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Overview of Artificial Intelligence Literacy Scales and a Proposed Conceptual Framework

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ABSTRACT. With recent developments, artificial intelligence (AI) literacy has become a key concern, and enabling people to become AI literate is crucial. Therefore, examining existing AI literacy scales will guide future steps. This study aims to review the scales measuring AI literacy. For this purpose, twenty-five research articles were reviewed. Based on the review of existing research, we present a conceptual framework for AI literacy. The framework comprises two levels, each consisting of five factors. The inner circle of the framework represents the AI literacy skills for general AI users, while the outer circle represents the AI literacy skills for expert AI users. Unlike existing unidimensional scales in the literature, the proposed framework provides a conceptual advancement by distinguishing basic operational skills for general users from advanced technical competencies required of expert users. This framework is intended to guide researchers who want to develop an AI literacy scale, school administrators or teachers who want to teach AI, and policymakers who want to take action regarding AI use.

Keywords: AI literacy, scale, adaptation, development, AI literacy framework.

Visão Geral das Escalas de Alfabetização em Inteligência Artificial e uma Estrutura Conceitual Proposta

RESUMO. Com os recentes avanços, a alfabetização em inteligência artificial (IA) tornou-se uma preocupação fundamental, e capacitar as pessoas a se alfabetizarem em IA é crucial. Portanto, examinar as escalas de alfabetização em IA existentes orientará os próximos passos. Este estudo tem como objetivo revisar as escalas que medem a alfabetização em IA. Para isso, foram revisados vinte e cinco artigos de pesquisa. Com base na revisão da literatura existente, apresentamos uma estrutura conceitual para a alfabetização em IA. A estrutura compreende dois níveis, cada um composto por cinco fatores. O círculo interno da estrutura representa as habilidades de alfabetização em IA para usuários gerais de IA, enquanto o círculo externo representa as habilidades de alfabetização em IA para usuários especialistas em IA. Diferentemente das escalas unidimensionais existentes na literatura, a estrutura proposta oferece um avanço conceitual ao distinguir as habilidades operacionais básicas para usuários gerais das competências técnicas avançadas exigidas dos usuários especialistas. Esta estrutura destina-se a orientar pesquisadores que desejam desenvolver uma escala de alfabetização em IA, administradores escolares ou professores que desejam ensinar IA e formuladores de políticas que desejam tomar medidas em relação ao uso da IA.

Palavras-chave: alfabetização em IA, escala, adaptação, desenvolvimento, estrutura de alfabetização em IA.

Descripción General de las Escalas de Alfabetización en Inteligencia Artificial y un Marco Conceptual Propuesto

RESUMEN. Con los recientes avances, la alfabetización en inteligencia artificial (IA) se ha convertido en una preocupación fundamental, y capacitar a las personas para que adquieran conocimientos en IA es crucial. Por lo tanto, examinar las escalas de alfabetización en IA existentes orientará los pasos futuros. Este estudio tiene como objetivo revisar las escalas que miden la alfabetización en IA. Para ello, se revisaron veinticinco artículos de investigación. Con base en la revisión de la investigación existente, presentamos un marco conceptual para la alfabetización en IA. El marco comprende dos niveles, cada uno compuesto por cinco factores. El círculo interior del marco representa las habilidades de alfabetización en IA para usuarios generales de IA, mientras que el círculo exterior representa las habilidades de alfabetización en IA para usuarios expertos. A diferencia de las escalas unidimensionales existentes en la literatura, el marco propuesto proporciona un avance conceptual al distinguir las habilidades operativas básicas para usuarios generales de las competencias técnicas avanzadas requeridas para usuarios expertos. Este marco está diseñado para guiar a los investigadores que desean desarrollar una escala de alfabetización en IA, a los administradores escolares o docentes que desean enseñar IA, y a los responsables políticos que desean tomar medidas con respecto al uso de la IA.

Palabras clave: alfabetización en IA, escala, adaptación, desarrollo, marco de alfabetización en IA.

Introduction

The concept of artificial intelligence (AI) can be defined as machines exhibiting human-like behaviors such as acting logically, communicating, completing tasks, and interacting (Gil de Zúñiga et al., 2024). According to another definition, AI refers to the ability of computers to imitate human intelligence (Sheikh et al., 2023). Although its emergence dates back to the 1940s, AI technology has become prevalent in many fields as a result of recent developments. In addition to fields such as health (Rajpurkar et al., 2022), engineering (Hu et al., 2024), tourism (Li et al., 2021), business and finance (Chen et al., 2023), AI applications can also be frequently encountered in education (Ottenbreit-Leftwich et al., 2023). As AI technology becomes widespread, learning how to use this technology effectively has become a necessity. In fact, it is predicted that AI literacy will be as important as traditional literacy in the near future (Kandlhofer et al., 2016). It is important for individuals to be able to make sense of AI technology, recognize AI tools and applications, choose appropriate tools and applications from a critical perspective, and evaluate their use; in other words, to be AI-literate.

AI Literacy

Traditionally associated with reading and writing, literacy is now used to indicate competencies across different domains. In this context, literacy can be defined as the ability to decode and encode meaning associated with a field (Eisner, 1991). Many forms of literacy have emerged to describe individuals' basic skill levels within specific domains, such as information literacy, computer literacy, digital literacy, visual literacy, AI literacy, technology literacy, economic literacy, mathematics literacy, and data literacy. This article mainly focuses on AI literacy.

The concept of AI literacy was first introduced by Burgsteiner et al. (2016) and Kandlhofer et al. (2016) to define the ability to understand basic information and concepts about AI (Su et al., 2023). According to Ng et al. (2021), AI literacy includes the skills to know, understand, use, apply, evaluate, and create AI, as well as ethical values and responsibilities that must be observed for social benefit. Liu and Xie (2021) state that AI literacy is closely related to the concepts of digital literacy, computational thinking, and programming skills. Long and Magerko (2020) define AI literacy as a set of competencies to use AI at home, at work or online, to evaluate AI critically, to communicate and collaborate with AI, and they associate AI literacy with 17 competencies: *Recognizing AI* (distinguish products that use AI technology), *Understanding intelligence* (critically analyze and discuss the characteristics that make an entity intelligent), *Interdisciplinary* (identify technologies developed with machine learning, such as cognitive systems and robots; and recognizes ways to develop these technologies), *General vs. narrow* (distinguish between AI technologies at different levels [general and narrow] of competency), *AI's strengths and weaknesses* (distinguish the strengths and weaknesses of AI technology, decide when and in what situations AI can be used instead of human intelligence), *Imagine future AI* (predict future developments of AI and imagine the possible impacts of these developments), *Representations* (understand what knowledge representation is, and explain with examples), *Decision making* (explain the decision-making mechanisms of computers that use AI), *Machine learning steps* (know the steps of machine learning; understand the requirements and potential challenges of the process), *Human role in AI* (realize the human role in AI applications and understand its importance), *Data literacy* (understand data literacy concepts), *Learning from data* (realize that AI systems learn from data), *Critically interpreting data* (know how data should be interpreted and realize its possible effects on the algorithm), *Action and reaction* (understand that AI systems have the ability to interact with the physical world), *Sensors* (understand what sensors are, and know their functions in AI systems), *Ethics* (recognize and explain different perspectives on ethical issues surrounding AI, such as privacy, bias, and misinformation), and *Programmability* (understand that AI systems are programmable).

On the other hand, according to Chiu et al. (2024), who emphasized the need for a new definition because the definition made by Long and Magerko (2020) is too broad and not suitable for K12 students, AI literacy is the ability of an individual to understand how AI technology works, to explain its effects on society, to use AI in a way that adheres to ethical values, and to cooperate and communicate with AI technologies. In other words, AI literacy refers to individuals' ability to use AI effectively.

The concept of AI literacy primarily refers to the knowledge and skills for end users to understand and use AI systems, rather than the specialized technical competencies required to develop those systems. In the digital age, where AI is ubiquitous, AI literacy is regarded as a core competency that the new generation should possess to ensure the optimal use of this technology. Individuals who acquire AI literacy skills at a young age make a good investment for their university education and career (Burgsteiner et al., 2016). Having this competency is also important to avoid mistakes caused by AI technologies, which are known to produce fabricated or misleading information occasionally. It has become necessary to make individuals AI literate across different educational levels. In this respect, content and curriculum development studies have been initiated on providing AI literacy skills to students at preschool (Su et al., 2023), K12 (Chiu et al., 2024), and university (Kong et al., 2021) levels. In developed countries such as the United States, China, and Germany, studies are being conducted to popularize policies that include AI strategies (Laupichler et al., 2022). Similarly, in Türkiye, in order to expand the production and use of AI technology, the National AI Strategy was developed for the years 2021-2025 in line with the studies of the Ministry of Industry and Technology and the Presidency of Digital Transformation Office, and was published in the Official Journal and put into effect (Presidency of the Republic of Türkiye, 2021).

Although recent studies have increasingly focused on the development and adaptation of AI literacy scales across different contexts and participant groups (e.g., Carolus et al., 2023; Kim & Lee, 2022; Laupichler et al., 2023b; Ng et al., 2023; Wang et al., 2023; Yuan et al., 2024), the existing literature still lacks a comprehensive conceptual synthesis that systematically integrates the fragmented competency dimensions proposed across different measurement tools. Most existing studies focus either on developing context-specific scales or adapting previously developed instruments to different cultures and samples. However, there is still limited understanding regarding how these dimensions collectively represent the broader structure of AI literacy across different user profiles and competency levels. Therefore, the present study aims to systematically review existing AI literacy scales and synthesizes their underlying dimensions into a theoretically grounded conceptual framework. More specifically, this study seeks to identify common and divergent competency areas embedded in current AI literacy instruments and to propose a two-tiered framework distinguishing general AI-user competencies from expert AI-user competencies. The study contributes to the literature by moving beyond descriptive scale reviews, and proposes a structured conceptual framework that can guide future research, scale development, curriculum design, and AI literacy policy initiatives.

Method

The purpose of this study was to examine studies with an intent to measure AI literacy. In this respect, this study employed a systematic review approach combined with thematic synthesis to construct a conceptual AI literacy framework. Systematic literature review is the review of the entire body of literature based on some criteria that informs the researchers on what is already known or studied, and provides a basis to make interpretations or plan new research (Gough et al., 2017). In accordance with recommended practices for conducting a systematic literature search (Creswell, 2009), the studies were accessed by scanning databases and search engines such as Web of Science (WOS), Scopus, Google Scholar, and Türkiye Measurement Tools Index (TOAD) in May 2025 using the keywords “AI literacy scale” and “artificial intelligence literacy scale”. Additionally, the reference lists of the identified studies were manually reviewed to identify further relevant articles. The inclusion criteria were that the scales developed from scratch, adapted from existing scales, or studies that structurally validate and integrate multiple existing scales to identify latent dimensions of AI literacy (e.g., Koch et al., 2024). Studies focusing on multiple-choice tests, item-pool development, or non-scale measurement approaches were excluded from the scope of the review. As a result, twenty-five articles were included in the study. No language restriction was applied during the search process.

Trustworthiness of the Study

To ensure methodological rigor and the trustworthiness of the thematic synthesis, several systematic steps were taken. First, to establish dependability and credibility, the review and coding processes were not left to a single researcher. Instead, adopting a researcher triangulation and stepwise replication approach (Ahmed, 2024; Kocaman, 2025), each of the 25 articles was independently reviewed and coded by both authors using a structured Excel spreadsheet with a variable set of author(s), publication year, scale type (development/adaptation), participant group, sample size, number of items, number of factors, sub-factors, and reliability coefficients. Comparing and cross-checking codes generated independently by multiple researchers is a fundamental strategy to establish qualitative reliability (Gibbs, 2007). Following the independent coding process, the authors engaged in a continuous dialogue and systematically compared their findings, discussing the conceptual categorizations until a full consensus was achieved (Kyngäs et al., 2020). At this stage, a thematic synthesis procedure was employed to identify recurring competency domains across the reviewed scales. During this stage, similar or overlapping sub-factors reported in different studies were systematically clustered and conceptually categorized. This aligns with the inductive process of qualitative data analysis, which involves organizing data into increasingly abstract units of information (Creswell, 2009). Finally, to ensure confirmability and transparency, the researchers established a clear audit trail and utilized data tables, a practice highly recommended to make the research process transparent and traceable (Adler, 2022; Ahmed, 2024; Kocaman, 2025). Particular attention was paid to distinguishing foundational competencies from higher-order technical, critical, and socio-ethical competencies. Based on this coding process, the identified dimensions were synthesized into a two-tiered conceptual framework representing competencies for general and expert AI users. The researchers presented all extracted raw data, factors, and reliability coefficients in Table 1, and explicitly explained the synthesis rationale for each proposed dimension in Table 2.

Results

Overview of Scale Development and Adaptation Studies for Measuring AI Literacy

Kim and Lee (2022) aimed to develop a tool to measure AI literacy among secondary school students, stating the increasing importance of AI literacy in the education system and the lack of existing measurement tools. Relevant factors and items were identified by a group of experts. A literature review, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA) were conducted to test the validity and reliability of the tool. Based on these studies, a 30-item scale with six factors and a 5-point Likert-type response format was developed. The sub-factors were: social impact of AI (eight items), understanding of AI (six items), AI execution plans (five items), problem solving with AI (five items), data literacy (four items), and AI ethics (two items). While the Cronbach's alpha (α) for the overall scale was .970, the sub-factor coefficients ranged from .861 to .939. The tool could be used to evaluate AI literacy, AI education and training, and AI applications in education.

Ng et al. (2023) aimed to develop a tool to assess students' AI literacy. In their preliminary study, the data analyses of the developed items were conducted using two different models, resulting in two initial scales. The first scale consisted of six sub-factors (intrinsic motivation, self-efficacy, behavioral intention, behavioral engagement, knowledge and understanding, and use and application of AI) and 25 items, with sub-factor Cronbach's α coefficients ranging from .58 to .88. The second scale consisted of four sub-factors (affective, behavioral, cognitive, and ethical) and 44 items, with Cronbach's α coefficients ranging from .91 to .94. Building upon this preliminary work, Ng et al. (2024) finalized the tool based on the Affective, Behavioral, Cognitive, and Ethical (ABCE) learning framework. They developed and validated the 32-item Artificial Intelligence Literacy Questionnaire (AILQ). The study was conducted with 363 secondary school students in Hong Kong. As a result of the CFA, a valid and reliable scale consisting of four sub-factors (affective, behavioral, cognitive, and ethical) and 32 items was confirmed. The scale demonstrated excellent internal consistency ($\alpha > .90$).

Wang et al. (2023) stated that significant changes had occurred in individuals' lives with the emergence of AI technology, and they stated that there was no complete framework for the use of these technologies and no applicable or useful tool to measure this. When developing the scale items, a total of 65 items related to the factors: awareness (24 items), usage (16 items), evaluation (15 items), and ethics (10 items) were generated. Content validity was assessed by five experts in three stages. In the first stage, experts were asked to classify the items, twenty-three of which could not be classified. In the second stage, experts were asked to provide a three-point Likert-type evaluation (1 = No fit, 2 = Moderate fit, 3 = Good fit) of the remaining items; 10 items were eliminated. The third stage was conducted with the remaining 31 items, which were selected as the final item set following focus group discussions and interviews. The scale was converted to a 7-point Likert-type format and administered electronically. Data were obtained from 926 individuals. Participants were divided into two groups: Sample 1 ($n = 601$) and Sample 2 ($n = 325$). Data obtained from Sample-1 were used for item reduction, while those from Sample-2 were used for verification and validity testing of the model. Both samples consisted of participants from different age groups. As a result of the analyses, a valid and reliable scale consisting of 12 items and four sub-factors (awareness, usage, evaluation, and ethics) was developed. The Cronbach's α for the scale was .83, and for the sub-factors were .73, .75, .78, and .73, respectively. In addition, the relationships among AI literacy, digital literacy, the daily usage rate of AI applications, and attitudes towards digital technology were tested in the study. Accordingly, AI literacy and digital literacy were related, and AI literacy was an important determinant of attitudes towards using AI applications.

The scale developed by Wang et al. (2023) was adapted to Turkish culture by Polatgil and Güler (2023). The study included different sample groups. Six academics participated in the study as the linguistic equivalence group, 50 people as the pre-test group, and 253 people as the EFA group, 283 people as the CFA group, and 57 people as the test-retest group. Although they conducted their main validity analyses (EFA and CFA) on 536 participants, the total sample size reached 643 when the pre-test (n = 50) and test-retest (n = 57) groups were included. The ages of the participants ranged from 18 to 60. This study confirmed the four-factor structure of the scale, as in the original (α = .939). As a result, it was stated that the adapted scale was valid and reliable, that it would fill a gap in the Turkish literature, and that it would contribute to the conduct of many studies. Compared with the original study, the present study achieved improved validity and reliability values. Although the adapted scale was suitable for all age groups, it was claimed to be more appropriate for individuals aged 18 to 55. When participants' educational backgrounds were examined, 58.8% were at the undergraduate level. In this respect, it might be more appropriate to apply the adapted scale to individuals at this level of education.

The same scale was adapted to Turkish culture by Çelebi et al. (2023) to measure the AI literacy of non-expert AI users. A total of 402 participants were included in the study; 274 were female and 128 were male. Although the participants' education levels ranged from primary school to postgraduate education, 77.4% had an undergraduate degree. The study included 33 participants under the age of 20, 193 participants between the ages of 20 and 30, 74 participants between the ages of 30 and 40, and 102 participants over the age of 40. The Cronbach's α was .85 for the overall scale, and .72, .74, .76, and .72 for the sub-factors, respectively. The validity and reliability of the scale, whose participants were undergraduate students, limit its use at lower levels of education. It was suggested that the relationship between participants' educational backgrounds, digital literacy, and AI literacy be investigated.

In another study, the scale developed by Wang et al. (2023) was adapted to Turkish culture by Uğraş et al. (2024) for pre-service teachers (PST). After a pilot study with 36 participants, the scale was administered to 440 preschool and classroom teacher candidates, and validity and reliability were then assessed. Unlike the original scale, this version was designed as a 5-point Likert-type scale. According to the reliability analysis results, the Cronbach's α for the overall scale was calculated as .85, while the coefficients for the sub-factors were found to be .82, .79, .87, and .69, respectively. As a result, the adapted scale was found to be valid and reliable.

Another adaptation study of the scale to Turkish language was conducted by Kırksekiz et al. (2024). The preliminary pilot study was completed with 15 students, the pilot study with 107 students, and the CFA analysis of the scale was conducted with 729 university students. The original scale, comprising 12 items and four sub-factors, demonstrated good internal consistency (α = .814). Latent profile analyses conducted by the researchers indicated that individuals' AI literacy levels varied significantly and that these differences were determined by the time spent with AI technologies and by the type of interaction. In addition, the researchers emphasized that AI literacy education, research, and applications should be organized to account for these individual differences.

The scale developed by Wang et al. (2023) was also adapted to Turkish by Eniş-Erdoğan and Ekşioğlu (2024). The study included 226 teachers who volunteered to participate. The Cronbach's α of the scale, which had four sub-factors as in the original scale, was .861. The Cronbach's α coefficients for the sub-factors awareness, usage, evaluation, and ethics were .891, .932, .907, and .821.

In addition, a study was conducted by Hobeika et al. (2024) to develop the Arabic version of the scale by Wang et al. (2023). This study aimed to evaluate the psychometric properties of the first Arabic adaptation of the AI scale, involving 1849 university students from four Arab countries (Lebanon, Saudi Arabia, Morocco, and Palestine). The average age of the participants was 21.37, and 74.3% were female. The Cronbach's α of the scale was found to be .92. In the Arabic adaptation, three items were removed due to low factor loadings, and the resulting nine-item, four-factor structure was found to be valid and reliable among Arabic-speaking undergraduate students. The uniqueness of this study lay in its contribution to the field of AI literacy in the Middle East, especially among the Arabic-speaking population. The introduction of this version could guide course design and development in higher education.

Later, Gökçearslan et al. (2024) adapted this scale to Turkish culture by adapting it as the "Generative AI (GenAI) Literacy Scale". As a result of the study involving 297 undergraduate and graduate students, a scale comprising four factors (awareness, usage, evaluation, and ethics) and 10 items was developed. What distinguished it from other studies was that two items of the scale were removed and that it aimed to determine generative AI literacy. The 5-point Likert-type scale had a Cronbach's α value of .74.

Biagini et al. (2024) aimed to develop an AI literacy scale based on the importance of AI literacy in higher education. The scale was based on the framework structure developed by Cuomo et al. (2022) and covered a wide range of knowledge and skills related to AI literacy. The sub-factors of the scale were: 1) knowledge-related, 2) operational, 3) critical, and 4) ethical. The validity and reliability studies of the questionnaire, composed of items taken from existing measurement tools and newly created ones, were conducted with 191 individuals aged 18-64. As a result, a measurement tool consisting of 40 items and four sub-factors was created. While the Cronbach's α coefficients of the sub-factors ranged between .858 and .941, the Cronbach's α of the overall scale was .953.

Laupichler et al. (2023b) applied the item set they prepared in their previous study (Laupichler et al., 2023a) to a heterogeneous and non-expert group, online in a 7-point Likert-type. The study was conducted with 415 participants from the United Kingdom, South Africa, the United States, Australia, and Canada. The mean age of the participants was 39.5 years, and 50.1% of participants were female. Validity and reliability studies revealed that the 31-item, three-factor structure (technical understanding, critical appraisal, and practical application) had the best model fit. The Cronbach's α coefficients of the sub-factors were .93, .91, and .85, respectively.

Karaoğlan-Yılmaz and Yılmaz (2023) aimed to adapt the scale developed by Laupichler et al. (2023b) to Turkish culture. This adaptation study was conducted using the snowball sampling method, with 653 participants aged 14 to 54 years (mean age 26.5 years) completing the personal information form and the scale electronically. The scale consisted of 31 items (no reverse-scored items) had three sub-factors; technical understanding (14 items), critical appraisal (10 items), and practical application (seven items); and used a 7-point Likert scale. The Cronbach's α was .99 for the overall scale and .98, .98, and .97 for the sub-factors, respectively. Consequently, the scale adapted to Turkish culture was found to be a valid and reliable instrument for assessing individuals' AI literacy levels.

Deveci-Topal et al. (2025) also adapted the scale developed by Laupichler et al. (2023b) to Turkish culture. The original scale consisted of 31 items with three sub-factors (technical understanding, critical appraisal, and practical application). The data required for the validity and reliability study of the scale were collected from 642 undergraduate and graduate students studying at different faculties of a state university in the fall semester of the 2023-2024 academic year. The final scale consisted of 28 items and three sub-factors. The Cronbach's α of the scale was .963; for the sub-factors it was .951, .958, and .806, respectively.

In another study, Carolus et al. (2023) developed an AI literacy scale for German-speaking people. They studied 300 participants from Germany and Austria, with an average age of 32.13 years. They developed the Meta AI Literacy Scale (MAILS), an 11-point Likert-type scale consisting of 34 items. The sub-factors were applying AI (six items), understanding AI (six items), detecting AI (three items), AI ethics (three items), creating AI (four items), AI self-efficacy (six items), and AI self-competency (six items). The Cronbach's α coefficients for the sub-factors ranged between .66 and .93.

Thinking that existing scales were not suitable for Chinese university students as they were developed with students studying in developed countries, Ma and Chen (2024) conducted their research with 546 Chinese undergraduate students. After the literature review and creation of an item pool, the scale was finalized by incorporating insights from student interviews. They developed a valid and reliable 15-item, 5-point Likert-type scale with four sub-factors (awareness, usage, evaluation, and ethics). The Cronbach's α of the scale was not presented in the article. In their analyses, the researchers also revealed that male students had better skills in understanding, using, and evaluating AI than female students.

Yuan et al. (2024) stated that the rapid evolution of AI technologies requires understanding and interacting with these technologies; however, a comprehensive framework for AI literacy had not yet been presented so far in existing studies. They aimed to develop an AI literacy scale to address this gap. For this purpose, they considered three factors: individual, interactive, and socio-cultural. The scale included cognitive, behavioral, and normative competencies. The research included 1173 participants aged 13 to 70 with varying educational levels. As a result, they developed a holistic scale comprising six sub-factors (AI features, AI processing, algorithm influences, user efficacy, ethical consideration, and threat appraisal) and 24 items across three levels. The Cronbach's α coefficients for the sub-factors ranged from .70 to .87.

Nong et al. (2024) aimed to develop a measurement tool to evaluate the AI literacy of the public. In the study conducted with 302 participants, the researchers developed a 12 item, 5-point Likert-type scale comprising five sub-factors (AI application ability, AI cognitive ability, AI morality, critical thinking, and self-efficacy). The Cronbach's α coefficients for the sub-factors were .831, .823, .839, .656, and .636, respectively, and .755 for the overall scale.

Fernandez and Calderon-Garrido (2024) adapted and validated two measurement tools (Technology Acceptance Survey and AI Literacy Survey) that showed excellent results in their original versions. They aimed to analyze the relationship between the two and conducted the study with 134 graduate students. In this study, the AI literacy survey from Ng et al.'s (2023) study was adapted into Spanish, preserving the sub-factors as in the original scale (affective, behavioral, cognitive, and ethics). The Cronbach's α for the scale was .81, based on the participants' responses.

Noh et al. (2024) focused on developing a productive AI literacy scale to determine the literacy levels of users in the AI age. They aimed to develop a measurement tool for Korean users by expanding the concept of literacy used in previous studies. Based on their study involving 500 participants, they developed a generative AI literacy scale comprising 12 items and four sub-factors (AI utilization ability, critical evaluation, ethical use, and creative application). The Cronbach's α coefficients for the sub-factors were .890, .818, .754, and .872.

Younis (2025) conducted a study aiming to develop an AI literacy scale for teachers with the participation of 292 teachers from six countries (Palestine, Jordan, United Kingdom, Canada, Australia, and Philippines). As a result, a scale consisting of nine sub-factors and 45 items was developed. The sub-factors of the scale were: teachers' attitudes toward AI use (α = .924), understand AI and computational thinking concepts (α = .921), understand AI social impact (α = .936), understand AI ethics (α = .935), search and locate AI tools (α = .945), motivate students to use AI tools (α = .949), integrate AI tools in the classroom (α = .937), evaluate AI tools features (α = .941), and apply AI tools for assessment (α = .924). The study also found that teachers with 1-5 years of teaching experience had higher AI literacy than their more experienced counterparts. Additionally, teachers with computer science and engineering backgrounds had the highest AI literacy scores, while those in arts-based fields had the lowest.

With the aim of determining teachers' AI literacy levels, Balıkçı and Yıldız-Durak (2025) conducted an adaptation study of the scale developed by Younis (2025) to Turkish culture. The study involved 209 teachers from different branches. It was determined that the nine-factor structure of the original scale was also valid in the Turkish sample. The Cronbach's α of the overall scale was calculated as .981, while the sub-factor coefficients ranged between .91 and .95.

Han and Zhang (2025) aimed to develop a tool with Chinese undergraduate and graduate students due to the fact that there were only a few measurement tools to assess AI literacy of university students. After creating the item pool, EFA was conducted with data collected from 386 students, and CFA was conducted with data collected from 401 students. As a result, a structure with 63 items and five factors emerged. The five-factor structure of AI knowledge (13 items), AI application (18 items), AI attitude (13 items), AI ethics (14 items), and AI innovation (five items) significantly described the AI literacy model. The Cronbach's α coefficients for the sub-factors were calculated as .955, .969, .947, .963, and .889.

Gökçe-Tekin (2025) aimed to develop an AI literacy scale for secondary school students. In the first stage, a draft 26 item scale was developed to assess knowledge and understanding of AI, application of AI, evaluation of AI applications, and AI ethics. The construct validity analyses of the scale were conducted using data obtained from 324 students. As a result, a 15-item, three-factor (know-understand, apply-evaluate, and ethics), 5-point Likert-type scale was developed. All items on the scale are positively worded. The general Cronbach's α of the scale was .926, while the sub-factor coefficients were .818, .868, and .800, respectively. It was stated that a high total score obtained from the scale should be evaluated as signifying high AI literacy for the students, and a low score should be evaluated as signifying low AI literacy.

Discussion

The current review demonstrated that existing AI literacy scales, developed/adapted with participant groups with diverse educational, cultural, and expertise demographics, largely converge on several recurring competency domains, particularly awareness, application or usage, evaluation, and ethics. As presented in Table 1, despite differences in terminology, participant groups, and scale structures, most studies conceptualized AI literacy as a multidimensional construct integrating cognitive, operational, and ethical competencies. For example, Wang et al. (2023), Ma and Chen (2024), and Gökçe-Tekin (2025) emphasized awareness, usage/application, evaluation, and ethics as foundational dimensions of AI literacy, while Kim and Lee (2022) expanded this structure by incorporating problem solving with AI and data literacy. Similarly, Laupichler et al. (2023b) proposed a three-dimensional model focusing on technical understanding, critical appraisal, and practical application, whereas Carolus et al. (2023) broadened the framework by including AI self-efficacy and AI self-competency dimensions. These findings indicated that although the terminology differed across studies, many scales attempted to measure similar underlying competencies related to understanding, using, evaluating, and interacting ethically with AI technologies.

The findings concern the increasing emphasis on technical and productive AI competencies in recent studies. Earlier AI literacy frameworks predominantly focused on awareness and usage dimensions, whereas more recent studies have increasingly incorporated competencies such as technical understanding, AI innovation, creative application, data literacy, and AI-supported problem solving (Carolus et al., 2023; Han & Zhang, 2025; Noh et al., 2024). This shift suggests that AI literacy is evolving from a passive, consumption-oriented construct toward a more productive and participatory area of competence. The inclusion of dimensions such as dataset creation, machine learning literacy, and AI-supported innovation suggests that AI literacy models may be increasingly extending toward competencies associated with computational thinking and data science.

Another important finding emerging from the synthesis is the diversification of participant groups and cultural contexts in AI literacy research. The analyses demonstrated that the reviewed studies included secondary school students (Gökçe-Tekin, 2025; Kim & Lee, 2022), secondary and high school students (Ng et al., 2023), university students (Han & Zhang, 2025; Hobeika et al., 2024; Ma & Chen, 2024), teachers and PST (Uğraş et al., 2024; Younis, 2025), and general adult users (Carolus et al., 2023; Wang et al., 2023). Moreover, the literature includes adaptation studies conducted in Turkish (Çelebi et al., 2023; Karaoğlan-Yılmaz & Yılmaz, 2023; Polatgil & Güler, 2023), Arabic (Hobeika et al., 2024), and Spanish (Fernandez & Calderon-Garrido, 2024) contexts. In addition to these adaptation efforts, researchers have also developed original context-specific scales, such as the generative AI literacy scale designed specifically for Korean users (Noh et al., 2024). This diversity suggests that AI literacy is increasingly recognized as a global and context-sensitive competence area requiring culturally adaptable measurement frameworks.

Despite this growing body of research, the review revealed several conceptual limitations in the current literature. Many existing scales appear to measure overlapping competency areas but use different terminology. For instance, sub-factors such as “usage”, “practical application”, “AI utilization ability”, and “apply AI” conceptually refer to similar operational competencies. Likewise, “AI ethics”, “ethical use”, “ethical consideration”, and “AI morality” substantially overlap in meaning across studies. This conceptual fragmentation makes it difficult to establish a coherent theoretical understanding of AI literacy and complicates comparisons across studies.

Furthermore, most of the existing scales conceptualize AI literacy as a single-layered construct without adequately distinguishing between foundational and expert user competencies (e.g. Biagini et al., 2024; Laupichler et al., 2023b; Ng et al., 2023). As an example, operational skills, technical knowledge, critical thinking, and ethical reflection are often merged into the same conceptual level with awareness or usage. Items like “describing what AI is” and “explaining how AI applications make decisions” are relevant to people at different levels of expertise. Therefore, separating the items considering the expertise level of AI users should be the first step in developing a more audience-focused scale.

Analyzing the scales and addressing the limitations, the current study synthesizes fragmented competency dimensions into a two-tiered conceptual framework that distinguishes general AI users from expert AI users. Building on the comparative findings summarized in Table 1 and the conceptual mapping presented in Table 2, the proposed framework introduces a depth-oriented structure based on cognitive and technical complexity. The inner layer represents foundational competencies necessary for general users to effectively and responsibly interact with AI technologies in daily life. These competencies include AI knowledge, AI applications, evaluation, ethical use, and digital literacy. In contrast, the outer layer represents advanced competencies associated with technical understanding, productive AI use, socio-technical analysis, and data-oriented reasoning. These competencies include technical understanding, problem solving with AI, critical appraisal, ethical appraisal, and data literacy.

The proposed framework differentiates basic “AI knowledge” with “technical understanding”. While the former means understanding basic AI concepts, the latter refers to a technical AI literacy of understanding the logic behind how AI systems work including knowledge about algorithms or machine learning. The analysis indicated (Table 1), knowledge of AI is conceptualized with different category names in the scales such as “knowledge-related” (Biagini et al., 2024), “awareness” (Wang et al., 2023), or “technical understanding” (Laupichler et al., 2023b); all indicating a different expertise level of being knowledgeable about AI.

As the framework shows, the use of AI can also be addressed at two different levels of expertise. Characterizing the use of AI for the general user base, “AI applications” refers to the selection and use of appropriate AI tools. On the other hand, for the expertise level, “problem solving with AI” is used in the meaning of designing, developing, or adapting solutions to solve problems. The analysis also indicated that the scales included these components under different factor names: “apply AI” (Carolus et al., 2023) or “creative application” (Noh et al., 2024) can be given as examples.

The analysis conducted revealed the relationship between the concept of AI literacy and different types of literacies, mainly digital literacy and data literacy. In fact, as the analysis indicated, the skills are not always referred to in a factor named literacy at the scales investigated in the scope of the research such as “AI processing” (Yuan et al., 2024). However, the analysis conducted has made it valid to examine this competency in a separate category. Studies further support this perspective by identifying digital literacy and data literacy not only as fundamental prerequisites of AI literacy (Caspari-Sadeghi, 2026; Koltay, 2024), but also as significant predictors of it (Polomoshnov et al., 2026; Seker et al., 2025). Therefore, these literacies should be conceptualized and examined alongside AI literacy. For the general user base, “digital literacy” refers to operating digital tools that use AI technology, and adapting to these technologies. On the expertise level, AI literacy is associated with “data literacy” because at this level of use, the users need to understand, manage, and evaluate the mechanisms in AI systems.

Another important theoretical contribution of the proposed framework is the differentiation between “evaluation” and “critical appraisal”. As observed across several studies summarized, evaluation-related competencies are often treated as a single dimension encompassing both operational judgments and broader critical reflections. However, these competencies differ substantially in terms of cognitive depth. Basic evaluation refers to users’ ability to assess the usefulness, suitability strengths, and weaknesses of AI tools after use. In contrast, critical appraisal involves higher-order questioning regarding the philosophical, social, and human implications of AI systems, including algorithmic influence, human-machine differences, and societal impacts. The distinction identified in studies such as Laupichler et al. (2023b), Yuan et al. (2024), and Nong et al. (2024) supports the argument that advanced AI literacy requires more than functional tool evaluation.

Finally, the framework proposes a conceptual distinction between “ethical use” and “ethical appraisal”. Existing AI literacy scales generally conceptualize ethics in terms of responsible and safe AI use, including privacy awareness and protection against misuse. While these competencies are essential for general users, the analysis also demonstrated that several reviewed studies include more advanced ethical dimensions, including algorithmic bias, human prejudice embedded in AI systems, misinformation risks, and decisions that may conflict with human values. Particularly, the dimensions of “ethical consideration” (Yuan et al., 2024), “threat appraisal” (Yuan et al., 2024), and “understanding AI social impact” (Younis, 2025) indicate that advanced AI literacy requires socio-ethical awareness extending beyond basic responsible use practices. Therefore, the proposed framework separates foundational ethical competencies from higher-order ethical appraisal competencies.

Synthesis of the Conceptual Framework

To address the descriptive aggregation of existing AI literacy scales and construct a theoretically grounded structure, a conceptual mapping process was conducted. The sub-factors extracted from the 25 reviewed studies (detailed in Table 1) were not merely listed but were systematically analyzed, clustered by thematic similarity, and deductively mapped onto two distinct proficiency levels: general AI users and expert AI users. Table 2 illustrates how the fragmented dimensions in the current literature were synthesized to derive the proposed framework.

As demonstrated in Table 1, the majority of the current literature conceptualizes AI literacy through basic structures encompassing four to nine sub-factors, often blending different proficiency levels into a single framework (e.g., Wang et al., 2023). The proposed framework provides a conceptual advancement by separating these dimensions into a two-tiered structure based on cognitive and technical complexity by considering AI literacy is not a one-size-fits-all set of competencies but rather a structurally layered phenomenon based on the user’s technical depth and productive capacity.

Table 1 - Comparative overview of reviewed AI literacy scales

Item No	Study	Scale	Original (O) Adaptation (A)	Number of Items	Number of Factors	Factors	Participants	Number of Participants	The Cronbach's α
1	Kim & Lee (2022)	AI literacy scale	O	30	6	1. Social impact of AI 2. Understanding of AI 3. AI execution plans 4. Problem solving with AI 5. Data literacy 6. AI ethics	Secondary school students	1222	.970
2	Wang et al. (2023)	AI literacy scale - AILS	O	12	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	General	601 325	.83
3	Hobeika et al. (2024)	AILS - Arabic version	A	9	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	University students	1849	.92
4	Polatgil & Güler (2023)	AILS	A	12	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	General	643	.939
5	Çelebi et al. (2023)	AILS	A	12	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	General	402	.85
6	Gökçearslan et al. (2024)	Gen-AI literacy scale	A	10	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	University students	297	.74
7	Uğraş et al. (2024)	AILS	A	12	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	PST	440	.85
8	Kırksekiz et al. (2024)	AILS	A	12	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	University students	107 729	.814

Table 1 (*Continue)*

9	Eniş-Erdoğan & Ekşioğlu (2024)	AILS	A	12	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	Teachers	226	.861
10	Ma & Chen (2024)	AILS-CCS	O	15	4	1. Awareness 2. Usage 3. Evaluation 4. Ethics	University students	546	-
11	Carolus et al. (2023)	MAILS	O	34	7	1. Apply AI 2. Understand AI 3. Detect AI 4. AI ethics 5. Create AI 6. AI self-efficacy • *AI problem solving* • *Learning* 7. AI self-competency • *AI persuasion literacy* • *AI emotion regulation*	General	300	.66–.93
12	Laupichler et al. (2023b)	SNAIL	O	31	3	1. Technical understanding 2. Critical appraisal 3. Practical application	General	415	.85–.93
13	Deveci-Topal et al. (2025)	SNAIL	A	28	3	1. Technical understanding 2. Critical appraisal 3. Practical application	University students	642	.963
14	Karaoğlan-Yılmaz & Yılmaz (2023)	AILS	A	31	3	1. Technical understanding 2. Critical appraisal 3. Practical application	General	653	.99
15	Biagini et al. (2024)	AI literacy questionnaire	O	40	4	1. Knowledge-related 2. Operational 3. Critical 4. Ethical	General	191	.953
16	Nong et al. (2024)	AILS	O	12	5	1. AI application ability 2. AI cognitive ability 3. AI morality 4. AI critical thinking 5. AI self-efficacy	General	302	.755

Table 1 (*Continue)*

17	Yuan et al. (2024)	AILS	O	24	6	1. Individual level: Cognitive dimensions ● *AI features* ● *AI processing* ● *Algorithm influences* 2. Interactive level: Behavioral dimensions ● *User efficacy* 3. Socio-cultural level: Normative dimensions ● *Ethical consideration* ● *Threat appraisal*	General	1173	.70–.87
18	Ng et al. (2023)	AI literacy questionnaire (AILQ)	O	25	6	1. Intrinsic motivation 2. Self-efficacy 3. Behavioral intention 4. Behavioral engagement 5. Know and understand 6. Use and apply AI	Secondary and high school students	363	.58–.88
		ABCE Model		44	4	1. Affective 2. Behavioral 3. Cognitive 4. Ethical			.91–.94
	Ng et al. (2024)	AILQ	O	32	4	1. Affective 2. Behavioral 3. Cognitive 4. Ethical	Secondary school students	363	> .90
19	Fernandez & Calderon-Garrido (2024)	AI literacy survey	A	-	4	1. Affective 2. Behavioral 3. Cognitive 4. Ethics	Graduate students	134	.81
20	Koch et al. (2024)	Overview of existing AI literacy measurement instruments	-	134	4	1. Use and interact with AI 2. Design/program AI 3. Cognitive operations regarding AI 4. Detect AI/Persuasion literacy	-	219	-

Table 1 (*Continue)*

21	Younis (2025)	AIL scale for teachers	O	45	9	1. Teachers' attitudes toward AI use 2. Understand AI and computational thinking concepts 3. Understand AI social impact 4. Understand AI ethics 5. Search and locate AI tools 6. Motivate students to use AI tools 7. Integrate AI tools in the classroom 8. Evaluate AI tools features 9. Apply AI tools for assessment	Teachers	292	.921–.949
22	Balıkçı & Yıldız-Durak (2025)	AILS for teachers	A	45	9	1. Teachers' attitudes toward AI use 2. Understand AI and computational thinking concepts 3. Understand AI social impact 4. Understand AI ethics 5. Search and locate AI tools 6. Motivate students to use AI tools 7. Integrate AI tools in the classroom 8. Evaluate AI tools features 9. Apply AI tools for assessment	Teachers	209	.981
23	Noh et al. (2024)	Generative AI literacy scale	O	12	4	1. AI utilization ability 2. Critical evaluation 3. Ethical use 4. Creative application	General (Korean Adults)	1000, 500	.754–.890
24	Han & Zhang (2025)	AILS for Chinese university students	O	63	5	1. AI knowledge 2. AI application 3. AI attitude 4. AI ethics 5. AI innovation	University students	386 401	.889–.969
25	Gökçe-Tekin (2025)	AILS	O	15	3	1. Know-understand 2. Apply-evaluate 3. Ethics	Secondary school students	324	.926

Source: authors.

Table 2 - Conceptual Mapping and Synthesis of AI Literacy Factors from Existing Literature

Proposed Factor (Current study)	Corresponding Factors in the Scales Examined	Example Sources	Synthesis Rationale
AI Knowledge	Awareness, Understanding of AI, Know and understand, AI cognitive ability	Wang et al. (2023), Kim & Lee (2022), Ng et al. (2023), Nong et al. (2024)	Fundamental awareness and knowledge skills are clustered under a single umbrella representing the baseline requirement for daily users.
AI Applications	Usage, Apply AI, Practical application, AI utilization ability	Wang et al. (2023), Carolus et al. (2023), Laupichler et al. (2023b), Noh et al. (2024)	Various "usage" dimensions in the literature are synthesized to reflect the goal of facilitating daily tasks for general users.
Evaluation	Evaluation, Evaluate AI tools features	Wang et al. (2023), Younis (2025)	Reflects the basic need of end-users to evaluate the suitability and features of standard AI tools after usage.
Ethical Use	Ethics, AI Ethics, Ethical use	Wang et al. (2023), Kim & Lee (2022), Noh et al. (2024)	Covers foundational ethical precautions in daily life, such as data privacy and basic information security.
Digital Literacy	AI usage and AI evaluation, Search and locate AI tools	Wang et al. (2023), Younis (2025)	Represents the foundational technological competence required to interact with digital AI-integrated tools.
Technical Understanding	Technical understanding, Algorithm influences, AI processing	Laupichler et al. (2023b), Yuan et al. (2024)	Differentiates the advanced understanding of machine learning logic, decision mechanisms, and how algorithms function from basic awareness.
Problem Solving with AI	Problem solving with AI, Create AI, Creative application	Kim & Lee (2022), Carolus et al. (2023), Noh et al. (2024)	Synthesizes high-level productive skills from the literature, such as building AI systems or creating datasets to solve specific problems.
Critical Appraisal	Critical appraisal, AI critical thinking, Critical evaluation	Laupichler et al. (2023b), Nong et al. (2024), Noh et al. (2024)	Represents the philosophical and sociological analysis of AI's deep impacts on humans and society.
Ethical Appraisal	Threat appraisal, Ethical consideration, Understand AI social impact	Yuan et al. (2024) Younis (2025)	Addresses complex ethical dilemmas, such as human bias in algorithms and decisions contrary to human values.
Data Literacy	Data literacy, AI processing	Kim & Lee (2022), Yuan et al. (2024)	Represents the advanced ability to comprehend big data concepts and controls whether data sources feeding AI are purposeful.

Source: authors.

Conclusion

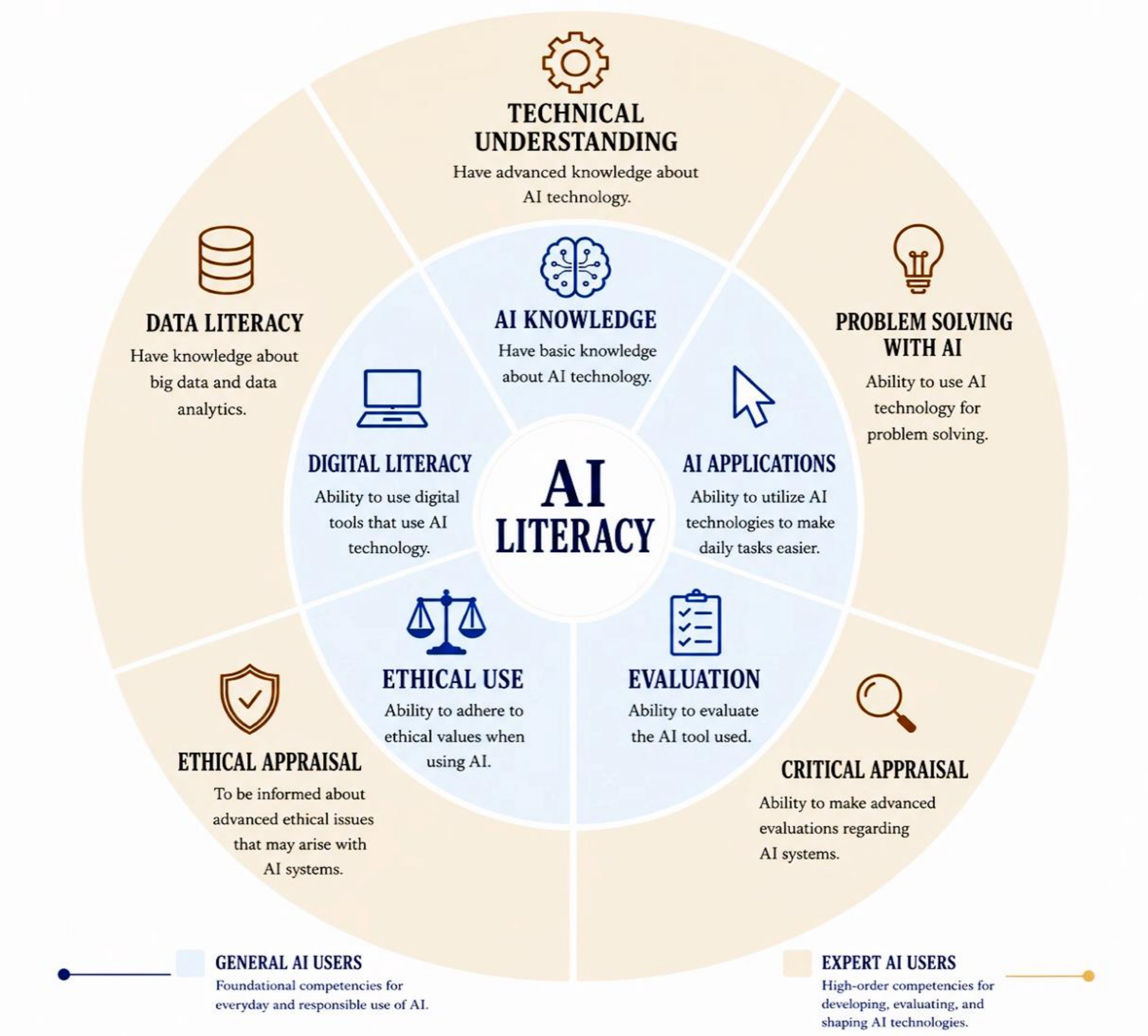
This study systematically reviewed existing AI literacy scale development and adaptation studies and synthesized their fragmented conceptual dimensions into a theoretically grounded AI literacy framework. The findings revealed that, although current AI literacy scales employ different terminologies, participant groups, and factor structures, they largely converge on recurring competency domains such as awareness, application, evaluation, ethics, and technical understanding. At the same time, the review highlighted that the current literature contains substantial conceptual overlap and lacks a clear distinction between foundational AI competencies and advanced technical competencies. To address this gap, this study proposes a two-tiered conceptual framework for AI literacy (Figure 1) that distinguishes competencies required of general AI users from those required of expert AI users. The framework constitutes the central theoretical contribution of the study by conceptualizing AI literacy not as a single-layered construct, but as a multidimensional and depth-oriented competency structure.

In Figure 1, the inner circle represents foundational competencies required of general AI users, while the outer circular layer represents higher-order competencies expected of expert AI users. This visual structure symbolically represents the progressive and layered nature of AI literacy, illustrating that advanced competencies are built upon foundational ones rather than existing independently (see Table 3 for the details). At the foundational level, the framework emphasizes competencies required for effective and responsible interaction with AI technologies in daily life. These competencies include AI knowledge, AI applications, evaluation, ethical use, and digital literacy. Together, these dimensions represent the minimum literacy requirements for individuals to recognize AI systems, use AI tools appropriately, evaluate their outputs, and engage with AI technologies responsibly and safely.

In contrast, the outer layer highlights advanced competencies associated with technical reasoning, socio-ethical awareness, and productive AI engagement. These competencies include technical understanding, problem solving with AI, critical appraisal, ethical appraisal, and data literacy. Unlike foundational competencies, these dimensions require deeper cognitive engagement with AI systems, including understanding machine learning mechanisms, evaluating algorithmic impacts, questioning ethical implications, and critically interpreting data-driven systems.

One of the most significant contributions of the proposed framework is its differentiation between operational competencies and higher-order reflective competencies. This distinction demonstrates that AI literacy extends beyond the functional use of AI technologies and includes critical, philosophical, and socio-ethical understanding of how AI systems influence individuals and society. Accordingly, the proposed framework contributes to the theoretical refinement of AI literacy by demonstrating that AI literacy should be understood as a layered construct encompassing technical, ethical, and cognitive dimensions.

Figure 1 - Conceptual framework for AI literacy



Source: authors.

Table 3 - Definitions and competencies of proposed AI literacy factors

	Factor	Definition	Example Competencies
General AI users	AI knowledge	Have basic knowledge about AI technology	Know what AI technology is Be able to distinguish between tools that use AI technology Recognize the evolving importance of AI Identify the strengths and weaknesses of AI
	AI applications	Ability to utilize AI technologies to make daily tasks easier	Be able to use AI tools easily Be able to choose the appropriate AI tool for your needs Be able to use AI tools to improve work quality
	Evaluation	Ability to evaluate the AI tool used	Be able to evaluate the strengths and weaknesses of an AI tool after using it Be able to evaluate different AI tools and choose the one that best suits your purpose
	Ethical use	Ability to adhere to ethical values when using AI	Be able to take precautions against AI misuse Be aware of issues such as privacy and information security
	Digital literacy	Ability to use digital tools that use AI technology	Be able to follow technological developments and innovations Be aware of what needs to be done to use a new digital tool
Expert AI users	Technical understanding	Have advanced knowledge about AI technology	Know what machine learning is and how it happens Understand the working principle of decision mechanisms used by AI technologies Realize that the system that makes a technology intelligent is based on data or algorithms
	Problem solving with AI	Ability to use AI technology for problem solving	Be able to develop AI technology to solve any problem Be able to create a dataset to be used to develop an AI system
	Critical appraisal	Ability to make advanced evaluations regarding AI systems	Explain the difference between humans and AI Recognize the potential impacts of AI systems on humans and society
	Ethical appraisal	To be informed about advanced ethical issues that may arise with AI systems.	Be aware that the algorithm an AI system uses which learns through interaction with humans, may negatively change due to people's prejudices and thoughts. Be aware that an AI system may make decisions that are contrary to human values.
	Data literacy	Have knowledge about big data and data analytics	Define the concept of big data Assess whether data sources are purposeful

Source: authors.

Outputs and Implications

The outputs of the present study may support multiple stakeholder groups and have important implications for future research and educational practice. First, the proposed framework may guide future AI literacy scale development and validation studies by providing a theoretically synthesized structure that reduces conceptual overlap and redundancy across dimensions that frequently recur in the literature. Second, the framework may support curriculum developers and educators in designing differentiated AI literacy education programs based on learner profiles and competency levels. For instance, foundational competencies may be prioritized for K12 students and general users, whereas advanced competencies may be emphasized in engineering and technical education programs. Third, policymakers and institutions may benefit from the framework when designing AI literacy initiatives, digital competency programs, and national AI education strategies. The framework may support future empirical studies investigating AI literacy across different cultures, educational settings, professions, and participant groups.

Limitations

Despite its contributions, several limitations of the study should be acknowledged. First, although no language restriction was applied during the search process, the reviewed studies were predominantly conducted in certain educational and cultural contexts, particularly higher education settings, which may limit the generalizability of the synthesized framework across diverse populations and learning environments. Second, the proposed framework was generated through systematic thematic synthesis and conceptual coding rather than through empirical statistical validation. Accordingly, the framework should be considered a theoretically synthesized model requiring further empirical examination. Future studies may validate the proposed framework through EFA and CFA with diverse participant groups and cross-cultural samples. Third, this review included a comprehensive factor analysis study (Koch et al., 2024) that integrated 134 items from previously developed scales. While this inclusion provided valuable insights into the core latent dimensions of AI literacy, it should be noted as a limitation that some scale items from original studies may have been indirectly overrepresented during the thematic synthesis process. Furthermore, both the preliminary phase (Ng et al., 2023) and the finalized validated version (Ng et al., 2024) of the AILQ were intentionally included in this review to demonstrate the structural evolution of the scale, which may lead to a partial overlap of the evaluated items in the conceptual synthesis. In addition, because the literature search was completed in May 2025, more recent AI literacy scale studies published after this period were not included in the review. Given the rapidly evolving nature of AI literacy research, future reviews may expand and refine the proposed framework by incorporating newly developed scales and emerging competency dimensions.

Recommendations for Future Research

Future studies may empirically validate the proposed framework through EFA and CFA with diverse participant groups and cross-cultural samples. In addition, longitudinal and mixed-methods studies may provide further insights into how AI literacy competencies evolve across different educational and technological contexts. Future research may also investigate whether the proposed two-tiered framework operates differently across age groups, professions, and educational systems. Furthermore, the development of domain-specific AI literacy scales for teachers, students, healthcare professionals, or workplace environments may contribute to a more context-sensitive understanding of AI literacy.

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