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Adaptation of the artificial ıntelligence literacy scale into Turkish: A cross-sectional application among healthcare workers, students, and children

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Abstract

In this study, the Meta-Artificial Intelligence Literacy Scale developed by Carolus et al. (Computers in Human Behavior: Artificial Humans, 1(2), 100014) was adapted to Turkish, and its validity and reliability were tested. This cross-sectional research was conducted with three distinct study groups to assess the scale's applicability and consistency in diverse contexts. Validity and reliability analyses were performed with 1167 participants between the ages of 12–74, representing a broad demographic range. Additionally, the scale's applicability was further evaluated with 583 children aged 12–18 and 122 healthcare workers. The Meta-AI Literacy Scale comprises four main dimensions—artificial intelligence literacy, artificial intelligence creation, artificial intelligence self-efficacy, and artificial intelligence self-competence—and eight sub-dimensions that cover a wide range of AI-related competencies. Cronbach Alpha and test–retest analyzes of the scale showed high consistency. Test–retest analyses confirmed the stability of the instrument over time. The findings revealed significant variations in artificial intelligence literacy based on age and education level, highlighting the influence of demographic factors. However, no significant differences were observed based on gender. This study concludes that the Meta-Artificial Intelligence Literacy Scale is a valid, reliable, and versatile tool for assessing AI literacy among Turkish-speaking individuals in various settings, including educational and healthcare contexts.

Keywords Artificial intelligence · Scale adaptation · Children · Healthcare workers

1 Introduction

Today, with rapidly advancing technology, access to information and communication are changing radically, and the importance of artificial intelligence (AI) technologies is increasing. Artificial Intelligence (AI) is a type of intelligence that emerged in the 1950 s and has become an integral part of the digital revolution.

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AI is a new technological science aimed at simulating and expanding human intelligence. This technological science is based on science and technology in disciplines such as information technology, biology, physiology, mathematics, etc. In addition, advances in AI will change the way individuals live and can revolutionize the business world. The main advantage of artificial intelligence is that a job is correct and time can be saved. In addition, people will be able to easily overcome challenging work using this technology (Bhbosale et al., 2020; Cataleta & Cataleta, 2020; Wang et al., 2022). Thanks to AI, the door will be opened to a more effective, efficient, fast, accurate and innovative world.

In the modern era, artificial intelligence, low cost, speed and increased production efficiency (Manyika et al., 2017), in healthcare services, patient care, rapid and accurate diagnosis (Harry, 2023; Paranjape et al., 2019), automation (Matheny et al., 2019), data analysis and forecasting (World Economic Forum, 2020), education; teaching and learning (Holmes et al., 2019), innovation (Cooper, 2024; Rakhmatullin & Hegyi, 2023) and content production—personalized content creation (Güzeldemirci, 2024) are used in fields such as business, education, electronics, software development, engineering, communication, gaming, healthcare, pharmacy, industry and the military (Aggarwal et al., 2022; Bhbosale et al., 2020) and contribute to many fields (Singil, 2022). Technology is present in almost every aspect of our lives, and artificial intelligence technologies extend from education to healthcare, from transportation to the financial sector, and into our daily lives (for example, smart home devices, smartphones, Google, Siri), social networks, online banking, autonomous vehicle movement, the use of robots in elderly care, and drone-based package delivery. Competencies, higher-order cognitive skills, and individual engagement are now considered fundamental requirements for navigating the various forms of AI-based technologies (Erdoğan & Ekşioğlu, 2024; Wienrich et al., 2022). Artificial intelligence (AI) will impact many aspects of human life; therefore, AI literacy has become a crucial skill that everyone must learn in this new era of intelligence (Ng et al., 2021). Many of the fears and concerns regarding the future development of AI stem from misunderstandings and confusion about what AI is and what it could become (Johnson & Verdicchio, 2017). With the emergence of AI technology, the ability to define individuals'competence in using this technology and ensuring its effective utilization has made the concept of AI literacy essential (Çelik, 2023; Wang et al., 2022).

Organizations such as UNESCO and the European Commission are developing policies on artificial intelligence (AI). As AI technologies continue to expand their influence globally, international organizations such as the European Commission aim to foster both the economic and technological advancement of these technologies while ensuring their safe and ethical use by considering their societal implications. However, as AI technology evolves rapidly with the continuous release of updated versions, national regulations struggle to keep pace with these innovations. The lack of effective national regulations in many countries compromises data privacy and leaves users largely unprepared to utilize these tools effectively (UNESCO, 2024; European Commission, 2025). Research emphasizes that AI literacy skills are crucial for individuals to participate effectively in the information society (Almatrafi et al., 2024; Kandlhofer et al., 2016; Kong et al., 2023; Laupichler et al., 2024). There is a global consensus on the integration of AI literacy into national curricula in countries such as the United States, China, and many others (Elçiçek, 2024; Southworth et al., 2023; Swed et al., 2022; Yang, 2022; Yeter et al., 2024; Wood et al., 2021). Moreover, ensuring AI literacy is accessible to all is recognized as essential for bridging the digital divide. Through AI literacy, individuals will acquire the fundamental skills needed to live, learn, and work in the digital world (Arduç-Kara, 2024).

AI literacy is a multidimensional concept that includes individuals'ability to understand, use and critically evaluate AI systems, and to use them effectively and ethically in daily life (Ng et al., 2022; Wang et al., 2022). At the same time, four skills related to technology, business, human–machine and learning are underlined with AI literacy, and it is said that it is important to operationalize AI literacy for professionals outside of AI. Individuals do not need to be experts in the theory and related developments underlying AI for AI literacy. Instead, if an individual has the ability to use AI products competently and reasonably, they can be considered AI literate (Çetindamar et al., 2022; Wang et al., 2022). The way to use AI technologies effectively is to be AI literate (Çelebi, Demir, et al. 2023a). For this reason, studies on developing or adapting scales for AI literacy have been conducted in many languages (Biagini et al., 2024; Çelebi, Yılmaz, et al., 2023b; Chai et al., 2021; Erdoğan & Ekşioğlu, 2024; Hornberger et al., 2023; Karaoğlan-Yılmaz & Yılmaz, 2023; Kim & Lee, 2022; Knoth et al., 2024; Laupichler et al., 2023; Laupichler et al., 2024; Li & Kim, 2024; Ng et al., 2024; Pinski & Benlian, 2023; Polatgil & Güler, 2023; Soto-Sanfiel vd. 2024; Su, 2024; Wang et al., 2022; Weber et al., 2023; Wood et al., 2021; Yau et al., 2022; Zhao et al., 2022). In addition, studies on digital interaction literacy and the ChatGPT literacy scale, an AI language model, have been conducted to encourage and implement literate interactions with AI-based systems (Carolus, Augustin, et al., 2023a; Lee & Park, 2024).

In the development of AI literacy, four key aspects are emphasized: knowledge, comprehension, application, evaluation, and ethics (Ng et al., 2021). Various scales have been developed in the literature to measure AI literacy, primarily focusing on technical knowledge, critical evaluation, usage skills, and ethical awareness (Laupichler et al., 2023; Wang et al., 2023). However, most of these scales do not comprehensively address the psychological effects of AI technologies on individuals or skills such as self-efficacy perception. In Türkiye, five studies have been identified related to the adaptation of AI Literacy Scales into Turkish. One of these is the adaptation of the AI Literacy Scale, developed by Laupichler et al. (2023), into Turkish culture by Karaoğlan-Yılmaz and Yılmaz (2023). The scale was validated and tested for reliability with individuals aged 14–54, consisting of three dimensions—technical understanding, critical appraisal, and practical application—comprising 31 items. The second study, conducted by Polatgil and Güler (2023), adapted the AI Literacy Scale developed by Wang et al. (2023) into Turkish. This adaptation involved validity and reliability analyses with individuals aged 18–60, and the scale comprises four dimensions—awareness, application, evaluation, and ethics—across 12 items. Similarly, Çelebi et al. (2023b) translated and conducted a validity and reliability study on the same scale developed by Wang et al. (2023). The fourth study, conducted by Erdoğan and Ekşioğlu (2024), adapted Wang et al.'s (2023) AI Literacy Scale to assess teachers'perceptions of AI literacy, ensuring its validity and reliability. The final study, conducted by Tekin (2025), aimed to develop a measurement tool for assessing AI literacy levels among middle school students. Based on the AI Literacy framework developed by Ng et al. (2022), this adaptation was structured around four dimensions: Knowing and Understanding AI, Applying AI, Evaluating AI Applications, and AI Ethics. Validity and reliability analyses were conducted with 324 middle school students, and the scale was adapted into Turkish.

This study involved the adaptation of the Meta-AI Literacy Scale (MAILS), developed by Carolus et al. (2023b), into Turkish. The scale was adapted based on studies conducted with individuals aged 12 to 72 and is designed to measure knowledge, awareness, and application skills related to AI technologies. It comprises four main dimensions: AI Literacy, AI Creation, AI Self-Efficacy, and AI Self-Competence. Additionally, the scale includes eight sub-dimensions that provide a more detailed assessment of cognitive processes and technological competencies. These sub-dimensions encompass AI tool usage and application skills, recognition and understanding of AI systems, identification of AI-based content, awareness of AI ethics, AI-assisted problem-solving abilities, AI-driven learning processes, evaluation of persuasion strategies in AI-based systems (persuasion literacy), and emotional regulation during AI interactions. A key distinction of this Turkish-adapted Meta-AI Literacy Scale is its comprehensive inclusion of psychological processes related to AI usage, such as self-efficacy and emotional regulation, making it more inclusive by covering a broad age range. Furthermore, the modular structure of the scale allows users to assess only specific dimensions, enabling flexibility to accommodate diverse research needs. While AI intelligence literacy scales generally focus on individuals'competencies, knowledge utilization, and ethical principles (Laupichler et al., 2023; Ng et al., 2022; Wang et al., 2023), MAILS takes a holistic approach, providing a broader and more in-depth evaluation of AI awareness. Given the necessity of assessing both cognitive and psychological competencies to ensure the sustainable and ethical use of AI technologies, the development of this scale fills a significant gap in the field. MAILS offers a more comprehensive assessment than existing AI literacy scales, providing a valid and reliable tool to measure individuals'multidimensional AI interaction skills. Additionally, Carolus, Koch, et al. (2023b) originally designed the MAILS scale in German, and it has since been translated into both Arabic and English for further application. By contributing to research across multiple languages and countries, MAILS enables international comparisons and highlights different aspects of AI literacy within various cultural contexts (Fu, 2025; Generale et al., 2024; Mansoor et al., 2024; Tseng et. Al., 2025).

In this study, the applicability of the scale was tested across three different sample groups, ensuring a comprehensive evaluation across a broad population.

Study 1: Validity and reliability analyses of MAILS were conducted with 1,167 participants aged 12 to 74, aiming to assess the psychometric properties of the scale within the general population.

Study 2: The study conducted with 583 children aged 12 to 18 aimed to examine their AI literacy levels and the factors influencing this competency. Developing AI awareness and literacy at an early age is a crucial step in enhancing digital skills and preparing children for the digital world (Kewalramani et al., 2021; Su & Zhong, 2022; Su et al., 2023).

Study 3: The study, conducted with 122 healthcare professionals, aims to examine the AI literacy levels of this group and the factors affecting this competence. Artificial intelligence in healthcare contributes to improving healthcare services in a wide range of areas, from nursing care to diagnosis and treatment processes, from patient monitoring to hospital management. It is also used in a wide range of areas, from triage to infection control, surgical field and smart hospital systems (Hoşgör & Güngördü, 2022; Nehir & Özcengiz, 2021; Özdemir & Bilgin, 2021). The use of AI in healthcare is rapidly increasing, and the literacy of healthcare professionals regarding these technologies is critical for patient care and clinical decisions (Mergen et al., 2023; Miotto et al., 2018; Şahin et al., 2019).

The primary aim of this study is to analyze the validity and reliability of the Turkish version of the Meta-AI Literacy Scale and assess its applicability among adults, children, and healthcare professionals. Measuring, conceptualizing, and enhancing AI literacy within Turkish-speaking communities will serve as a foundation for future research and educational practices, aiding in personnel selection, addressing knowledge gaps, and evaluating psychological competencies. The findings will provide valuable insights into the varying trends of AI literacy across different age and professional groups, serving as a key reference for the development of strategic educational policies. Furthermore, the fact that a significant portion of AI literacy research is based on English-language sources creates a knowledge and accessibility gap for Turkish-speaking individuals. The limited number of studies focusing on measuring and improving AI literacy in Türkiye and other Turkish-speaking communities highlights the urgent need for a validated and reliable assessment tool in this field. Within this framework, the study is expected to have a significant impact on academia, educational practice, and society, providing a scientifically validated instrument to support AI literacy assessment and development.

The research questions of the studies are listed below:

1. Is the Turkish adaptation of the Meta-AI Literacy Scale a valid and reliable measurement tool?
2. Is there a relationship between children's AI literacy levels and their demographic characteristics?
3. Is there a relationship between healthcare professionals' AI literacy levels and their demographic characteristics?

2 Method

This cross-sectional study consists of three separate studies aiming to adapt the MAILS to Turkish and test its validity in different sample groups. In the first study, the MAILS was adapted to Turkish and validity and reliability analyses were conducted. The second study aimed to validate the MAILS with 583 children aged 12–18 and t and its usability in studies targeting children was evaluated. In the third study, the applicability of the scale in the health sector was examined with the participation of 122 health workers. The screening model, a quantitative research method, was used in Study 2 and Study 3.

2.1 Study group

2.1.1 Study 1

This study was conducted with the participation of individuals with different demographic characteristics to reflecting Turkey in general. The inclusion criteria for the participants were to be between the ages of 12–74, to speak and read Turkish, to give informed consent, and to respond voluntarily to all data collection tools.

In order to reflect the regional diversity in Turkey in the sample, the Turkish Statistical Regional Units Classification (SRUS) was used as the basis for sample selection. According to this classification, Turkey was divided into 12 regions to reflect socio-economic and demographic diversity (Development Agency, 2024). During the sample selection process, care was taken to ensure that demographic factors such as age, gender, education level, and occupational distribution were distributed in a balanced manner to represent the 12 regions. Participants were individuals living in different settlements such as metropolitan cities (41.1%), cities (36.8%), districts (16.8%) and villages-towns (5.2%).

In order to ensure the adequacy of the sample size, statistical criteria commonly used in scale adaptation studies were taken into account (Bryman & Cramer, 2002; Tabachnick & Fidell, 2007; Weston & Gore, 2006). For factor analysis studies, a sample size of at least 10 times the number of scale items is recommended (Boateng et al., 2018). In line with these criteria, in order to ensure that the sample size was sufficient and to increase the reliability of factor analysis and multivariate statistics, the sample was expanded and a total of 1167 participants were reached. The profile of the participants is given in Table 1.

In this context, 66.6% of the participants determined were female and 33.4% were male, the age range of the participants was 12–74 (Mean =31.18, SD =12.15), the education level was 0.2% literate, 1.5% primary school, 3% secondary school, 12.2% high school, 17.9% associate degree, 37% undergraduate, 13.1% master's degree, 15.2% doctorate level, 7.5% housewife, 29.6% student, 18.9% academician, 17.5% teacher, 3.3% worker, 14.5% civil servant, 3.3% engineer, 0.8% retired, 4.5% in other occupational group, socio-economic status was 10.9% lower, While 83.5% are at the middle and 5.7% are at the upper level, 45.3% have children.

2.1.2 Study 2

In the second study, a new validation study was conducted with 583 children aged 12–18 to provide an additional resource for the use of the AI Literacy Scale, adapted

Table 1 Demographic characteristics of Study 1 participants

Demographics	Grup	n (%)
Gender	Female	777 (66,6)
	Male	390 (33,4)
Age Group	12–17	72 (6,2)
	18–44	886 (75,9)
	45–59	183 (15,6)
	60–74	26 (2,4)
Education Level	Literate	2 (0,2)
	Primary School	17 (1,5)
	Middle School	35 (3)
	High School	142(12,2)
	Associate Degree	209 (17,9)
	Bachelor's Degree	432 (37)
	Master's Degree	153 (13,1)
	Doctorate	177 (15,2)
Occupation	Student	346 (29,6)
	Housewife	87 (7,5)
	Academician	221 (18,9)
	Teacher	204 (17,5)
	Engineer	39 (3,3)
	Civil Servant	169 (14,5)
	Retired	9 (0,8)
	Worker	39 (3,3)
	Other	53 (4,5)
Perceived Socioeconomic Status	Lower	127 (10,9)
	Middle	974 (83,5)
	Upper	66 (5,7)

into Turkish in Study 1, with children. Initially, 597 children volunteered to participate in the study, but after removing identified outliers from the data set, analyses were conducted on data from 583 children. Of the children, 14.9% were 12 years old, 13.4% were 13, 12.7% were 14, 13.7% were 15, 16% were 16, 13.7% were 17, and 15.6% were 18 years old. 54% of the children were female, and 46% were male. Regarding maternal education, 27.6% of mothers had completed primary school, 34% had completed middle school, 26.2% had completed high school, and 12.2% had completed university or higher education. Regarding paternal education, 18.9% of fathers had completed primary school, 26.2% had completed middle school, 37% had completed high school, and 17.8% had completed university or higher education. In terms of AI awareness, 25.9% of the children reported not knowing any AI tools, 38.8% could name one tool, usually ChatGPT or Siri, and 35.3% could name two or more AI tools. In terms of AI usage, 24.4% of the children reported never using AI, 35% used AI for research related to their homework and studies, 18.7% used AI for games and entertainment, 12.3% used AI for various tasks such as design, navigation, chatting, and asking questions, and 9.6% reported using AI for multiple purposes. Additionally, 78.6% of the children had their own smartphone, while 21.4% did not. 69.8% of the children had their own tablet or computer, while 30.2% did not.

2.1.3 Study 3

This study was conducted to provide an additional resource demonstrating the applicability of the AI Literacy Scale, adapted into Turkish in Study 1, in studies conducted with healthcare professionals. The study group consisted of 122 healthcare professionals. Of the participants, 37.7% were aged 21–26, 34.4% were aged 27–37, and 27.9% were aged 38–55. Women comprised the majority of the group at 77.9%, while men accounted for 22.1%. In terms of education, 33.6% of the healthcare professionals had a high school or associate degree, 36.9% had a bachelor's degree, and 29.5% had a master's or doctoral degree. In terms of profession, 20.5% were doctors, 39.3% were nurses, 37% were health technicians, and 9.8% were dietitians, physiotherapists, or pharmacists. Of the healthcare professionals, 47.5% reported never or rarely using AI, while 52.5% reported using AI frequently or always.

2.2 Data collection ınstruments

A personal information form was used in the studies to determine the demographic characteristics of the participants. This form includes questions about the demographic information of the participants such as age, gender, city of residence, education level, profession, socio-economic status, and questions investigating the frequency of use of AI tools, the purpose for which they use them, and which AI tools they use.

The"Meta-AI Literacy"scale developed by Carolus et al. (2023b) was used as the main measurement tool of the study. The original scale contains 34 items and 4 main dimensions. Carolus et al. (2023b) examined the existing literature on AI literacy in depth and developed the MAILS to address this gap in the literature due to the lack of a questionnaire that can be applied modularly depending on the objectives and includes more psychological competencies in addition to the typical aspects of AI literacy. The scale was created by a team of researchers working in the fields of psychology and human–computer interaction. This scale aims to measure the participants'level of literacy in AI in various dimensions (Carolus et al., 2023b).

Participants'statements regarding their AI abilities are graded using an 11-point Likert scale (0–10). A value of"0"indicates that a skill is not at all or almost not evident, while a value of"10"indicates that a skill is very well or (almost) perfectly evident. Validity and reliability studies have been conducted on the original scale. The Kaiser–Meyer–Olkin (KMO) value of the scale was found to be 0.81.

2.3 Procedure

2.3.1 Study 1: Scale adaptation process

In the adaptation of the MAILS into Turkish, scale adaptation techniques in the literature were examined in order to minimize the changes in the original scale and to ensure adaptation to the translated language and culture. The process of adapting the scale to Turkish was carried out based on the linguistic and cultural adaptation steps suggested by Hambleton and Patsula (1999) and the standard techniques determined by the International Test Commission (ITC) (2019). The scale adaptation process steps are presented in Fig. 1.

In the first stage of the scale adaptation study, the conceptual framework, structures and measured components of the original form of the MAILS were examined in detail. In order to ensure conceptual equivalence, elements related to daily life and some descriptions were addressed within the framework of experiential equivalence; the changing meanings of words in different cultures were carefully evaluated (Hambleton & Patsula, 1998). Considering the purpose and content of the development of the original scale, it was evaluated whether the scale was suitable for Turkish culture. A literature review of AI literacy in the context of Turkey was conducted. It was concluded that the original dimensions of the scale were suitable for measuring the AI literacy of individuals in the context of Turkey. Attention was paid to preserving the conceptual framework and an attempt was made to ensure cultural and contextual equivalence of the scale items.

The language validation process of the scale includes the translation of the scale from its original language, the evaluation of the translation, and the preparation of a trial form to assess its consistency with the original scale (Weir, 2005). In this study, the scale was translated into Turkish by three independent, bilingual (Turkish and English) experts. Translations should be made by taking into account the cultural, psychological and grammatical differences of both languages (ITC, 2019). These independent translations were brought together to evaluate the differences and a common Turkish form was created. This version was then translated back into English by three independent experts (back translation process) and the back-translated text was compared with the original scale to analyze possible semantic shifts. The back translation process of the scale should preferably be done by translators who are not part of the research group and have no knowledge of the scale (International Test Commission, 2019). Linguistic inconsistencies and translation errors were identified and the scale items were revised. As a result of these stages, it was confirmed that the scale was both linguistically and culturally appropriate.

Fig. 1 Scale adaptation process. Note: The scale adaptation process conducted within the scope of this study was based on the scale adaptation steps determined by Hambleton and Patsula (1999) and the International Test Commission (ITC) (2019)

Following the language adaptation, **content validity** was assessed. The content validity of the scale was evaluated using language, expert opinions, and statistical methods. An evaluation form was prepared and submitted for expert opinion in order to ensure the content validity and translation equivalence of the Turkish translation of the scale. Content validity is used to determine whether the items in the scale are sufficient to measure the desired feature in terms of quality and quantity. In addition, the suitability of the scale to the structure and demographic characteristics of the society in which it will be used is also determined. The most frequently used method to determine content validity is to obtain expert opinion (Büyüköztürk, 2018). In this study, in order to determine the content validity of the scale, forms containing the first translation of the scale and the revised translation were sent to three experts (one engineer and two faculty members), one sociologist, and one child development expert who have studies in the field of AI. The experts were asked to state their opinions about the items of the scale in terms of suitability for the purpose as "suitable", "not suitable", and "correction…". Expert opinions were collected in a form, and content validity calculations were performed using the laswe technique. The content validity rates were calculated for each item, and the content validity rate was obtained as the ratio of the number of experts who said "appropriate" for an item minus one to the total number of experts who expressed an opinion on the item. The minimum value for the content validity rate for five experts was determined as 1 (Ayre & Scally, 2014).

A pilot study was conducted to complete the content validity. The pilot study is the last stage before moving on to psychometric studies in order to test the comprehensibility and applicability of the scale translated into Turkish (ITC, 2019). The pilot study is the trial application of the adapted version of the test on a small group that will represent the target audience. This stage is important for determining the problems that may be encountered in the application (Hambleton & Patsula, 1999). In this study, which was applied to a group of 30 people representing the target audience, participants provided feedback on whether the scale items were understandable. In line with the feedback obtained, final adjustments were made by making a few items simpler and clearer.

Finally, confirmatory factor analysis (CFA) was applied to test the psychometric validity of the scale. Fit indices such as RMSEA, CFI and SRMR were used to assess whether the factor structure of the scale was preserved in the Turkish version. In addition, Cronbach's alpha coefficient and test–retest analysis were performed to examine the internal consistency and stability of the scale over time.

2.3.2 Study 2: Implementation of MAILS for children aged 12–18

Within the scope of Study 2, the data collection process was planned to evaluate the validity and reliability of the scale for children aged 12–18. In accordance with the age range of the participants, parental consent was obtained and data collection was carried out in accordance with the ethical requirements of the study. The scale was applied via a face-to-face survey method. The scale took an average of 15–20 min to complete.

2.3.3 Study 3: Implementation of MAILS for healthcare professionals

Within the scope of Study 3, the applicability of the scale was tested to assess the AI literacy levels of healthcare professionals. For this purpose, doctors, nurses, health technicians and other healthcare personnel working in hospitals, family health centers and private healthcare institutions were included in the study group. Participation in the study was completely voluntary and informed consent was obtained from the participants. The scale was applied via face-to-face and online survey methods. The scale took an average of 10–15 min to complete.

2.4 Data analysis

Since the research is a scale adaptation study, validity and reliability analysis processes were applied and SPSS 22 and AMOS 24 programs were used during these analyses. The validity of the scale was ensured through linguistic validity, content validity, and construct validity, respectively. To establish linguistic validity, two approaches were considered: obtaining expert opinions and conducting a statistical analysis. However, performing a statistical analysis requires access to a sample group proficient in both the target and source languages (Seçer, 2015). Due to the unavailability of such a sample group under the current research conditions, linguistic validity was ensured through expert opinions. Similarly, expert opinions were consulted for content validity, and the Lawshe technique, which is frequently employed in psychometric scale development and adaptation studies, was utilized. By quantifying expert evaluations, subjective judgments were minimized (Ayre & Scally, 2014; Lawshe, 1975). The construct validity of the scale was assessed through confirmatory factor analysis, a widely used method in adaptation studies to determine the extent to which the predefined factor structure of a scale aligns with the collected data (Effendi et al., 2019; Hambleton & Patsula, 1999). The chi-square fit index was used to compare the fit of different models. Due to its sensitivity to sample size (Meade et al., 2008), other values recommended in structural equation modeling (SEM), including RMSEA (Root Mean Square Error of Approximation), CFI (Comparative Fit Index), and SRMR (Standardized Root Mean Square Residual), were also reported (Hooper et al, 2008; Kline, 2023). The original model from the scale's form was used, and these values were also taken into account in interpreting the model (Carolus et al., 2023b). Modifications were made to improve model fit, and covariances were added between the errors of specific items (Nye, 2023). Factor loadings for the final model were calculated.

To assess the reliability of the scale, internal consistency was tested, and Cronbach's Alpha values for the total scale and its sub-dimensions were calculated. Additionally, corrected item-total correlations were computed to determine how well the individual items differentiated among respondents. Differences in item mean scores between the top 27% and bottom 27% groups were analyzed using an independent samples t-test. Another method used to test reliability was test–retest reliability, and Pearson correlation coefficients were calculated for this purpose.

In Studies 2 and 3, which validated the scale with different sample groups (children and healthcare professionals), the data were first tested for normal distribution. Skewness and kurtosis values were checked, and the values obtained (Study 2 AI Literacy: −0.477, −0.319; Create AI: 0.144, −0.889; AI Self-efficacy: −0.246, −0.588; AI Self-competency: −0.514, −0.262; Study 3 AI Literacy: −0.543, 0.306; Create AI: 0.564, −0.585; AI Self-efficacy: 0.112, −0.751; AI Self-competency: −0.117, −0.027) were within the range of −1 to +1, indicating that the data followed a normal distribution (Hair et al., 2013). Therefore, parametric tests such as the t-test and one-way analysis of variance (ANOVA) were used for analyzing demographic variables. A significance level of $p < 0.05$ was considered, and effect sizes for significant values were calculated using Cohen's d. Effect sizes were interpreted as small (0.20), medium (0.50), or large (0.80 or higher) (Cohen, 1988).

2.5 Ethical principles

For the validity and reliability studies of the MAILS in Turkish, the necessary permissions were first obtained from the researchers who developed the scale via e-mail. Then, in order to conduct the study, ethical approval was obtained by the Çankırı Karatekin University Scientific Publication and Ethics Board with the decision numbered 11 dated 17/01/2024. The collection, analysis, interpretation and storage of the research data were carried out in accordance with the principles of the Helsinki Declaration regarding human rights.

All participants who participated in the study were given instructions about the purpose of the study. Ethical procedures were strictly adhered to, especially in studies conducted with young age groups and healthcare professionals. Written consent was obtained from the parents for participants under the age of 18. The participation of children was completely voluntary and it was guaranteed by the ethics committee that they were not subject to any pressure. The personal data of the healthcare professionals who participated in the study were protected, participation was based on a voluntary basis and written/verbal consent was obtained, and no institutional obligation was imposed. The data of the study was collected using face-to-face and online survey methods.

3 Findings

The findings are presented under three main headings in line with the study objectives. In the first section, the results of the validity and reliability analyses conducted during the adaptation of the MAILS to Turkish are provided. The second part presents the findings from the validation of the scale with children aged 12–18, while the third part focuses on the validation study with health professionals.

3.1 Findings of study 1

In Study 1, validity and reliability analyses were conducted for the adaptation of the scale to Turkish. In this context, firstly, language validity was ensured and it was examined whether the scale preserved its semantic integrity with its original form. Then, content validity was evaluated and whether the scale adequately and comprehensively represented the structures it aimed to measure was analyzed in line with expert opinions. Within the scope of construct validity, the factor structure was tested with confirmatory factor analysis (CFA) and model fit indices were examined. Finally, the reliability analysis of the scale was conducted and its internal consistency and temporal stability were evaluated with the test–retest method. The findings related to these stages are presented in detail below.

3.1.1 Language validity findings

The first step in the adaptation of the MAILS was to ensure the language validity of the scale. According to the determined guidelines (Weir, 2005), this process includes the translation of the scale from its original language, the evaluation of the translation, and the preparation of a trial form to evaluate its consistency with the original scale.

Translation process The scale was first translated into Turkish by three academics who are proficient in the original language (English) and the target language (Turkish). Experts completed the translation process independently, considering the linguistic and cultural suitability of the scale. An experimental form was prepared to be presented to the experts who performed the translation process in order to evaluate the suitability of the Turkish language in terms of word structure and meaning. This form included the items in the original form and the items translated by the experts. As a result of the experts'final opinions, the item translations that were most compatible with the original text in terms of language consistency and meaning were determined and the first Turkish version of the scale was created with these translations.

Back-translation process Three faculty members who are fluent in two languages were selected to ensure the equivalence of the expressions in the Turkish form and the original form. The experts translated the scale back into English and examined the consistency with the original text. A rating scale was used for this purpose. A 4-point rating scale (1: not equivalent/clear, 2: needs major revision, 3: needs minor revision, and 4: equivalent/clear) was used to mark their evaluations.

The back translations were compared with the original scale and the accuracy and clarity of the translation were evaluated. In line with the expert opinions, four items (11, 24, 25, and 33) were revised to increase linguistic consistency. Accordingly, item 11, "Yapay zeka için yeni kullanım alanlarını düşünebiliyorum (I can think of new uses for artificial intelligence)" was corrected to "Yapay zeka için yeni kullanım alanlarını düşünebilirim (I can think of new areas of use for artificial intelligence)". Item 24, "Yapay zekayla ilgili sorunların çoğunu kendi başıma başarılı bir şekilde halledebilirim (I can handle most problems in dealing with artificial intelligence well on my own)" was revised to "Yapay zekayla ilgili sorunların çoğunu kendi başıma halledebilirim (I can handle most problems in dealing with artificial intelligence on my own)" by removing unnecessary words. Similarly, item 25, "Yapay zeka ile çalışırken genellikle zor ve karmaşık görevleri de başarılı bir şekilde çözebilirim (I can also usually solve strenuous and complicated tasks when working with artificial intelligence well)" was revised to "Yapay zeka ile çalışırken genellikle zor ve karmaşık görevleri başarılı bir şekilde çözebilirim (I can usually handle difficult and complex tasks successfully when working with AI)". Item 33, "Yapay zeka ile etkileşimler beni sinirlendirdiğinde veya korkuttuğunda bununla başa çıkabilirim (I can handle interactions with AI frustrate or frighten me)" was revised to "Yapay zeka ile etkileşimler beni hüsrana uğrattığında veya korkuttuğunda bununla başa çıkabilirim (I can handle interactions with AI when they make me frustrated or frighten me)" to provide a more meaningful and culturally appropriate translation. The updated translations were re-evaluated by an English instructor, a Turkish teacher, and the researchers in terms of word structure and cultural appropriateness. In this way, the Turkish language validity of the scale was ensured.

3.1.2 Content validity findings

In order to evaluate the contents validity of the scale, expert opinions were consulted and content analysis was conducted. In line with the feedback received from the experts, it was evaluated whether the scale adequately and comprehensively represented the structures it aimed to measure. In addition, a pilot study was conducted to determine the suitability of the scale for Turkish culture. The findings obtained during this process are presented in detail below.

Since the calculated content validity value was greater than the minimum value, no item was removed from the scale. The experts confirmed that the translated scale was suitable for individuals living in Turkey, that there was no fundamental and theoretical change in the meaning of the scale, and made some suggestions. These suggestions were evaluated by the researchers, and a decision was made to keep the items in their current form.

A pilot study was conducted to complete the content validity. In order to conduct the pilot study of the scale, a target audience of 30 people, 15 boys and 15 girls in the specified age ranges, was determined. The scale was applied to the target audience and the participants were asked to provide feedback on the items in the scale in terms of clarity, comprehensibility and appropriateness. As a result of the pilot study, items (8 and 17) that were difficult to understand and not clear enough were identified by the participants. These items (8–17) were re-evaluated by the researchers and the necessary arrangements were made to make them more comprehensible without distorting their meaning. During this process, revisions were made by obtaining approval from the language experts who translated the scale. Accordingly, the 8 th item, "Yapay zekanın tanımlarını biliyorum (I know the definitions of artificial intelligence)", was corrected to "Yapay zeka tanımını biliyorum (I know the definition of artificial intelligence)" in order to provide a simpler and clearer expression. Similarly, the 17 th item, "Yapay zeka tarafından sağlanan verileri kullanırken etik hususları dikkate alabilirim (I can incorporate ethical considerations when deciding whether to use data provided by artificial intelligence)", was made more explanatory by adding examples and was edited as "Yapay zekâ tarafından sağlanan verileri kullanırken etik hususları (kullanıcı gizliliği, veri güvenliği, vb.) dikkate alabilirim. (I can take ethical issues (user privacy, data security, etc.) into consideration when using data provided by artificial intelligence". With these adjustments made in line with expert opinions, the wording of the scale was improved and the final Turkish form was created.

3.1.3 Construct validity findings

Confirmatory factor analysis (CFA) was applied to test whether the factor structure of the scale was preserved. Various fit indices were used to evaluate the fit of the model and the values obtained were examined in terms of their conformity with the structure in the original form of the scale.

To verify the existing structure of the original scale, Chi-square fit index, RMSEA, CFI, and SRMR values were used. The fit indices taken into account in the original study were taken into account in interpreting the model. The non-significance of the Chi-square fit index, or if significant, a $\chi 2$/df ratio of 5 or less, is considered an indicator of acceptable fit (Hoyle, 1995). An RMSEA value between 0.08 and 1.00 (MacCallum et al, 1996), a CFI value of ≥ 0.90 (Hu & Bentler, 1999), and an SRMR value of ≤ 0.80 indicate acceptable fit (Browne & Cudeck, 1992). The fit indices of all the models applied to the current data are presented in Table 2.

The model was structured in accordance with the original scale, which includes four primary sub-dimensions and 34 items. Upon examining the fit indices ($\chi 2$/df $= 12.38$; RMSEA $= 0.09$, CFI $= 0.87$, SRMR $= 0.05$), it was determined that the $\chi 2$ and CFI values were not sufficient. To improve model fit, modifications were made by creating covariances between item errors with high indices (Nye, 2023). Before creating covariances, the content of these items was reviewed to ensure their similarity. In Model a, items 13 and 14, both related to"AI recognition,"were found to express similar concepts, justifying the covariance between them. After this covariance, the values of the new model showed improved fit ($\chi 2$/df $= 11.52$; RMSEA $= 0.09$, CFI $= 0.88$, SRMR $= 0.05$). However, the $\chi 2$ and CFI values still did not reach sufficient fit. Therefore, another covariance was added to create Model b. This covariance was between items 29 and 30, both related to"preventing AI's influence on individual decisions."The fit indices of Model b ($\chi 2$/df $= 10.81$; RMSEA $= 0.09$, CFI $= 0.88$, SRMR $= 0.05$) still did not reach the required fit. As a result, Model c was developed, where a covariance was created between items 17 and 18, both

Table 2 Fit indices of confirmatory factor models

	χ2	df	p	RMSEA	CFI	SRMR
Model	6453.106	521	0.000	0.09	0.87	0.05
Model a	5994.358	520	0.000	0.09	0.88	0.05
Model b	5610.150	519	0.000	0.09	0.88	0.05
Model c	5281.600	518	0.000	0.08	0.89	0.05
Model d	5018,015	517	0.000	0.08	0.90	0.05
Original Model	886,87	513	0.001	0.05	0.92	0.07

addressing"ethical considerations in AI usage."The values of the new model ($\chi 2$/df = 10.19; RMSEA = 0.08, CFI = 0.89, SRMR = 0.05) showed better fit than the previous models, but the $\chi 2$ and CFI values still did not meet the required thresholds. Another modification was made by adding a covariance between items 2 and 3, both addressing"advantages of AI usage."The values of Model d ($\chi 2$/df = 9.70; RMSEA = 0.08, CFI = 0.90, SRMR = 0.05) showed acceptable fit for RMSEA (0.08 ≥ 1.00), CFI (0.90 ≥ 0.90), and SRMR (0.052 ≤ 0.80), while the $\chi 2$ values did not fit the original model ($\chi 2$/sd = 1,72; RMSEA = 0.05, CFI = 0.92, SRMR = 0.07) in any case. Given that $\chi 2$ is sensitive to sample size (Meade et al. 2008), Model d was accepted due to the acceptable levels of other fit indices. Upon reviewing the factor loadings of the model, it was found that the loadings were quite high, ranging from 0.67 to 0.92. A visual representation of the model and the factor loadings for the items are presented in Fig. 2.

3.1.4 Reliability findings

Ensuring the reliability of a scale is crucial in psychometric evaluations to confirm its consistency in measuring the intended construct. Internal consistency was assessed by calculating Cronbach's alpha values to evaluate the scale's reliability in measuring the intended construct.

The results presented in Table 3 show high consistency in all sub-dimensions of performance. The Cronbach Alpha reliability values for the total scale and its subscales were found to be quite high, ranging between 0.89 and 0.96. Figure 3 shows the Pearson Correlation Analysis results regarding the relationships between the sub-dimensions of the MAILS.

It was determined that there were positive and significant correlations ($p < 0.01$) between the total score and the subscales. The highest correlation was found between"Know & Understand AI"and"Use & Apply AI"($r = 0.83$), indicating that AI knowledge has a strong relationship with the ability to use this technology effectively. Similarly, the high correlation between"AI Self-Efficacy"and"AI Problem Solving"($r = 0.82$) reveals that individuals'self-confidence in AI is linked to their problem-solving skills. On the other hand, the"Create AI"sub-dimension has a lower correlation with other dimensions, and the lowest correlation was observed between"Create AI"and"AI Persuasion Literacy"($r = 0.37$). In general, the obtained correlations show that the sub-dimensions of the scale exhibit consistent relationships and reflect different components of AI literacy. For detailed statistical values corresponding to Fig. 3, see Supplementary Table 1.

In relation to reliability, the corrected item-total correlation values for the AI Literacy scale items were calculated, and these values, along with the results of the t-test to determine the scale's discriminative power, are presented in Fig. 4.

The corrected item-total correlation values for all items on the AI Literacy scale ranged from 0.72 to 0.92. Significant differences were found in item mean scores between the top 27% and bottom 27% groups for all items, demonstrating the scale's discriminative power. Additionally, the t-value for the total scale score was significant (*$p < 0.01$), further supporting the discriminative ability of the scale items.

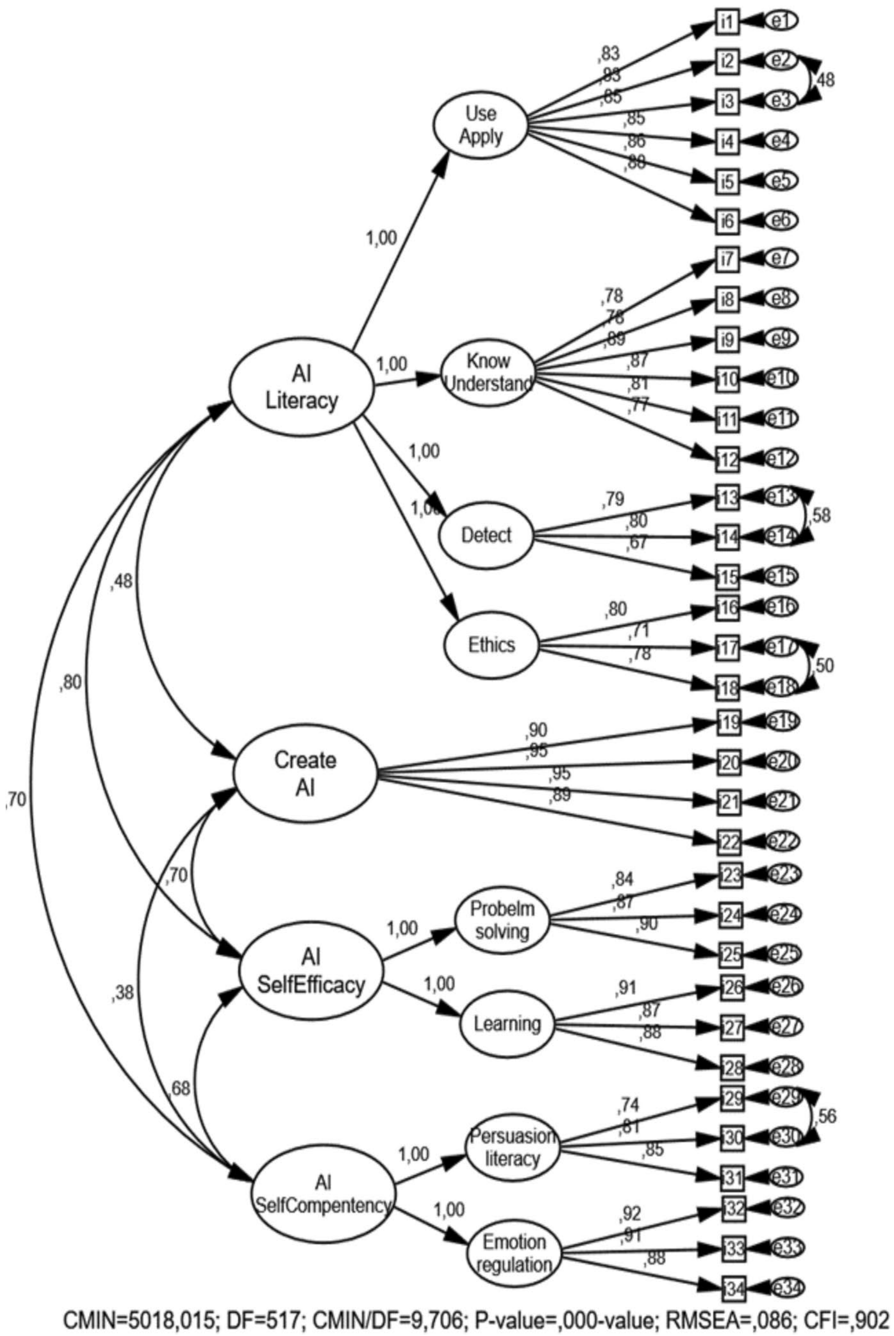

Fig. 2 Graphical representation and factor loadings of the mode

Table 3 Cronbach Alpha values of AI Literacy subscales

	Cronbach Alpha (Turkish)	Cronbach Alpha (Original)
1. Use & Apply AI	0.96	0.93
2. Know & Understand AI	0.93	0.87
3. Detect AI	0.90	0.77
4. AI Ethics	0.89	0.75
5. Create AI	0.95	0.92
6. AI Problem solving	0.93	0.84
7. AI Self-Efficacy	0.94	0.84
8. AI Persuasion literacy	0.91	0.66
9. AI Emotion regulation	0.93	0.71

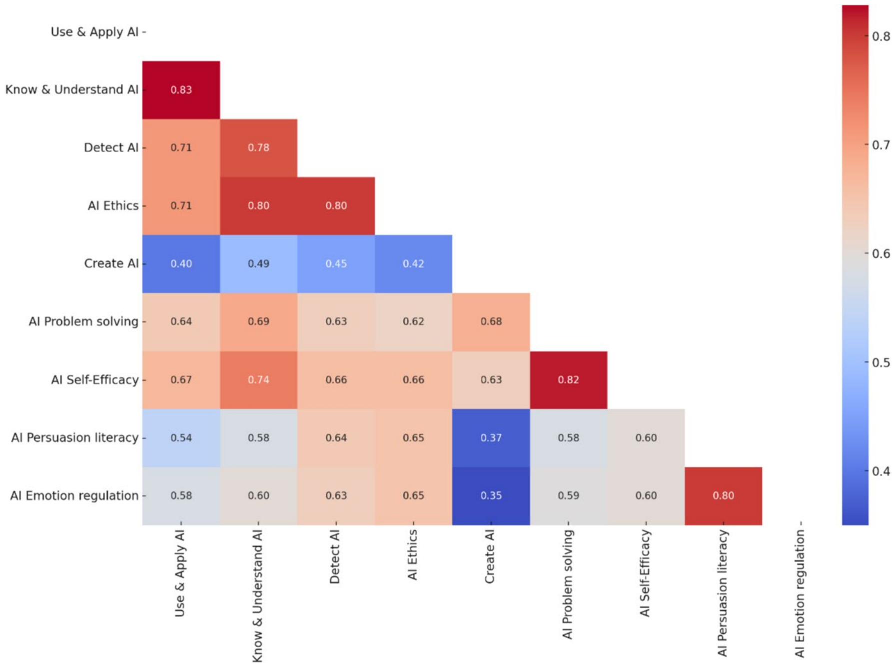

Fig. 3 Pairwise correlation values of AI literacy subscale

For test–retest reliability, the scale was re-administered to a randomly selected group of 30 participants with a balanced distribution across age ranges two to three weeks after the initial administration. The correlations between the two sets of data were examined. The correlation values were calculated as 0.91 for the AI Literacy subscale, 0.79 for the Create AI subscale, 0.88 for the AI Self-efficacy subscale, 0.84 for the AI Self-competency subscale, and 0.92 for the AI Literacy Total Score. Correlation values between 0.70 and 1.00 indicate

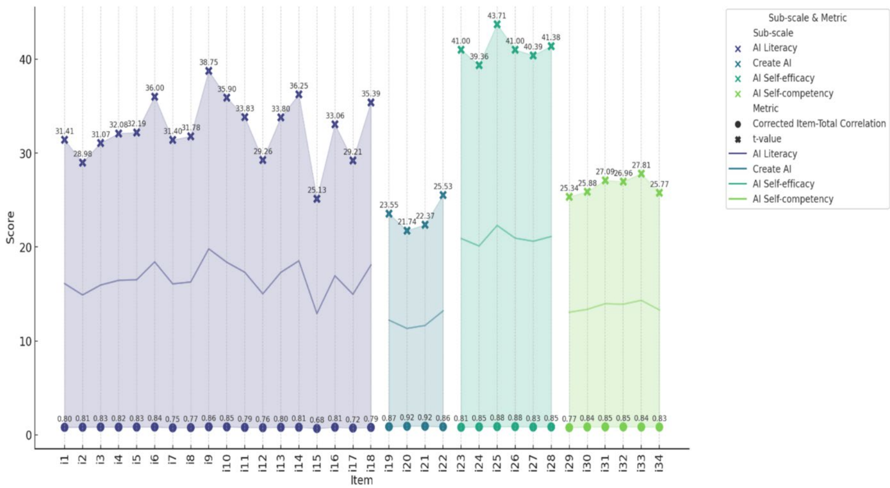

Fig. 4 AI Literacy corrected item total correlations and t-test results between Top 27% and bottom 27% scores

a high relationship, between 0.30 and 0.70 indicate a moderate relationship, and between 0.00 and 0.30 indicate a low relationship (Büyüköztürk, 2018). Based on these values, it can be concluded that the measurement tool provides highly consistent measurements. For detailed statistical values corresponding to Fig. 4, see Supplementary Table 2.

3.2 Findings of study 2

To verify whether the AI Literacy scale, whose validity and reliability were demonstrated in Study 1, provided reliable results when used with children, the Cronbach Alpha values of the subscales were examined. The reliability values were calculated as 0.95 for the AI Literacy subscale, 0.90 for the Create AI subscale, 0.91 for the AI Self-efficacy subscale, and 0.92 for the AI Self-competency subscale, indicating reliable results.

The results of the t-test and ANOVA test, conducted to determine the relationship between the variables related to children and the AI Literacy score averages, are presented in Fig. 5.

The analysis results presented in Fig. 4 indicate that age significantly influenced the mean scores across all subscales, with older children scoring higher ($p < 0.05$). No significant relationship was found between gender and any AI literacy subscale ($p > 0.05$). Children whose mothers held a university degree or higher had higher mean scores across all subscales, which accounted for the significant differences observed ($p < 0.05$). A similar pattern was found for fathers' education, with children of university-educated fathers scoring higher on all subscales. However, significant differences were only observed in the AI Literacy, Create AI, and AI Self-efficacy subscales ($p < 0.05$), while no significant difference was found for AI Self-competency ($p > 0.05$). Ownership of a smartphone was associated with

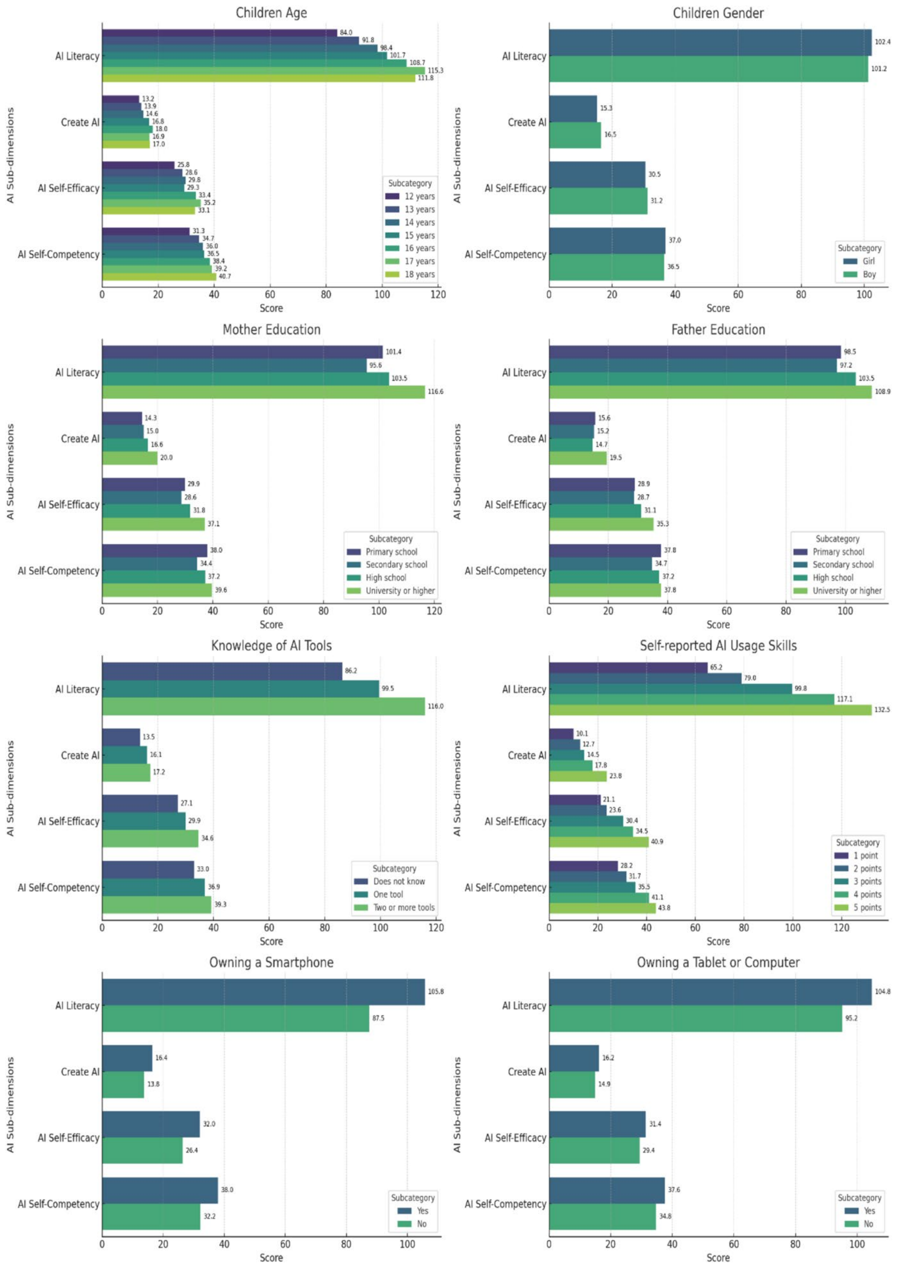

Fig. 5 Results of t-test and ANOVA test on mean scores of MAILS according to variables of children

significantly higher scores across all subscales ($p < 0.05$). Additionally, owning a tablet or computer had a significant effect on AI Literacy and AI Self-competency scores ($p < 0.05$), but no significant effect on the Create AI and AI Self-efficacy subscales ($p > 0.05$). For detailed statistical values corresponding to Fig. 5, see Supplementary Table 3.

3.3 Findings of Study 3

To test the reliability of the data obtained for this study, the Cronbach Alpha values for the subscales of the scale adapted in Study 1 were examined. The reliability values were calculated as 0.96 for the AI Literacy subscale, 0.94 for the Create AI subscale, 0.96 for the AI Self-efficacy subscale, and 0.90 for the AI Self-competency subscale, indicating reliable results.

The results of the t-test and ANOVA test, conducted to examine the relationship between healthcare professionals'variables and their AI literacy scores, are presented in Fig. 6.

When the analysis results related to the healthcare professionals'variables presented in the table were examined, it was found that age had a significant effect on the mean scores for all subscales ($p < 0.05$). Participants aged 21–26 had significantly higher mean scores compared to those aged 38–55. No statistically significant difference was found between gender and any subscale of AI literacy ($p > 0.05$). Healthcare professionals with a high school diploma or associate degree had higher mean scores than other groups. This created a significant difference in the Create AI and AI Self-efficacy subscales ($p < 0.05$). In terms of profession, significant differences were again found in the Create AI and AI Self-efficacy subscales, with health technicians identified as the group responsible for this difference ($p < 0.05$). Healthcare professionals who reported frequently or always using AI had higher mean scores compared to those who reported never or rarely using AI, and this created a significant difference in the AI Literacy and AI Self-efficacy subscales ($p < 0.05$). For detailed statistical values corresponding to Fig. 6, see Supplementary Table 4.

4 Discussion

AI technologies, which have spread to almost every area of modern society, lead to significant developments and changes. Individuals who are AI literate understand these technologies better, use them more effectively, know their potential and limitations, and fulfill the ethical responsibilities required by their use. Measuring AI literacy not only increases individuals'awareness of AI technologies, but is also important for developing and evaluating educational programs to address deficiencies in this area. Therefore, the current study aimed to adapt the MAILS developed by Carolus et al. (2023b) to Turkish.

Based on the validity and reliability analyses conducted in Study 1, it was found that the scale preserved its original structure and could be used as a valid and reliable measurement tool in Turkish culture. The validity of the scale was ensured by language validity, content validity and construct validity, and the Turkish adaptation of the scale showed acceptable level of fit.

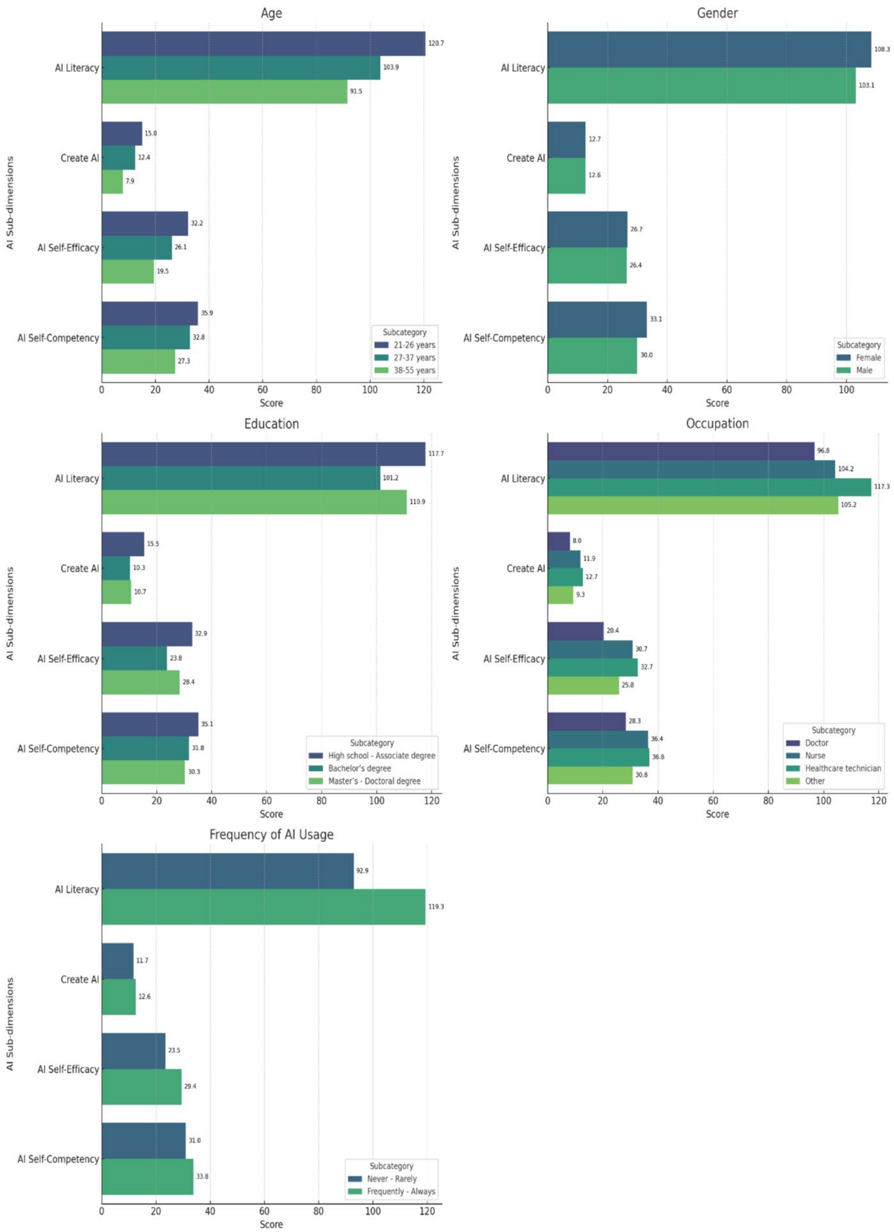

Fig. 6 Results of t-test and ANOVA test on average scores of MAILS according to variables of healthcare professionals

The construct validity values in the Turkish model of the scale (RMSEA $=0.08$; CFI $=0.90$; SRMR $=0.05$) are quite close to the values in the original model (RMSEA $=0.05$; CFI $=0.92$; SRMR $=0.07$) (Table 1). The Turkish model of the scale has a structure very close to the original scale and has high construct validity for measuring AI literacy.

Cronbach Alpha values were calculated to determine the reliability of the scale and test–retest reliability analyses were used. The t-test results calculated between the scores of the 27% upper and lower groups showed that there was a significant difference for all item score means ($p < 0.01$). The high correlation values obtained from the test–retest reliability analyses (ranging from 0.79 to 0.92) indicate that the scale provides consistent measurements. Cronbach Alpha internal consistency coefficients were found to be between 0.89 and 0.96 for the subscales, indicating high reliability. Table 3 shows that the Turkish model of the scale has higher Cronbach Alpha values in all subscales. This shows that the Turkish version of the scale is more reliable. The improvement observed especially in the Detect AI and AI Persuasion Literacy dimensions is remarkable.

In the Turkish version of the scale, there were positive and significant correlations ($p < 0.01$) between the total score and subscales. The Create AI subscale, as in the original scale, showed lower correlations with the other dimensions. This shows that the scale may not be a direct part of AI literacy, but is a skill related to it (Carolus et al., 2023b). Due to the modular structure of the scale, the Create AI subscale can be measured modularly when necessary. This result is consistent with the literature in which Create AI is generally not directly included in AI literacy (Dai et al., 2020; Kong et al., 2021; Long & Magerko, 2020). These studies treat"Create AI"as an independent skill. However, in some studies (Ng et al., 2021),"Create AI"is considered a subscale of AI literacy. These two different approaches explain why the correlation values are low but significant.

The AI Self Efficancy and AI Self Compitency dimensions in the original structure of the scale have been particularly preserved. While the Problem Solving sub-dimension measures the level of confidence in solving technical, cognitive and ethical problems encountered in artificial intelligence technologies on one's own, the Learning sub-dimension measures the ability to follow developments in the field of artificial intelligence. These two sub-dimensions also allow us to measure AI literacy in terms of behavioral competencies. It has also been emphasized in the literature that these skills increase the individual's desire and success in using technology in the long term (Carolus et al., 2023b; Cetindamar et al., 2022; Dai et al., 2020). The AI Persuasion Literacy sub-dimension in the AI Self Compitency dimension, which is related to the ability to recognize the impact and persuasive power of artificial intelligence, is important in terms of measuring whether individuals realize the impact of artificial intelligence. The emotion regulation sub-dimension is important in terms of distinguishing the scale from other scales and measuring the emotional effects that interaction with artificial intelligence technologies can create on individuals. Therefore, with this structure, the scale will be useful in understanding individuals'emotional and critical awareness towards artificial intelligence technologies and in developing them through education and awareness-raising activities. Carolus et al. (2023b) state that learning, problem-solving and emotion regulation skills increase individuals'self-confidence in using artificial intelligence; this supports both their desire to use it and their actual use of technology.

No major cultural and linguistic difficulties were encountered in the adaptation of the scale in terms of general content and meaning of the items. However, minor linguistic adjustments were made to some of the scale items (items 8, 11, 17, 24, 25 and 33) in order to ensure a clearer and more accurate understanding by Turkish-speaking individuals. These adjustments were made in accordance with the international standards recommended for the adaptation of the scale to the target culture (Hambleton & Patsula, 1999; ITC, 2019). During the adaptation process, the suitability of the scale to the Turkish language structure and cultural context was meticulously evaluated; In particular, cultural attitudes towards technology (e.g., trust, privacy concerns, usage habits) and social differences in the expression of emotions were taken into account (Van de Vijver & Tanzer, 2004). In this way, it was observed that potential cultural differences did not have a negative impact on the validity and reliability properties of the scale.

In this study, 1167 people from twelve regions of Turkey participated in the scale adaptation study. The original scale was tested with a sample of 300 participants. While this led to higher reliability values in this study (Büyüköztürk, 2018), it caused a small decrease in factor loadings and fit indices (CFI: 0.902, RMSEA: 0.086 in Turkish scale; CFI: 0.94, RMSEA: 0.05 in original scale). The limited adaptations of the MAILS in other cultures also coincide with the high reliability and internal consistency findings of our current study (Fu, 2025; Generale et. al., 2024; Tseng et. al., 2025; Mansoor et. al., 2024).

It is important to compare the findings of the current study with adaptation studies conducted in other cultures in order to evaluate the validity of the scale in the international arena more comprehensively. In China, Fu (2025) and Tseng et al. (2025) reported high internal consistency values in the Chinese context. Similarly, in the present study, the Cronbach Alpha values of the Turkish version of the scale were above 0.90 in all sub-dimensions, supporting that the scale is a reliable measurement tool in the Turkish context. Tseng et al. (2025), in their study conducted in the Taiwanese context, reported that especially the "Create AI" dimension stood out as an independent construct and showed low correlation with AI Literacy. Similarly, in this study, it was observed that the "Create AI" dimension was perceived as a skill independent of AI Literacy. Generale et al. (2024), in their study on 325 university students in the Philippines, made some of the statements of the scale more appropriate to the cultural context. In the Turkish version, direct translation and conceptual equivalence were achieved without such changes.

Mansoor et al. (2024) examined AI literacy in the context of cultural and academic variables in a study with 1800 university students in four different countries (Saudi Arabia, Egypt, India and Malaysia). In the study, significant differences were observed across countries, and it was determined that the AI literacy levels of students in Malaysia were higher compared to other countries. These results suggest that AI literacy may vary depending on education systems and technology policies of the country. This scale, which has been adapted into Turkish, will enable comparative analysis of AI literacy in different cultural contexts, including Turkey.

The findings of Study 2 and Study 3, which were conducted to provide resources for the use of the AI Literacy Scale in different demographic groups, also showed that the scale was valid and reliable. AI literacy skills are crucial for digital natives growing up in an environment increasingly influenced by AI technologies. In Study 2, the relationship between the AI literacy skills of 583 children between the ages of 12–18 and the variables of age, gender and parental education was examined. According to the findings of the study, there is a significant and positive relationship between AI literacy skills and children's age. The finding that AI literacy skills increase as children grow older is consistent with the view that cognitive skills increase with age as stated in Piaget's developmental theory (Berk, 2013). As children mature, they develop critical thinking and problem-solving skills necessary for understanding AI technologies.

Research reveals that the way children of different age groups perceive AI varies. Moon et al. (2024), in a study involving 825 Korean elementary school students, found that 6 th grade students had higher AI literacy compared to 5 th grade students. Similarly, Su (2024), in his study with 215 kindergarten children and 19 experts, showed that age improves AI literacy skills and older children have a better understanding of AI concepts. These studies reveal that children understand AI better as they get older, are able to interpret more complex ideas and analyze algorithms more consciously. Younger children often perceive AI as a magical, mysterious or fantastic technology, while older age groups develop awareness of more complex issues such as data privacy, ethics, algorithmic biases (Su and Yang, 2024). Long and Magerko (2020), in their article discussing important issues related to the design of the concept of AI literacy in the field of education, stated that as children get older, they better understand that AI systems are programmable and how to interact with these systems.

Another finding from Study 2 is that AI literacy skills do not vary according to gender. This result is in line with the findings of the studies conducted by Sanusi et al. (2022) and Dai et al. (2020). In these studies, it was determined that AI literacy skills did not differ by gender and both male and female students had similar levels of knowledge and skills.

Studies conducted in different countries reveal contradictory findings about the relationship between gender and AI literacy. In a study conducted with primary school students in South Korea (Moon et al., 2024), male students were found to have significantly higher levels of AI literacy. In contrast, a study conducted with middle school students in China (Wang et al., 2023) showed that female students'AI literacy was significantly higher than male students. In this study, female students scored higher in AI awareness, technology application skills and ethical responsibility, but male students performed better in creative problem solving and innovative thinking. Moreover, it has been reported in some studies that female students rate themselves lower in AI literacy when self-assessment methods are used, but no gender difference is observed when objective tests are applied (Laupichler et al., 2024). This suggests that women may tend to evaluate their own skills more critically.

Research on the reasons for the gender gap shows that socio-cultural factors, self-efficacy perception, differences in experience and educational policies are effective in different countries. Female students'access to technology, equal opportunities in education and the level of orientation to STEM fields vary from country to country (Wang et al, 2023). This may cause the opportunities that female students encounter in the process of developing AI literacy to differ. In some studies, it has been observed that female students evaluate their technological skills lower and have lower self-efficacy perceptions compared to males (Laupichler et al., 2024). It is stated that this perception may cause women to not consider themselves as competent in AI-related fields and therefore show less interest. Especially the fact that male students have the opportunity to meet programming and technology at an earlier age creates experience differences (Moon et al., 2024). This early exposure may contribute to male students developing AI literacy faster. In addition, educational policies implemented in some countries have been shown to have different effects on male and female students in terms of the way AI education is delivered (Sanusi et al., 2022). This provides an important indicator of how designing education systems to reduce or increase the gender gap can affect students'development in the field of AI.

In Study 2, AI literacy skills were found to be positively associated with the educational attainment of mothers and fathers. Parents with higher levels of education may provide their children with more educational support, a better learning environment, and access to technology. This indirectly affects children's AI literacy skills. Druga et al. (2019) examined the AI literacy of children from different social, economic, and cultural environments in their study of 102 children aged 7–12 from the USA, Germany, Denmark, and Sweden. The study interpreted that higher AI literacy skills of children in schools with high socioeconomic status were associated with more interaction with technological devices. This is consistent with the result in Study 2 that children with their own tablets or phones had higher AI literacy skills. Children with their own tablets or phones may become familiar with AI technologies earlier and gain more experience, and through these personal devices, they may develop independent exploration skills and increase their self-confidence in using AI technologies. Therefore, access to technology plays an important role in developing AI literacy in children (Long & Magerko, 2020).

The adoption of AI in the healthcare sector is increasing, and AI-based technologies are expected to impact not only patient care but also the working practices of healthcare professionals. In this regard, healthcare professionals must develop competencies in evaluating, interpreting, and effectively integrating AI-assisted health information into clinical practice. Furthermore, patients and caregivers also require AI literacy skills to make informed decisions regarding their health and well-being (Adegboye, 2024; Tursunbayeva & Renkema, 2023).

In Study 3, no statistically significant difference was found between gender and AI literacy levels. Similarly, research on medical and dental professionals in Saudi Arabia reported no relationship between gender and AI readiness levels (Aboalshamat et al., 2022). Likewise, a study conducted in Syria found that the rate of good AI application did not differ based on gender among physicians and medical students (Swed et al., 2022). However, some studies in the literature present findings that do not align with our results. For instance, Çapuk et al. (2025) found that male healthcare professionals exhibited higher AI literacy levels compared to female professionals. Similarly, Laupichler et al. (2024) reported that female medical students had significantly lower AI literacy levels than their male counterparts. The lack of a significant relationship between gender and AI literacy in this study could be attributed to sample characteristics, research methodology, educational background, or cultural factors. Furthermore, the absence of gender-based differences in AI literacy can be interpreted as a positive indicator of equal opportunities in professional development and education.

In Study 3, a significant relationship was found between age and AI literacy levels among healthcare professionals. The mean AI literacy scores of those aged 21–26 were significantly higher than those in the 38–55 age group. Similarly, Özçevik-Subaşı et al. (2025) identified a relationship between age and AI literacy among pediatric nurses in Türkiye, reporting that AI literacy levels decreased with age. A study conducted in Syria also found that participants aged 21–30 had a higher rate of good AI application compared to other age groups. Additionally, graduates classified as students demonstrated better AI application rates than residents and other graduate categories (Swed et al., 2022). Another study on physicians and medical students revealed a negative correlation between age, years of experience, and familiarity with AI applications in healthcare. The study found that older physicians with longer experience were less familiar with AI and its medical applications (AlZaabi et al., 2023). Furthermore, when analyzed from a generational perspective, Hoşgör and Bozkurt (2023) found that Generation Z (born between 1997 and 2012) was more familiar with AI compared to Generation X and Y. These differences may stem from generational factors, professional experience, exposure to AI in education, and attitudes toward technology. Overall, the literature supports our study's findings, suggesting that younger adults tend to demonstrate higher AI literacy skills and are more proficient in engaging with AI-based technologies.

In Study 3, healthcare professionals with a high school or associate degree had higher mean AI literacy scores compared to other groups. Additionally, a statistically significant difference was found between AI literacy levels and healthcare technicians, indicating a profession-based variation in AI literacy. Zaleski et al. (2024) found that the readability level of AI-generated programs corresponds to a university-level understanding. In contrast, Çapuk et al. (2025) reported that healthcare professionals with postgraduate degrees had significantly higher AI literacy scores. However, nurses, midwives, and healthcare technicians were found to have lower AI literacy scores compared to physicians. In Saudi Arabia, medical and dental professionals exhibited low AI readiness levels, with dentists demonstrating significantly better AI readiness than medical professionals (Aboalshamat et al., 2022). Similarly, Alelyani et al. (2021) found that radiologists were more inclined to read about AI than other specialists. In an Italian study, Bellini et al. (2022) found that healthcare professionals working in clinical laboratories had limited knowledge about AI and big data applications. However, no significant differences were observed in AI usage among biologists, physicians, technology specialists, laboratory managers, and other professionals. Given the diverse findings in literature, variations in sample sizes, the limited number of studies, and methodological differences could explain the inconsistencies. However, the impact of education level and age on AI literacy skills remains evident, reinforcing the role of educational background and professional exposure in AI competency.

In this study, the majority of healthcare professionals reported that they frequently or always use AI. However, findings from previous studies in the literature indicate that healthcare professionals do not use AI applications at a sufficient level or frequently (Özçevik Subaşı et al., 2025; Bellini et al., 2022; Ahmed et al., 2022;

Swed et al., 2022). Additionally, Chen et al. (2022) highlighted that while most physicians and medical students are aware of clinical AI applications, they lack sufficient experience and knowledge in utilizing these technologies effectively.

Studies indicate that AI literacy research among healthcare professionals remains limited. Many healthcare workers lack the necessary knowledge and skills to effectively utilize AI technologies, which may hinder the proper and efficient integration of AI in healthcare. This limitation underscores the need for further research focusing on AI literacy among healthcare professionals to ensure responsible and effective use of AI in medical practice.

5 Practical implications

This study aimed to examine the impact of AI literacy on individuals from different age groups and occupational fields by adapting the MAILS into Turkish. The analysis of the psychometric properties of the adapted scale in Study 1 shows that the scale can be used as a valid and reliable measurement tool in the Turkish context. The findings from Studies 2 and 3 reveal that the scale can be used as a functional tool for assessing AI literacy in different disciplines and application areas.

This study has revealed the levels of AI literacy in different age and occupational groups in Turkey. However, longitudinal studies are needed to monitor the changes in these competencies over time. In addition, in line with the findings, MAILS-based training programs should be developed, especially for children and healthcare professionals. It is recommended that practical trainings that will support the conscious and ethical use of AI be designed by conducting comparative analyses appropriate to the needs of different groups.

The adaptation of the MAILS into Turkish was an important step towards assessing AI literacy in the fields of education and health. In the field of education, the scale can be used to determine the AI literacy levels of students, teachers and preservice teachers (Ng et al., 2022; Wang et al., 2023) and to evaluate the effectiveness of educational programs to be developed in these fields (Laupichler et al., 2024). When designing digital learning platforms, STEM-based courses and educational materials to develop AI literacy, the dimensions of the scale can be guiding. The ethical awareness component of the scale can be a reference point for policy makers to avoid issues such as the effects of AI systems on society, misinformation and prejudices (Johnson & Verdicchio, 2017).

The adaptation of the MAILS (Carolus et al., 2023b) into Turkish will serve as a valuable tool for researchers, practitioners, and educators in shaping the content of professional development and training programs related to healthcare professionals’interactions with AI-supported systems. This scale can enables the assessment of AI literacy levels among different groups of healthcare professionals in AI-assisted processes. Furthermore, it can serve as a guide for improving educational quality, addressing concerns regarding academic integrity, and managing ethical challenges (Tseng et al., 2025). Based on these evaluations, patient safety can be enhanced, and the quality of healthcare services can be improved.

The findings of Study 2 reveal that children's AI literacy skills increase with age and that children's access to AI technologies is an important factor in developing their AI skills. Children's cognitive development levels should be taken into account when designing AI education programs for children. An AI education that starts with exploration through games at a young age should be reinforced with more structured coding activities in the middle age group, and analytical thinking skills for ethical and advanced AI applications should be developed in young people. To reduce inequalities in access to technology, technology laboratories should be established in economically disadvantaged regions, public AI learning centers should be created, and mobile AI education platforms should be developed.

The findings of Study 3, which was conducted for healthcare professionals, revealed that AI literacy differs according to age, occupational groups and education level. Accordingly, AI training programs tailored to different professional groups and age groups should be developed to enhance the effective use of AI-based systems in hospitals and healthcare institutions. Additionally, AI literacy courses should be integrated into all healthcare education programs.

These practical applications will contribute to raising technology-compatible individuals and professionals by supporting the conscious and effective use of AI technologies in education and health fields.

6 Conclusion

In conclusion, during the adaptation of the scale into Turkish, language and content validity were ensured through expert opinions, and construct validity was tested through confirmatory factor analyses. Within the scope of the reliability studies, Cronbach Alpha values were found to be high, and the test–retest analysis results also showed consistency. The findings of Study 2 and Study 3, conducted with healthcare professionals and children aged 12–18, indicate that AI literacy may vary depending on demographic variables. In particular, age and education level were found to be factors affecting AI literacy, while gender did not have a significant effect on these skills. Consequently, in today's world, where AI technologies are becoming increasingly prevalent, this scale for measuring AI literacy is accepted as a valid and reliable tool for Turkish-speaking individuals. The adaptation of the scale into Turkish will contribute to future research and educational programs related to AI literacy.

In this study, individuals between the ages of 12–74 who live in Turkey, speak Turkish and can read and write were determined as the population and the Classification of Statistical Regional Units (İstatistiki Bölge Birimleri Sınıflandırması-İBBS) was taken into account in the sample selection. The fact that Turkey is a country with a young population (TÜİK, 2023) and that the age distribution within the scope of the study covers a wide range shows that the findings obtained are compatible with the general demographic structure. However, there are limitations in our study such as the higher number of female participants compared to male participants and the higher number of individuals with higher education. These factors may limit the generalizability of the results. In future studies, a more balanced distribution of gender balance and education level will increase the generalizability of the results to a wider population.

In addition, the participation of health workers was more limited compared to the participants in the education field. This situation is presumed to stem from the low voluntary participation of healthcare professionals due to their intense workload. Consequently, the sample size in the healthcare sector could not be expanded during the data collection process. In future studies, creating a larger and more balanced sample in the health sector may provide an opportunity to examine the differences of AI literacy in the occupational context in more depth.

No linguistic or conceptual difficulties were experienced during the scale adaptation process and the scale was found to be psychometrically valid and reliable. However, applying the scale in different occupational groups and examining how AI literacy differs in the occupational context can provide an important contribution for future research.

The data collection tool used in this study is a self-report-based scale. Although self-report methods are practical and widely preferred because they provide data based on individuals'own perceptions and evaluations, they also have certain limitations. Participants'responses may be shaped by effects such as social desirability bias, cognitive distortions, or higher or lower perceptions of their technological competence (Paulhus & Vazire, 2007). This may limit the consistency of the findings obtained from the scale with actual behaviors. In addition, since self-reports only measure individuals'"intentions"and"perceived competences,"they may not always accurately reflect their actual technology use behaviors. Therefore, future studies may include observation, performance-based tasks, or mixed-method approaches to assess AI literacy more holistically.

This study is limited to the adaptation of the MAILS into Turkish and its application in Turkey; therefore, no evaluation of how the scale functions in different cultural contexts was made. By conducting multicultural comparison studies including Turkey, the effect of cultural factors on AI literacy can be investigated.

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S.T.H.: Data Analysis, Data Collection, Writing.

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Data availability The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethical approval The study received ethical approval from the Scientific Publication and Ethics Committee of Çankırı Karatekin University (Decision No. 11, dated 17/01/2024).

Informed consent All participants were informed about the study's purpose and content, and verbal informed consent was obtained. For participants under 18 years of age, parental consent forms were secured. Participation was voluntary, and only those who completed the survey were included in the study.

Competing interests The authors declare no competing interests.

Use of artificial intelligence tools During the preparation of this manuscript, artificial intelligence (AI)-assisted tools, including ChatGPT and DeepL, were utilized for language editing and translation purposes. The authors reviewed and edited all AI-generated content to ensure accuracy and coherence.

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