to validate these frameworks. The lack of

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unified standards for evaluating public AI literacy further complicates efforts to assess and compare literacy levels across different populations. Without consistent metrics, it is challenging to determine whether individuals possess the necessary skills and knowledge to effectively engage with AI technologies. Furthermore, most studies have focused on specific groups, such as primary and secondary school students, teacher trainees, or college students, largely neglecting the general public. This narrow focus limits the generalizability of findings and leaves a critical gap in understanding how AI literacy manifests across diverse demographics.

Expanding research to include broader populations is essential for addressing this limitation. The general public, as the primary users and beneficiaries of AI technologies, plays a pivotal role in determining the societal impact of these innovations. Understanding their level of AI literacy is crucial for designing educational interventions and policies that promote equitable access to and engagement with AI tools. For example, a standardized AI literacy evaluation metric tailored to the public could serve as a benchmark for assessing literacy levels and identifying areas for improvement. Such a metric would also enable researchers to explore the relationship between AI literacy and key user perceptions, such as perceived ease of use and perceived usefulness. These perceptions not only influence user attitudes toward AI technologies but also affect their likelihood of adoption and continued use.

By addressing these gaps, this study seeks to make both theoretical and practical contributions to the field of AI literacy. It develops a comprehensive measurement framework that captures the multifaceted nature of AI literacy and validates its effectiveness through rigorous empirical testing. Using Structural Equation Modeling (SEM), the study examines the impact of different AI literacy dimensions on perceived ease of use and perceived usefulness, providing insights into how literacy levels shape user experiences with AI. For instance, individuals with high application ability are more likely to perceive AI technologies as useful, while those with strong moral awareness may be better equipped to navigate the ethical challenges associated with AI adoption. Similarly, self-efficacy, or confidence in one's ability to use AI effectively, plays a critical role in enhancing both perceived ease of use and perceived usefulness, ultimately improving user performance in various contexts.

In summary, this research not only constructs and validates a robust AI literacy assessment tool but also explores its practical implications for public education and policy. By bridging the gap between theoretical frameworks and empirical evidence, it establishes a solid foundation for future studies on AI literacy and its role in shaping user interactions with technology. The findings have far-reaching implications for educators, policymakers, and technology developers, offering a roadmap for fostering a more informed and capable society in the age of AI. Through its comprehensive approach, the study contributes to the growing body of knowledge on AI literacy while addressing critical challenges in its measurement and application, paving the way for large-scale social surveys and targeted interventions. Based on the above analysis, this study proposes a research agenda focused on developing a national AI literacy evaluation index system to address the following research questions:

- What are the components of the AI literacy evaluation index system?
- How do the sub-dimensions of AI literacy impact perceived usefulness and ease of use in relation to AI?

2. Preliminaries

AI literacy represents an evolution and extension of various types of literacy, particularly information and digital literacy. Its definition varies across different groups, generally manifesting in three primary dimensions. First, there is an emphasis on the individual's basic understanding and application capabilities related to AI technology. This includes knowledge of AI's fundamental principles, algorithms, and operational mechanisms, as well as the ability to apply AI in solving real-life and work-related issues [2]. Second, ethical and regulatory awareness requires individuals to be sensitive to AI ethics and regulations, ensuring adherence to ethical standards and legal requirements to prevent misuse of technology and infringement on others' rights. Third, critical thinking skills highlight the importance of analyzing and assessing AI's effects, impacts, and application contexts. This involves a rational evaluation of AI's limitations and potential risks [13].

While the specific AI literacy requirements vary across different groups, they generally adhere to a common foundational framework. At the core of this framework are four key aspects: first, an in-depth understanding of AI technology, including its principles, applications, and developmental trends; second, proficiency in using AI tools and technologies to address real-world problems or improve work efficiency; third, the ability to produce content using AI, creatively leveraging AI to generate value; and fourth, the capacity to accurately assess the quality and impact of AI-generated outputs to ensure the technology is applied appropriately [7, 10]. Specific research findings are presented in Table 1.

Based on a thorough analysis of existing research on AI literacy, it becomes increasingly apparent that there is an urgent and growing need for the public to enhance their understanding, skills, and critical thinking capabilities related to artificial intelligence. As AI technologies become deeply embedded in daily life and permeate diverse professional fields, the ability to engage meaningfully with AI systems is transitioning from a desirable skill to a fundamental necessity. Effective interaction with AI now demands not only basic technical literacy but also a nuanced understanding of its mechanisms, implications, and societal impacts. However, despite the growing significance of AI literacy, the current academic and practical research landscape does not

Table 1
Overview of AI literacy scale: Indicators and key references

Source	AI Literacy Indicator	Content
H. Z. Hou, Y. G. Wang et al. [7, 16]	Application Ability	Effectively learning and utilizing AI technologies and applications, including the ability to promote AI in real-life contexts and solve personal issues, exploring its application to required knowledge, and the ability to use AI and domain knowledge appropriately.
S. H. Kim [9]	Advanced Ability	The adaptability to obtain and utilize practical solutions from intelligent visual technologies and tools.
	Advanced Ability	The ability to apply AI in augmented reality and data-driven service applications.
	Information Processing Ability	Skills in acquiring, analyzing, and evaluating information. The capability to handle information effectively, managing inputs required in daily life.
Hengming Zhong et al.	Self-efficacy	The confidence and belief in effectively managing, controlling, and utilizing AI skills to complete specific tasks, solve problems, or achieve goals. The degree of confidence in integrating AI skills into everyday life and work when faced with technical challenges.
H. Z. Hou, Y. G. Wang et al. [7, 16]	Cognitive Ability	The ability to reflect on the impact of AI on society, promoting the role of AI technology in key developments.
S. Nikou, M. De Reuver, M. Mahboob Kamari et al. [15, 19]	Critical Thinking Ability	The capability to comprehensively understand the development of human-centered AI technologies (such as AI reasoning systems), learn about their real-world impacts, and produce effective outcomes.
C. G. Jang, W. J. Sung et al. [8, 20]	Perceived Usefulness	Understanding the impact gained from using AI, learning skills, and adopting new skills to achieve results.

adequately address the challenges associated with measuring and fostering this form of literacy.

Most existing studies on AI literacy have focused on qualitative approaches, offering valuable discussions on topics such as the ethical implications of AI, its applications across industries, and its potential risks and benefits. These theoretical explorations have provided critical insights into AI's role in shaping society, yet they lack the empirical foundation needed to translate these insights into actionable outcomes. Quantitative studies that aim to systematically assess AI literacy levels remain scarce, and there is a notable absence of large-scale, representative research that captures the diverse experiences and abilities of different demographic groups. Without robust, data-driven assessments, it is difficult to accurately gauge the readiness of the general population to effectively navigate an increasingly AI-driven world or to identify specific gaps in knowledge and skills that require targeted educational interventions.

Moreover, while qualitative studies are valuable for exploring specific contexts and generating hypotheses, they are insufficient for developing standardized frameworks capable of assessing AI literacy on a broad scale. This limitation underscores the need for more comprehensive methodologies that integrate both qualitative and quantitative insights, enabling researchers to measure AI literacy in a way that is both precise and adaptable to various social and cultural contexts. The lack of large-scale studies also means that existing research often fails to account for the diverse ways in which individuals and communities interact with AI, resulting in an incomplete understanding of AI literacy's scope and requirements.In light of these gaps, it is clear that further efforts are needed to build a comprehensive body of research on AI literacy that balances theoretical exploration with empirical rigor. Such research should aim to establish standardized metrics for measuring AI literacy across different populations, investigate the factors influencing literacy levels, and explore the educational strategies most effective in addressing these disparities. Only through a combination of qualitative depth and quantitative breadth can we begin to fully understand how prepared the public is to engage with AI technologies and what steps are needed to ensure equitable access to the benefits of AI. This holistic approach will be essential for developing meaningful interventions and policies that empower individuals to thrive in a rapidly evolving technological landscape.

3. Construction of the AI Literacy Evaluation Index System

Building on the findings of previous scholars, this study selected five dimensions as evaluation indicators for digital literacy: application ability, morality, critical thinking, cognitive ability, and self-efficacy. The survey questionnaire is shown in Table 2. The AI literacy evaluation index system developed in this study was organized into a Likert five-point scale questionnaire. Data were collected through both physical and online questionnaires, with the target respondents being members of the general public.

4. Empirical Analysis

4.1. Descriptive Statistics

To ensure broad representativeness, this study purposefully selected respondents from the general public, aiming to maximize diversity in terms of gender, age, education, occupation, and income levels. Ultimately, 302 valid questionnaires were collected. To confirm the effectiveness of the constructed evaluation index system, the study employed a

Table 2
Survey items

Dimension	Item No.	Indicator	Survey Item
Application Ability	YY1	Ability to use AI in daily life	I can use AI technology frequently in my daily life.
	YY2	Ability to use AI to assist with work or study	I can use AI to help complete my work or study tasks.
	YY3	Ability to choose AI tools	I can identify and select appropriate AI tools based on my needs.
Morality	DD1	Ability to recognize bias in algorithms	I am aware of potential biases in AI algorithm design.
	DD2	Ability to recognize AI risks	I believe that AI risks, such as email phishing, should be considered.
Critical Thinking	PP1	Ability to validate the authenticity of AI content	I am skeptical about the accuracy of AI-generated content.
	PP2	Ability to verify the reliability of AI content	I try to verify the reliability of information presented by AI.
Self-Efficacy	XN1	Confidence in using AI independently	I am confident in using AI to make decisions on my own.
	XN2	Ability to maintain continuous learning in AI	I actively seek new knowledge and skills related to AI.
Cognitive Ability	RS1	Understanding of AI fundamentals	I understand the basic concepts and functions of AI.
	RS2	Ability to identify AI systems	When receiving a call, I can recognize whether it's from a person or an AI.
Perceived Ease of Use	PEU1	Perceived ease of using AI services	I find AI services easy to use, without much guidance needed.
	PEU2	Perceived efficiency of AI services	I can accomplish tasks effectively with the help of AI services.
Perceived Usefulness	PRU1	Perceived usefulness of AI tools	I find the information provided by AI apps (e.g., navigation) useful.
	PRU2	Perceived convenience of AI information	I can easily access useful information through AI.

Table 3
The scale and reliability of artificial intelligence literacy

Variable	Cronbach's Alpha	Number of Items
AI Application Ability	0.831	3
AI Cognitive Ability	0.823	3
AI Morality	0.839	2
AI Critical Thinking	0.656	2
AI Self-Efficacy	0.636	2
AI Literacy	0.755	12
AI Perceived Ease of Use	0.660	2
AI Perceived Usefulness	0.667	2
AI Perception	0.738	4

Table 4
Model fit test

Index	Reference Criteria	Actual Result
CMIN/DF	1-3 Excellent, 3-5 Good	1.833
RMSEA	<0.05 Excellent, <0.08 Good	0.043
NFI	0.9 Excellent, >0.8 Good	0.950
NNFI	0.9 Excellent, >0.8 Good	0.965
CFI	0.9 Excellent, >0.8 Good	0.976

two-step approach to assess reliability and validity. Specifically, it applied Exploratory Factor Analysis (EFA) followed by Confirmatory Factor Analysis (CFA). Additionally, the results of these analyses provided robust evidence for the soundness of the index system, strengthening the credibility of subsequent findings.

4.2. Reliability Analysis

In this study, scales were employed to measure the primary factors, necessitating a thorough assessment of data quality to ensure the validity of subsequent analyses. To evaluate the internal consistency of each dimension, Cronbach's alpha coefficient was calculated. This coefficient, ranging from 0 to 1, reflects the reliability of the data, with higher values signifying stronger internal consistency. Specifically, an alpha value below 0.6 suggests poor reliability, potentially requiring a redesign of the questionnaire or re-collection of data. Values between 0.6 and 0.7 are considered acceptable, those between 0.7 and 0.8 indicate moderate reliability, while values in the range of 0.8 to 0.9 denote high reliability, and values exceeding 0.9 suggest excellent reliability. As illustrated in Table 3, the Cronbach's alpha values for AI literacy, perceived overall score, and each secondary dimension all fell within the range of 0.6 to 1, demonstrating strong internal consistency and confirming the reliability of the scales applied in this study. These results validate the robustness of the data and support its suitability for further analysis.

4.3. Validity Analysis

4.3.1. CFA Model Fit Test for AI Literacy Scale

According to the model fit test results presented in Table 4, the CMIN/DF (Chi-square divided by degrees of freedom) ratio is 1.833, which lies within the acceptable range of 1 to 3, indicating a reasonable fit. The RMSEA (Root Mean Square Error of Approximation) is 0.043, suggesting an excellent fit, as it falls below the commonly accepted threshold of 0.05. Furthermore, the values for IFI (Incremental Fit Index), TLI (Tucker-Lewis Index), and CFI (Comparative Fit Index) all exceed 0.9, signifying a high level of model fit. These indicators collectively confirm that the CFA model for AI literacy achieves a robust fit, validating its suitability for analyzing the data.

Building on the CFA model's demonstrated good fit for the AI literacy scale, we proceeded to evaluate the scale's convergent validity, measured through Average Variance Extracted (AVE), and composite reliability (CR). This process involved calculating the standardized factor loadings for each measurement item within its corresponding dimension using the validated CFA model. Subsequently, the AVE and CR values for each dimension were computed based on standard calculation formulas.

To meet the benchmarks for convergent validity and composite reliability, the AVE for each dimension should meet or exceed 0.5, indicating that the items adequately explain the variance of their underlying construct. Similarly,

Table 5
Validation of convergent validity and composite reliability for each dimension

Path Relationship	Indicator	AVE	CR
Application Ability	YY1 YY2 YY3	0.624	0.832
Cognitive Ability	RS1 RS2 RS3	0.628	0.833
Morality	DD1 DD2	0.751	0.855
Critical Thinking	PP1 PP2	0.535	0.735
Self-Efficacy	XN1 XN2	0.566	0.735
Perceived Ease of Use	PEU1 PEU2	0.559	0.705
Perceived Usefulness	PRU1 PRU2	0.589	0.726

the CR should be 0.7 or higher, reflecting strong internal consistency among the measurement items. Dimensions meeting these criteria demonstrate satisfactory levels of both convergent validity and composite reliability, ensuring the robustness of the measurement model.

Calculation Formulas:

$$\mathrm{AVE} = \frac{\sum \lambda_k^2}{\sum \lambda_k^2 + \sum \mathrm{var}(\varepsilon_k)} \tag{1}$$

$$\rho = \frac{\mathrm{var}\left(\sum_{i=1}^{p} \lambda_i \xi\right)}{\mathrm{var}\left(\sum_{i=1}^{p} \lambda_i \xi\right) + \sum_{i=1}^{p} \mathrm{var}(\delta_i)} \tag{2}$$

As shown in the analysis results in Table 5, the AI literacy scale validity test revealed that the Average Variance Extracted (AVE) values for all dimensions consistently met or exceeded the threshold of 0.5. This benchmark indicates an adequate level of convergent validity, confirming that the items within each dimension effectively capture the underlying construct. Furthermore, the Composite Reliability (CR) values for each dimension were 0.7 or higher, meeting the recommended standards for internal consistency and reliability in measurement models.These results highlight the robustness of the scale, as the items within each dimension consistently reflect the intended constructs with clarity and coherence. The combined findings of AVE and CR provide strong evidence that the AI literacy scale demonstrates both excellent convergent validity and reliable internal consistency.

In reference to the analysis results shown in Table 6, it is evident that this discriminant validity test produced favorable outcomes for the AI literacy scale. Specifically, the standardized correlation coefficients between each pair of dimensions were all lower than the square root of the AVE values corresponding to each respective dimension. This finding indicates that each dimension is distinct from the others and that there is minimal overlap or redundancy among them. Discriminant validity ensures that the dimensions are measuring different aspects of AI literacy rather than overlapping constructs, thereby confirming the multidimensionality of the scale. By meeting this requirement, the scale not only demonstrates strong theoretical support for its structural components but also reinforces the effectiveness of its design in capturing unique and separate facets of AI literacy. This result confirms that each dimension exhibits good discriminant validity, adding to the overall credibility and utility of the measurement model.

4.3.2. CFA Model Fit Test for the AI Perception Scale

Based on the analysis results in Table 8, it can be observed that in this validity test of the AI literacy scale, the AVE values for each dimension reached above 0.5. This overall finding indicates that each dimension demonstrates good convergent validity and composite reliability.

Based on the analysis results in Table 9, it can be observed that in this discriminant validity test, the standardized correlation coefficients between each pair of dimensions are all lower than the square root of the AVE values corresponding to each dimension. This indicates that all dimensions exhibit good discriminant validity, meaning each dimension is distinct and measures a unique aspect of AI literacy.

4.4. SEM Modeling

4.4.1. Normality Test

Table 10 displays the descriptive statistics and normality test results for the factors considered in this study. A closer examination of the descriptive statistics reveals that the mean scores for each variable lie between 3 and 4 on a 5-point scale, suggesting that participants' levels of AI literacy and perception are above the average threshold. This implies that, generally, the study participants possess a positive disposition and a moderate to high level of familiarity with AI-related concepts and skills, indicating a promising engagement with AI in their daily lives or professional contexts.

To ensure the appropriateness of the data for advanced statistical analysis, the normality of each measurement item was assessed using skewness and kurtosis values. According to Kline's guidelines, data can be assumed to approximate a normal distribution if skewness values remain within an absolute value of 3 and kurtosis values within an absolute value of 8. As illustrated in Table 11, all items in this study fall within these prescribed limits, suggesting that the distribution of data for each measurement item is close to normal. This validation of normality is essential, as it supports the reliability and robustness of using Structural Equation Modeling (SEM) in the next phase of analysis.

The adherence to normality assumptions provides a solid foundation for applying SEM to examine interrelationships between variables and assess model fit, allowing for more nuanced and statistically sound conclusions. Thus, the data's alignment with normality criteria ensures the validity of subsequent SEM-based path analyses, making the results

Table 6
Discriminant validity: Pearson correlation and square root of AVE

Variable	Application Ability	Cognitive Ability	Morality	Critical Thinking	Self-Efficacy
Application Ability	0.790	0.764 (0.000)***	0.266 (0.000)***	0.024 (0.681)	0.637 (0.000)***
Cognitive Ability	0.764 (0.000)***	0.792	0.376 (0.000)***	0.191 (0.001)**	0.641 (0.000)***
Morality	0.266 (0.000)***	0.376 (0.000)***	0.867	0.142 (0.013)*	0.265 (0.000)***
Critical Thinking	0.024 (0.681)	0.191 (0.001)**	0.142 (0.013)*	0.660	0.683 (0.000)***
Self-Efficacy	0.637 (0.000)***	0.641 (0.000)***	0.265 (0.000)***	0.683 (0.000)***	0.772

Table 7
Model fit test

Index	Reference Criteria	Actual Result
CMIN/DF	1-3 Excellent, 3-5 Good	1.452
RMSEA	<0.05 Excellent, <0.08 Good	0.032
NFI	0.9 Excellent, >0.8 Good	0.998
NNFI	0.9 Excellent, >0.8 Good	1.012
CFI	0.9 Excellent, >0.8 Good	1.002

Table 8
Convergent validity and composite reliability test for each dimension

Path Relationship	Indicator	AVE	CR
Perceived Ease of Use	← PEU1 ← PEU2	0.517	0.676
Perceived Usefulness	← PRU1 ← PRU2	0.505	0.670

both reliable and generalizable within the studied population. This foundation also enhances the potential for future studies to replicate and extend findings on AI literacy and perception in broader demographic contexts.

4.4.2. *Model Fit Test for the SEM Model of AI Perception Influencing Factors*

Model fit assesses how well the theoretical model corresponds to the observed data. In this study, both absolute fit indices (such as Chi-square/DF, GFI, and RMSEA) and incremental fit indices (such as NFI and CFI) are utilized to evaluate the model's adequacy. The degrees of freedom (df) are determined by the number of effective parameters in the model versus the parameters requiring estimation. A lower Chi-square to degrees of freedom ratio (χ^2/df) indicates a better alignment between the theoretical covariance matrix and the actual data, with a value less than 3 generally considered acceptable.The GFI (Goodness-of-Fit Index) reflects how well the model fits the data, with values above 0.9 indicating a strong fit. RMSEA (Root Mean Square Error of Approximation) values between 0.05 and 0.08 suggest good fit, while values below 0.05 indicate excellent fit. Incremental indices, including NFI (Normed Fit Index) and CFI (Comparative Fit Index), also require values above 0.9 for a model to be deemed well-fitting. As shown in Table 11, the CMIN/DF ratio (χ^2/df) is 1.721, which falls within the ideal range of 1 to 3, while the RMSEA is 0.049, meeting the threshold for an excellent fit. Furthermore, the GFI, NFI, and CFI values all exceed 0.9, indicating a high level of model fit.Based on these results, it can be concluded that the SEM model for factors influencing AI perception exhibits a good fit, confirming the model's validity and suitability for further analysis.

4.4.3. *Results of the Path Relationship Hypothesis Test for the SEM Model of Factors Influencing AI Perception*

As shown in Figure 1, we used AMOS 21.0 software to test the structural equation model, initially establishing a model without mediators to test the direct effects of AI literacy on AI perception. Based on the results in Table 12, the following conclusions can be drawn from the path hypothesis testing in this study:

- **Application Ability** positively predicts AI perceived ease of use significantly ($B = 1.078$, $p < 0.01$), so hypothesis H1 is supported.
- **Application Ability** negatively affects AI perceived usefulness, but this effect is not significant ($B = -0.747$, $p = 0.103$), so hypothesis H2 is not supported.
- **Cognitive Ability** negatively and significantly affects AI perceived ease of use ($B = -0.146$, $p < 0.01$), so hypothesis H3 is not supported.
- **Cognitive Ability** negatively affects AI perceived usefulness, but this effect is not significant ($B = -0.146$, $p = 0.734$), so hypothesis H4 is not supported.
- **Morality** negatively and significantly affects AI perceived ease of use ($B = -0.245$, $p < 0.01$), so hypothesis H5 is not supported.
- **Morality** positively and significantly affects AI perceived usefulness ($B = 0.279$, $p < 0.1$), so hypothesis H6 is supported.
- **Critical Thinking** positively affects AI perceived ease of use, but this effect is not significant ($B = 0.306$, $p = 0.147$), so hypothesis H7 is not supported.
- **Critical Thinking** positively affects AI perceived usefulness, but this effect is not significant ($B = -0.308$, $p = 0.207$), so hypothesis H8 is not supported.

Table 9
Discriminant validity: Pearson correlation and average variance extracted (AVE) square root

	Perceived Ease of Use	Perceived Usefulness
Perceived Ease of Use	0.719	
Perceived Usefulness	0.498 (0.000)***	0.711

Table 10
Descriptive normality test results for each dimension

Dimension	Measurement Item	Means	SD	Skewness	Kurtosis
Application Ability	YY1	3.248	1.170	-0.306	-0.814
	YY2	3.338	1.158	-0.402	-0.673
	YY3	3.636	1.112	-0.674	-0.164
Cognitive Ability	RS1	3.432	1.075	-0.375	-0.579
	RS2	3.607	1.224	-0.059	-0.981
	RS3	2.818	1.224	0.123	-1.001
Morality	DD1	3.834	1.120	-0.754	-0.254
	DD2	3.603	1.136	-0.591	-0.454
Critical Thinking	PP1	4.695	0.576	-2.168	5.527
	PP2	4.298	0.869	-1.352	1.911
Self-Efficacy	ZW1	3.974	0.878	-0.752	0.462
	ZW2	3.844	0.866	-0.373	-0.302
Perceived Ease of Use	PEU1	3.593	0.931	-0.372	-0.302
	PEU2	3.844	0.866	-0.373	-0.360
Perceived Usefulness	PRU1	3.911	0.887	-0.544	-0.095
	PRU2	4.030	0.837	-0.707	0.432

Table 11
SEM model fit test for factors influencing artificial intelligence perception

Index	Reference Value	Result
CMIN/DF	1-3 excellent, 3-5 good	1.721
RMSEA	<0.05 excellent, <0.08 good	0.0492
GFI	>0.9 excellent, >0.8 good	0.942
NFI	>0.9 excellent, >0.8 good	0.929
CFI	>0.9 excellent, >0.8 good	0.969

- **Self-Efficacy** positively and significantly affects AI perceived ease of use ($B = 0.722$, $p < 0.1$), so hypothesis H9 is supported.
- **Self-Efficacy** positively and significantly affects AI perceived usefulness ($B = 1.867$, $p < 0.001$), so hypothesis H10 is supported.

The following hypotheses were confirmed:

- **H1**: Application Ability has a significant positive impact on AI perceived ease of use. Users with higher application ability are likely to have a more positive perception of system ease of use. Those with strong application skills are generally more familiar with system functions and operations, which allows them to adapt to system interfaces and interactions more readily. Such users tend to understand system features better and can use them effectively to solve problems, enhancing efficiency and satisfaction.
- **H6**: Morality has a significant positive impact on AI perceived usefulness. Users' moral perspectives are influenced by societal and cultural values. If an AI system aligns with these values, it is more likely to be perceived as useful as it meets users' expectations and needs. Growing awareness of AI ethics motivates users to seek out morally responsible AI systems, pushing for ethical considerations in AI design and use, thereby enhancing perceived usefulness.
- **H9**: Self-Efficacy has a significant positive impact on AI perceived ease of use. Self-efficacy refers to users' confidence in their abilities within a particular task or field. Users with higher self-efficacy are more confident and capable in overcoming challenges, which positively impacts perceived ease of use. These users are more willing to try new technologies and tools, making it easier for them to adapt to and master AI systems, enhancing ease of use.
- **H10**: Self-Efficacy has a significant positive impact on AI perceived usefulness. Users with high self-efficacy are generally more confident and skilled in utilizing the features of AI systems, thereby increasing perceived usefulness. High self-efficacy influences users' understanding and approach to AI systems, enabling them to evaluate the system's capabilities more effectively and judge if it meets their needs.

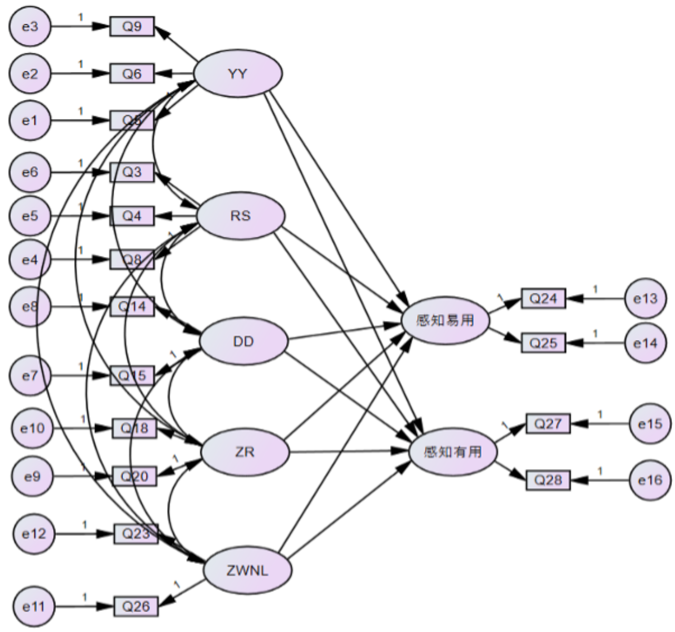

Figure 1: SEM model of factors influencing perception of artificial intelligence

Table 12
Results of hypothesis testing on path relationships in the SEM model of factors influencing perception of artificial intelligence

Y		X	Estimate	S.E.	C.R.	P Label
Perceived Ease of Use	←	Application Ability (YY)	1.078	0.229	2.598	0.009
Perceived Ease of Use	←	Cognitive Ability (RS)	-1.110	0.213	-2.718	0.007
Perceived Ease of Use	←	Morality (DD)	-0.245	0.089	-1.724	0.085
Perceived Ease of Use	←	Critical Thinking (PP)	0.306	0.215	1.449	0.147
Perceived Ease of Use	←	Self-Efficacy (XN)	0.722	0.271	2.205	0.027
Perceived Usefulness	←	Application Ability (YY)	-0.747	0.312	-1.631	0.103
Perceived Usefulness	←	Cognitive Ability (RS)	-0.146	0.277	-0.340	0.734
Perceived Usefulness	←	Morality (DD)	0.279	0.126	1.709	0.087
Perceived Usefulness	←	Critical Thinking (PP)	-0.308	0.307	-1.263	0.207
Perceived Usefulness	←	Self-Efficacy (XN)	1.867	0.430	4.438	***

Two AI literacy subdimensions, Application Ability and Self-Efficacy, have a significant positive impact on AI perceived ease of use. Additionally, Self-Efficacy positively influences both AI perceived ease of use and perceived usefulness [3], which demonstrated that individuals with higher digital technology skills are more likely to accept new digital technologies, thereby enhancing their understanding of these technologies.

5. Conclusion

This research seeks to explore the importance of AI literacy in the context of artificial intelligence and to create a scale and questionnaire for evaluating public AI literacy. Through a review of relevant prior studies, the key sub-dimensions of AI literacy were identified, forming the basis for the development of a measurement questionnaire. An initial pool of 25 questions was created and later streamlined to 15 items following reliability and validity testing. AI literacy in the digital era is characterized by five core competency dimensions: application skills, cognitive understanding, ethical awareness, critical analysis, and self-confidence. By conducting exploratory and confirmatory factor analyses on these 15 items, the validity of the framework's indicators was substantiated. The findings suggest that AI literacy in the era of artificial intelligence predominantly comprises these five sub-dimensions:

1. **AI Application Ability** — the capacity to utilize AI to solve problems in daily life and learning.
2. **AI Morality** — awareness of information ethics and the ability to use AI responsibly.
3. **AI Cognitive Ability** — the knowledge of fundamental AI technologies and the ability to contemplate AI's impact on society and its role in human development.

4. **AI Critical Thinking** — the ability to interpret and analyze the authenticity, objectivity, and informational richness of content presented by AI-recommended services.
5. **AI Self-Efficacy** — confidence and belief in one's ability to effectively operate, control, and utilize AI technologies to accomplish tasks, solve problems, or achieve goals.

Additionally, this study confirmed that certain dimensions of AI literacy can have a positive or negative impact on perceived usefulness and ease of use of AI. This finding implies that when users have high application ability, their perceived usefulness of AI technology improves. When users exhibit high morality, their perceived usefulness of AI technology increases. When users possess high self-efficacy, both their perceived usefulness and ease of use of AI technology are enhanced, thereby improving their performance in work or study.

To keep pace with the rapid evolution of AI technology and address the multifaceted challenges it introduces, a comprehensive approach is needed to enhance AI literacy across diverse populations. Key measures include promoting universal access to AI-related education by embedding it within formal educational systems, community programs, and workplace training. Furthermore, integrating ethical and moral considerations into AI literacy curricula is critical, emphasizing responsible AI usage, algorithmic transparency, and societal impacts to foster public trust and awareness. Bridging the digital divide remains an essential priority, requiring targeted resource allocation, infrastructure development, and community-based technology initiatives to ensure equitable access to AI tools and resources. Lowering barriers to AI development and promoting technology inclusion are also vital for democratizing innovation. Governments and organizations should collaborate to provide accessible platforms and tools that enable broader participation in the AI ecosystem, particularly for non-technical users and developers. Equally important is the safeguarding of data privacy and the elimination of algorithmic biases, necessitating clear ethical guidelines and legislative measures to regulate AI applications and uphold fairness and transparency.In addition, encouraging public participation in AI policy formulation through education and feedback mechanisms can ensure that regulations reflect societal needs and values. Interdisciplinary education, integrating AI with fields like language, political science, and engineering, is crucial to preparing individuals with the diverse skills needed in an AI-driven future. These initiatives not only create an inclusive and equitable AI ecosystem but also empower individuals to navigate and leverage AI technologies effectively in both personal and professional contexts.

The limitations of this study and suggestions for future research are as follows. First, future studies should evaluate the practical application of the constructed indicator system, refining it through real-world investigations. Expanding research to include broader demographic groups beyond students and professionals would improve the generalizability of findings. Additionally, a deeper understanding of AI literacy concepts is needed, integrating technical skills, ethical reasoning, and critical thinking for a more holistic assessment framework. Future research should also account for the rapidly evolving nature of AI technologies, updating the framework to stay aligned with advancements. Finally, incorporating qualitative methods such as interviews and case studies could provide richer insights into user interactions with AI technologies, complementing the quantitative approach used in this study.

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