Humanities and Social Sciences Communications

Article in Press

https://doi.org/10.1057/s41599-026-07838-0

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Received: 17 January 2025

Accepted: 26 May 2026

Cite this article as: Kaçmaz, C., Çelik, O.T. Development of an artificial intelligence competency scale for early childhood educators (ACES). *Humanit Soc Sci Commun* (2026). https://doi.org/10.1057/s41599-026-07838-0

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Development of an Artificial Intelligence Competency Scale for Early Childhood Educators (ACES)

This study aims to develop an AI competency scale for Early Childhood Education (ECE) teachers and to conduct its validity and reliability analyses. In the study, the deductive method was used to develop a scale. The sample consisted of 508 ECE teachers. A 31-item draft form was created based on a literature review and expert opinions. Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Cronbach's Alpha reliability analysis were conducted for validity and reliability. Item-total test correlations, item discrimination power for the lowest and highest 27% groups, convergent validity, content validity, discriminant validity, and test-retest reliability were examined. As a result of validity and reliability analyses, 6 items were removed from the scale. The findings supported a 25-item, four-factor structure of the ACES scale, including AI Knowledge, AI Skills, Attitude towards AI, and Ethics in AI Usage. This structure explains 77.03% of the variance. The Cronbach's Alpha internal consistency coefficients were calculated as .91 for AI Knowledge, .94 for AI Skills, .92 for Attitude towards AI, .84 for Ethics in AI Usage, and .93 for the scale overall. The findings provide initial psychometric evidence for the self-report-based ACES scale as a tool for assessing ECE educators' perceived AI competencies.

Keywords: Artificial Intelligence, Competence, Early Childhood Education, Teacher, Validity Analysis, Reliability Analysis

Introduction

Artificial Intelligence (AI) is a computer system capable of perceiving, reasoning, and learning like humans (Kewalramani et al. 2021). Today, AI-based technologies are widely utilized across various fields, including business, healthcare, and education. Within the educational domain, these technologies enhance students' learning experiences while fostering collaboration and creativity in the classroom. Many countries have recognized AI policies and industries as critical technologies for future development. Furthermore, advancing AI technologies is regarded as a fundamental skill set that individuals must acquire in the future, underscoring its importance (Lim, 2023). AI technologies typically uses for support and enhance student learning, enriching teaching practices and students' learning experiences with technology-driven capabilities (Chen et al. 2019).

Despite the potential of AI to transform education, how to integrate AI practices into the teaching process and what skill sets teachers should have as AI is a new field remain important questions to be answered (Ding et al. 2024; Velander et al. 2024). In recent years, there has been limited research to develop theoretical explanations and evidence-based measurement tools to frame teachers' AI competencies (Delcker et al. 2024; Kim and Kwon, 2023; Ng et al. 2021). As a rapidly developing field, academics, policymakers, school administrators, and teachers face challenges identifying and securing AI competencies. In addition, in early childhood education settings with highly diverse pedagogical practices, it is more challenging for early childhood educators to identify competence areas. Pedagogical approaches of early childhood educators require specialized knowledge, skills, and attitudes based on the developmental characteristics of

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children. To fully utilize the potential of AI in education, ECE educators need various skill sets. In this context, this study aims to develop a measurement tool to determine the AI competencies of ECE educators based on previous AI competence and literacy frameworks. AI competencies for ECE educators were conceptualized in the context of AI literacy and based on the understanding of relevant experts. Identifying ECE educators' AI competencies can guide the identification of teacher needs and the design of professional development programs aligned with these needs. It may also contribute to adding competencies for effective AI practices to ECE educators' preparation programs. Moreover, this research can potentially contribute to the AI teacher competencies research line.

Literature review

In recent years, developments in AI have excited educators, researchers, and policymakers, and a tremendous interest in research in this field has emerged. In this line of research, theoretical and conceptual discussions and evaluations based on stakeholder views are predominant. However, there are research gaps in evidence-based practices on how to integrate AI into educational settings and what its current contributions and negative impacts are.

The potential contributions of AI to educational processes are one of these research lines. AI offers various innovative educational solutions, improving learning processes and making them more inclusive. First of all, AI eliminates the limitations of school hours by providing students with accessible learning opportunities around the clock, enables students to receive support when they need it through chatbots (Devi et al. 2022), reduces teacher workload, provides students with personalized learning experiences, and facilitates assessments (Alwaqdani, 2024; Ifenthaler et al. 2018). Moreover, AI tools can be used for analyzing student data, planning, and decision-making for administrative purposes (Zhang and Aslan, 2021). In addition, it is thought that AI can provide potential benefits in ECE, such as recording children's learning processes and behaviors, increasing creativity and imagination, creating virtual learning environments, providing customized learning experiences, helping children better understand complex topics, and connecting teachers, children, and parents remotely (Ramu et al. 2022). AI applications help children's neurocognitive development, small-muscle skills, hand-eye coordination, and increased focusing time (Chen et al. 2019). In addition, it has been found that AI significantly improves children's concepts related to AI, machine learning, computer science, and robotics, and skills such as creativity, emotion control, collaborative inquiry, literacy skills, and computational thinking (Su and Yang, 2022). All these potential contributions of AI create new roles and competencies for teachers. Teachers are the primary users of AI in educational settings. As critical elements for effective design and implementation and ethical use, teachers should be supported to benefit from the potential contributions of AI (Miao and Cukurova, 2024).

Some studies on the use of AI in education also focus on teacher competencies and professional development (Chiu et al. 2024; Çelik, 2023; Delcker et al. 2024; Long and Magerko, 2020). Teachers can use AI tools in educational practices to promote student achievement and development and align their practices with learning goals (Alwaqdani, 2024). Teachers are the critical element in fully utilizing the possibilities of AI in education and integrating it into teaching processes. However, research on teachers' AI competencies is still in its infancy, and our

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understanding of this area is still limited. There are urgent calls for tailored professional development programs to support teachers' AI skills (Ding et al. 2024; Kim and Kwon, 2023; Lee and Perret, 2022). Recently, Ding et al. (2024) investigated the effectiveness of a case-based AI literacy support program for integrating AI applications into teaching processes. The results showed that the program supported teachers' AI literacy in the knowing and understanding dimension. In addition, the researchers advocated the need for teachers' AI literacy development for the integration of AI into education.

Another important research area in AI is student competencies (Huang, 2021; Sanusi et al., 2022). There is a growing interest in research on children's AI competencies, especially in the context of ECE (Kewalramani et al. 2021; Lee et al. 2024). AI-based education is now offered with concrete materials and interactive methods for older students and preschool children (Chen et al. 2019; Su and Yang, 2022). In some developed countries, AI-based education is included in national curricula from 4-5 (Ali et al. 2021). Some research (Su et al. 2023) suggests that young children's AI literacy can be improved. However, a lack of curriculum design, teaching guidelines, and teacher shortages are significant challenges for teaching AI in ECE. However, teaching AI to young children seems challenging without effective integration of AI, teacher competencies, evidence-based practices, and appropriate behavioral targets.

Researchers also address teachers' attitudes, use, readiness, and intentions toward AI. Galindo-Domínguez et al. (2024) determined that significant relationships exist between teachers' digital competencies and their attitudes toward AI in their research with Spanish teachers. However, the researchers found that although teachers showed high interest in AI, they had low levels of personal experience. In a study on Nigerian teachers, Ayanwale et al. (2022) found that teachers' confidence in teaching AI predicts teachers' intention, and their interest in AI predicts their readiness for AI. In addition, research has shown that positive attitudes toward AI are associated with more frequent use of AI in educational processes (Kurshumova, 2024; Yue et al. 2024). In another study investigating teacher attitudes towards using AI in ECE (Mohammed, 2023), teachers rated AI for ECE settings as promising due to its potential to provide personalized education and promote children's development. However, teachers expressed concerns about privacy and ethics.

An important line of research on AI is the ethical debate about using AI in educational settings. Privacy practices that collect information about students' and teachers' preferences and conduct surveillance, bias, and discrimination are critical concerns in AI discussions (Akgun and Greenhow, 2022). AI is considered more destructive than other digital tools. Therefore, teachers need to be more careful and competent about ethics, security, and privacy (Falloon, 2020). Younger children have less awareness about the use of AI and its basic working principles. This makes them more vulnerable. Ethical use is an important dimension of teacher competence in AI, especially in ECE.

Although developments in AI in recent years have created great excitement in ECE with the innovative solutions it brings to educational processes, teacher competencies play a critical role in effectively integrating this technology. Using this technology in a pedagogically meaningful and appropriate way for children's developmental levels depends on the competencies of early

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childhood educators. In this context, it is important to comprehensively define and frame teacher competences for the effective use of AI in educational processes in ECE.

Conceptual Framework

There is a common understanding towards the acceptance of the potential contributions of AI with its integration into education. However, the critical point about integration is how to integrate AI applications into natural classroom environments meaningfully (Ding et al. 2024). In this context, teachers have a critical role in the responsible and effective use of AI in education (Çelik, 2023; Delcker et al. 2024). In addition, teachers are the driving force in expanding the use of AI in educational environments (Zhang et al. 2023).

There are two important areas of discussion about AI applications in ECE. One is AI teaching, and the other is teaching with AI. Numerous studies have shown that children can acquire basic knowledge and skills about AI in the early period when the right methods and practices are used (Bers et al., 2014). The second area of discussion, teaching with AI, is also necessary for teaching AI in ECE and is closely related to the competencies of ECE teachers. However, the unique aspects of the ECE context and the developmental characteristics of children distinguish teacher competencies in ECE from other school contexts. Firstly, children who do not have abstract thinking skills in the early years need more concrete experiences and social interactions to develop social skills. In this context, it is important to underline the need for human interaction when using AI in teaching with AI in ECE due to the limitations of AI in interpreting social cues (Bukahri et al., 2024). Indeed, ineffective use of AI may limit children's interaction with adults and peers and hinder the development of their social competencies (Chen and Lin, 2024). In addition, studies report that using digital technology in early childhood education leads to attention problems in children, triggers aggressive behaviours, inadequate physical activity, and sleep problems (Mustafaoğlu et al., 2018). Another important issue in ECE is the integration of AI into the teaching process with appropriate pedagogical approaches. The basic pedagogical approach in ECE is game and discovery-based learning. AI can enrich children's natural developmental processes through personalised learning experiences and play-based learning opportunities (Öztürk, 2025). Finally, the ethical use of AI in ECE is a major concern for parents, teachers, and policymakers, as young children have limited competencies to evaluate AI tools critically. Children may not have sufficient resources to recognise biased facts or correct inaccurate data (World Economic Forum, 2022). Moreover, using AI in ECE may involve collecting and analysing confidential and sensitive information about children (Wu, 2024). Considering these issues, it is an important competence area for teachers in ECE to take necessary precautions about data security and to have knowledge about ethical use. As a result, teacher competences in the selection and ethical use of appropriate pedagogical methods to support the holistic development of children with AI in ECE emerge as a necessity, and teachers need ECE-specific competences for teaching with AI.

For AI-based tools to facilitate teaching and learning and create effective learning environments, teachers should have the necessary knowledge, skills, and attitudes about AI (Chai et al. 2024; Chiu et al. 2024). However, research on teachers' AI competencies is still early, and existing research cannot provide a holistic perspective on AI competencies (Delcker et al. 2024;

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Chai et al. 2024). In addition, research on teacher AI competencies is at an early stage, focusing on theoretical explanations, professional discussions, and qualitative research. Moreover, there is no recognized AI competence frameworks and measurements (Chiu et al. 2024).

The first AI-related measurement tools focused on general attitudes, concerns, and preparedness. For example, Schepman and Rodway (2020) developed the "General Attitudes Towards Artificial Intelligence Scale (GAAIS)". This scale determines the positive and negative perceptions of individuals towards AI. Wang and Wang (2022) focused on measuring anxiety towards the use of AI. For educators, Üzüm et al (2024) developed the scale of teacher perceptions of AI use. This scale consists of dimensions of learning perception, teaching perception, and ethical perception. Although these scales help measure general attitudes toward the use of AI, they are far from measuring teachers' AI competencies.

Previous digital competencies and established frameworks on ICT competencies find strong support in developing an AI competence framework for teachers (Mikeladze et al. 2024). The digital competence areas of educators at all levels of education have been identified in the European Framework for the Digital Competence of Educators (DigCompEdu) and organized under six main headings. These are professional engagement, digital resources, teaching and learning, assessment, and facilitating learners' digital competence (Redecker, 2017). The SELFIEforTEACHERS scale was developed based on DigCompEdu, the European conceptual framework for measuring educators' digital competencies (Economou, 2023). In DigComp 2.2, the current version of the digital competence domains for all individuals, AI-related competencies have been added, especially in information and data literacy, communication, collaboration, and security (Vuorikari et al. 2022). However, there are no AI-related indicators in SELFIEforTEACHERS. An international framework proposed for teachers' AI competencies is the AI competence framework proposed by UNESCO (2024) for K-12 teachers. This framework has five competence areas: human-centered mindset, AI foundations and practices, AI pedagogy, AI ethics, and AI for professional development. This draft framework continues to be developed.

Another widely used framework for teachers' AI competencies is the Technological Pedagogical Content Knowledge (TPACK) framework. In Kim and Kwon's (2023) research on primary school teachers' AI competencies in South Korea, a 22-item AI competencies scale was derived from the TPACK framework. However, these competencies cover teachers' competencies in teaching AI to young children. Recently, Celik (2023) developed a scale to measure teacher knowledge about using AI-based tools in education within the TPACK framework. This scale was extended by adding an ethical dimension to the TPACK framework. Falloon's (2020) digital competencies framework is also used to assess teachers' AI competencies. In this context, Chiu et al. (2024) developed the "Teacher Artificial Intelligence (AI) Competence Self-efficacy Scale (TAICS)". The scale is based on Falloon's (2020) teacher digital competence framework, which adds two sets of competencies, personal-ethical and personal-professional, to TPACK. This scale, developed for K-12 teachers, comprises AI knowledge, AI pedagogy, AI assessment, AI ethics, human-centered education, and professional engagement dimensions. More recently, Delcker et al. (2024) developed the AI Competence Educators scale based on a literature review and expert opinion. The dimensions of this scale are Theoretical Knowledge about AI, Legal Framework and

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Ethics, Implications of AI in Education, Attitude towards AI, Teaching and Learning with AI, and Ongoing Professionalisation.

There are criticisms of existing frameworks for teachers' AI competencies. Although these frameworks are valuable for using teacher AI competencies, it is difficult to use one of these frameworks as a blueprint due to its shortcomings (Delcker et al. 2024). Firstly, the majority of these frameworks focus on general attitudes and perceptions (Schepman and Rodway, 2020; Üzüm et al. 2024; Wang and Wang, 2022), so it is difficult for teachers to capture the details in AI competencies. Secondly, although the internationally proposed frameworks specifically for AI competencies provide a comprehensive theoretical overview, they do not provide a valid measurement tool. Third, AI competencies largely overlap with ICT utilization or digital competence areas. However, these competence domains are insufficient to present AI competencies comprehensively. Fourth, newer scales (Chiu et al. 2024; Delcker et al. 2024) are far from capturing dynamic AI competencies as a rapidly developing field. Existing frameworks have limitations for measuring teacher competencies in the ECE context. For example, the DigCompEdu framework focuses on general digital competences, and the competence indicator related to AI is quite limited (Vuorikari et al. 2022). However, unlike digital technologies, AI can perform more specific functions that are the product of human-like intelligence, such as processing information, inferring meaning, and creating patterns (Stamova and Draganov, 2020). Therefore, DigCompEdu does not focus on teacher competencies in the ECE context, reflecting the nature of AI. Similarly, TPACK provides a general framework that integrates teachers' technological, pedagogical, and domain competences but does not reflect the developmental characteristics of children and ECE-specific pedagogical practices in the ECE context (Çelik, 2023). In addition, Falloon's (2020) Digital Competence Model does not provide a framework for pedagogical practices in the ECE context, although it includes ethical and professional dimensions in TPACK.

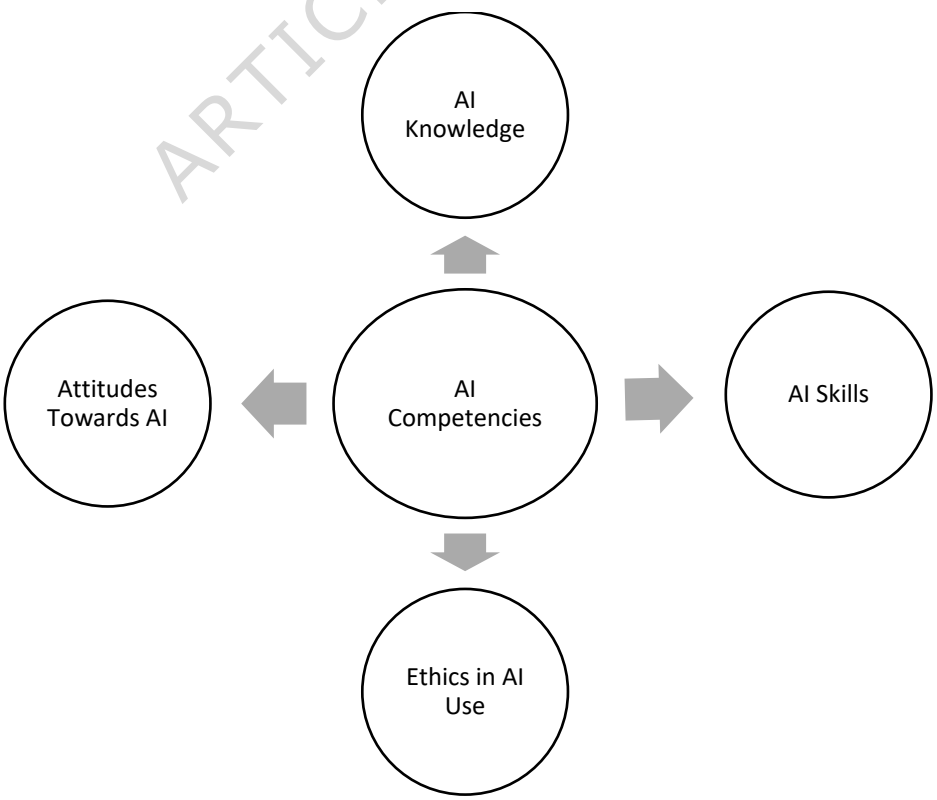
Existing research shows that teachers have a limited understanding of the application of AI in education and that they acquire knowledge about AI through incidental learning (Velander et al. 2024). In addition, since teachers have not received any training on AI, the complexity and abstractness of AI make it difficult for teachers to develop an understanding of the integration of AI into educational environments (Kim and Kwon, 2023). In addition, since the use of AI for educational purposes is still in its infancy (Üzüm et al. 2024), teachers lack sufficient practical knowledge and real experiences. In this context, we propose a competency framework based on AI literacy that covers more fundamental areas for ECE teachers to use AI in educational settings.

The competencies related to AI are also defined as AI literacy (Velander et al. 2024). In addition, measurements based on AI literacy allow for a better understanding of user competencies in the use of AI (Wang et al. 2023). AI literacy is having reasonable and sufficient skills to use AI applications and tools effectively and ethically (Ng et al. 2021). In the educational context, teachers' AI literacy is characterized by the necessary knowledge and skills, methods of interacting collaboratively with AI, and the capacity to evaluate the pedagogical and ethical implications of AI integration efforts in teaching and learning (Ding et al. 2024). In addition, in previous AI competency studies, an approach that focuses on technical details related to AI has been adopted by approaching the subject from an engineering perspective (Chiu et al. 2024). However, we argue that it would be more beneficial to focus on competence areas covering more fundamental areas

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rather than AI's technical details for teacher competencies. In the other case, with the rapid developments in AI, we will have to constantly change our focus on teacher AI competencies. In this context, AI literacy provides a good framework for capturing teachers' core AI competencies.

Based on AI literacy frameworks (Ding et al. 2024; Wang et al. 2023; Wilson et al. 2015; Su and Zhong, 2022), extensive literature review, and consideration of pedagogical approaches specific to the ECE context, we conceptualise teachers' AI competencies as a four-dimensional construct (Figure 1). In addition to this conceptualization based on empirical literature, the structure and indicators are grounded in Piaget's cognitive development theory and Vygotsky's sociocultural theory, which are consistent with child-centered ECE contexts. According to Piaget's cognitive development theory, children are not passive recipients of the world; they learn by exploring and constructing knowledge (Piaget, 1973). In this context, ECE teachers' AI competencies are positioned to provide concrete experiences for children in ECE during the concrete operations stage and to support their active participation. The most fundamental concept of Vygotsky's sociocultural theory is the zone of proximal development. The zone of proximal development is the area between a child's current actual level of development and the potential area of development that can be achieved through social interaction with adults or more capable peers (Kaya, 2010). Accordingly, we consider ECE teachers' AI competencies to be an element that supports children's collaborative learning and development.Within this framework and in light of theoretical explanations, teachers' AI competencies are defined as the ability to implement and use AI tools in educational processes, possess foundational knowledge to use AI tools in teaching effectively, maintain positive attitudes toward AI, and recognize responsibilities related to ethical use.



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Figure 1. ECE's AI competence framework

The knowledge dimension related to AI competencies refers to teachers' awareness of AI tools and having professional knowledge to use these tools in the educational environment. Within the scope of the knowledge dimension, teachers are also expected to know the basic principles of AI and to be able to select appropriate AI tools that can support the development of students (Chiu et al. 2024). Skill is related to the ability to carry out processes (Vuorikari et al. 2022). In this context, the skill dimension refers to the ability of ECE teachers to integrate their knowledge of AI tools and pedagogical competencies to carry out appropriate activities to support the development of children in the educational environment. The attitude dimension represents ECE teachers' perspectives, feelings, and thoughts about using AI-based tools in educational environments. Teachers should be open to and interact with AI (Delcker et al. 2024). With a positive attitude, teachers are also expected to participate in professional development activities to use AI effectively. Finally, the ethical dimension is defined as the ability to be aware of the risks and responsibilities in the use of AI technologies (Wang et al. 2023). This dimension defines the principles that include responsible and transparent approaches that respect children's rights, principles of justice, and social values in the development and implementation of AI systems, as well as taking into account the possible effects of using these technologies. We argue that these four dimensions will frame the AI competences of ECE teachers well. Firstly, integrating AI into educational settings is still in its infancy. In this context, AI literacy focusing on more general competences may offer a feasible framework for teacher competences in ECE. Second, previous research underlines ECE teachers' knowledge and skills for integrating information and communication technology (ICT) in their classrooms and their attitudes towards ICT (Kerckaert et al., 2015; Yang and Hong, 2022). Therefore, these dimensions are represented in AI competences. Third, it is largely the teacher's responsibility to create environments and activities appropriate to children's developmental characteristics in the ECE environment. In this context, how to use AI pedagogically rather than its technical aspects is closely related to teachers' knowledge, skills, and ethical use. Finally, a positive attitude is an antecedent for AI use and professional development in the ECE environment (Kerckaert et al., 2015).

The teacher is the key factor in structuring learning processes, integrating technology, and implementing activities in ECE. Understanding teacher competencies is vital to identifying teachers' professional development needs in this field and to evaluating the impact of these competencies on educational processes. In addition, there is a need to develop valid and reliable measurement tools to expand the research framework on AI competencies. This study aims to develop a self-report-based scale to assess AI competencies for early childhood educators. In particular, this scale, which will be used to assess teachers' knowledge, skills, attitudes, and ethical beliefs about using AI-based tools in early childhood education, aims to guide educators to use AI technologies effectively.

Methods

The teacher is the key factor in structuring learning processes, integrating technology, and implementing activities in ECE. Understanding teacher competencies is vital to identifying teachers' professional development needs in this field and to evaluating the impact of these

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competencies on educational processes. In addition, there is a need to develop valid and reliable measurement tools to expand the research framework on AI competencies.

In the process of developing a scale to measure the AI competencies of ECE teachers, the following stages, which are widely recognized in the literature (Carpenter, 2018; DeVellis and Thorpe, 2021), were followed: (1) defining the theoretical construct, (2) generating an item pool, (3) content validity, (4) pilot study, (5) sample and collecting data, (6) validity and reliability analyses, and (7) reporting.

Phase 1: Defining the theoretical construct

In the first stage, the AI competencies of ECE teachers were formalized as a construct. In this context, AI competencies were framed based on previous empirical research and theoretical explanations (e.g., Ding et al. 2024; Piaget, 1974; Su and Zhong, 2022), and similar scales (Chiu et al. 2024; Çelik, 2023) were critically evaluated. Detailed explanations regarding how the current scale fills the gap in the field are provided in the introduction section.

Phase 2: Generating an item pool

At this stage, we first reviewed the literature on teachers' digital competencies, AI competencies, AI literacy, ICT competencies, and the use of AI tools in educational environments to identify behavioral indicators appropriate to the dimensions within our conceptual framework. The criteria we considered when determining behavioral indicators (Bandalos, 2018; Johnson and Morgan, 2016) are as follows: being appropriate to the structure, being appropriate to the target audience, being distinctive, not containing ambiguity, and being clear and understandable. During the scale development process, it is recommended that the item pool contain at least 2-3 times the number of items targeted (DeVellis and Thorpe, 2021). Additionally, Zwick and Velicer (1986) stated that an implicit feature should have at least three indicators. In line with these recommendations, we decided that the structures we specified in the conceptual framework should have at least three indicators. In the first phase, 28 items were added to the draft scale form as a result of the literature review.

In the second stage, expert opinions were sought to refine the items and gather suggestions for new ones. Two associate professors in educational sciences, one professor, and two associate professors in early childhood education were consulted through a semi-structured interview focusing on the scale's structural components. Based on their feedback, six additional items were included, and revisions were made to the existing items. For example, the expression "basic principles" was added to the item "I know the application areas of artificial intelligence-based tools" in line with the expert opinion. In another correction, the statement "I have difficulty in integrating artificial intelligence-based tools into the teaching program", which was written as a reverse item in the scale structure, was rearranged positively as "I know how to integrate artificial intelligence-based tools into the teaching program". In the last stage, 34-item draft scale form was created as a result of the interviews with the experts. The draft scale was designed as a 5-point

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Likert scale (1: strongly disagree to strongly agree). A 5-point Likert scale is recommended for new scales (Likert, 1932).

Phase 3: Content validity

At this stage, content validity was assessed with input from five experts—four specializing in early childhood education and one in ICT. Expert feedback is a recognized method for determining content validity (Karasar, 2005). The experts evaluated each item as "essential," "useful but not essential," or "not essential" (Lawshe, 1975). For the evaluation, an "expert evaluation form" was sent to the experts via e-mail (see Appendix 1; Ermis-Demirtas, 2018). The feedback from the experts was evaluated using the following formula in the CVR calculation.

$$CVR = \frac{ne - (\frac{N}{2})}{(\frac{N}{2})}$$

In the formula, "*ne*" denotes the number of experts who evaluated the scale item as "essential," and "N" denotes the total number of experts who made the evaluation. The content validity ratio (CVR) was calculated for each item, ranging from +1 to -1. Items with a CVR between 0 and -1 were deemed to lack content validity and were removed from the scale (Ayre and Scally, 2014; Yeşilyurt and Çapraz, 2018). After this calculation, three items with CVR values between -0.2 and -1 were removed from the draft scale, and the final draft scale, consisting of 31 items, was obtained. Detailed content validity evidence, including item-level CVR values and S-CVI, is presented in Appendix 2.

Phase 4: Pilot study

At this stage, a pilot study was conducted to determine how the draft scale items were perceived by the participants and whether they were perceived as intended by the researchers. The pilot study was conducted with 15 teachers similar to the characteristics of the group in which the scale would be applied, and the clarity and comprehensibility of the scale items were evaluated. All participants provided positive feedback.

Phase 5: Sample and collecting data

The study participants were teachers in ECE centers affiliated with the Ministry of National Education in Türkiye. Eligibility criteria required that participants had previously attended a course or professional development activity related to AI. Because the field of AI is not yet widespread in education, it would be difficult for teachers with no experience in applying AI in education to self-evaluate their competencies through concrete examples. However, to compensate for this limitation in sample selection, the research sample was designed to include teachers of different genders, institutions, and levels of professional experience. The data were collected through a Google Form that was sent to the schools where their colleagues working in this field were working by utilising the background of one of the researchers in the field of early childhood education. In addition, various early childhood education institutions with which the universities where the researchers work are in cooperation were also included in the process. The participants accessed all the information about the research (purpose of the research, voluntary participation principles,

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informed consent, data confidentiality, research scope, and expectations from the participants) through the explanation text on the login screen of the Google Form and participated voluntarily. Ethical approval for this study was obtained from the Bingöl University Scientific Research and Publication Ethics Committee of Social and Human Sciences (Date: 16.06.2023, No: E.108984).

There are no strict recommendations for sample size in scale development, though several guidelines exist. Kline (2014) suggests a minimum of 200 participants, while Tabachnick et al. (2013) recommend at least 300. Other researchers propose sample sizes based on the number of items, such as at least five times (Şencan, 2005) or three times (Sönmez and Alacapınar, 2016) the number of items. In this study, the analyses were designed to be conducted on three separate groups for exploratory factor analysis (EFA), confirmatory factor analysis (CFA) and test-retest reliability. The first group included 268 ECE teachers, of whom 19% (n=51) were male and 81% (n=217) were female. Among these participants, 63.8% (n=171) had 1-10 years of experience, while 36.2% (n=97) had over 11 years of experience. The second group, used for CFA, consisted of 240 ECE teachers, 19.6% (n=47) male and 80.4% (n=193) female. In this group, 64.2% (n=154) had 1-10 years of experience, and 35.8% (n=86) had over 11 years of experience. The third group of the study consisted of 39 ECE teachers who completed the ACES for the second time with a two-week interval for test-retest reliability.

Phase 6: Validity and reliability analysis

Data analyses were performed using SPSS 25.0, Mplus 9.0 and JASP 0.96.0 statistical software. Within the scope of validity and reliability analyses, exploratory factor analysis (EFA) was conducted first. EFA is a method to decide the scale structure and calculate item loadings under different factors (Çokluk et al. 2012). Before EFA, the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were performed to determine the suitability of the data for factor analysis. It is recommended to use rotation methods consistent with the expected correlations of the factors for EFA (Howard, 2015). Given the ordinal nature of the 5-point Likert-type items, EFA was re-estimated by treating the items as ordered categorical indicators. The analysis used the WLSMV estimator with oblimin rotation, consistent with the CFA approach and the theoretically expected correlations among factors. Factor retention was determined by considering parallel analysis, the scree plot, and the theoretical interpretability of the factor structure. Items were evaluated based on their factor loadings and cross-loadings.

- The load value of the item under a factor must be at least .32 (Tabachnick et al. 2013; Yong and Pearce, 2013).
- If an item has a loading value of .30 and above in more than one dimension, then it is expected that there should be a difference of at least .10 or, ideally, .20 between the factor loading values in the two dimensions in question (Özdamar, 2016).
- Retention of factors based on parallel analysis, scree plot inspection, and theoretical interpretability (Iacobucci et al., 2022).

Following the EFA, reliability was assessed by calculating Cronbach's Alpha reliability coefficient. A Cronbach's Alpha value of at least .70 is generally accepted as the threshold for

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reliability in scale development studies (Gaur and Gaur, 2006; Seçer, 2018). Corrected item-total for item level discriminative validity were calculated. Corrected item-total correlations are recommended to be above .20 (Pallant, 2020). The mean scores of the lowest and highest 27% of the sample were compared to determine the discriminatory power of the scale items. An item that fails to differentiate between these groups is considered non-discriminatory (McCowan and McCowan, 1999).

Confirmatory factor analysis (CFA) was conducted after EFA to test the conceptual model we presented regarding ECE teachers' AI competencies through the remaining items in the scale. Given the ordinal nature of the Likert-type items, the CFA was re-estimated using weighted least squares mean and variance adjusted (WLSMV), an estimator recommended for ordered categorical variables and more appropriate than ML when multivariate normality cannot be assumed (Brown, 2015). CFA is a confirmatory technique that evaluates an existing model's model-data fit (Demir, 2022). The model fit was evaluated by reporting the chi-square, chi-square/degree of freedom, Root Mean Square Error of Approximation (RMSEA), Standardised Root Mean Square Residual (SRMR), Comparative Fit Index (CFI) and Tucker Lewis Index (TLI) fit indices. In addition, average variance extracted (AVE) composite reliability (CR) was calculated to examine convergent validity over CFA data. CR value should be .70 and above, and the AVE value should be .50 and above (Fornell and Larcker, 1981). Finally, Heterotrait-Monotrait (HTMT) ratio of correlations for discriminant validity, correlations between the sub-dimensions and total score of the scale and Intraclass Correlation Coefficient (ICC) for test-retest reliability were calculated. For test–retest analysis, the ICC was used as the reliability coefficient, based on measurements taken at two different time points. ICC was evaluated according to the following criteria: poor (<0.40), moderate (0.41-0.59), good (0.60-0.74), excellent (>0.75) (McDowell, 2006).

Phase 7: Reporting

The stages of development of the ACES scale, important choices and decisions made during this process, statistical analyses, and evaluations are reported in detail. The discussion of the findings and conclusions of the study is presented in the following sections.

Results

The KMO value (.92) and Bartlett's test of sphericity (5878.88, $p < .001$) indicated that the sample size and correlation matrix were suitable for factor analysis. As a result of EFA, it was seen that 3 items in different dimensions had loading values lower than .32 (.16, .21, .18). These items are as follows: "I can use artificial intelligence-based tools to support children's socialization," "I can use artificial intelligence tools in family involvement activities," and "I inform parents about the use of artificial intelligence-based tools in the classroom." The items with the lowest loading values were removed, respectively, and the analyses were repeated. These three items that did not have sufficient loading values were removed from the scale. In addition, 3 more items with high and close loadings under different factors were removed from the scale by following the same steps. These items are: "I can evaluate the effect of artificial intelligence-based tools on the educational process," "I can customise artificial intelligence-based tools according to the

individual needs of children," "Artificial intelligence-based tools can be used as a useful educational tool in early childhood education."

The ordinal exploratory factor analysis conducted with the WLSMV estimator and oblimin rotation supported a four-factor structure for the ACES. Parallel analysis indicated that four factors should be retained, and this decision was also consistent with the scree plot (see Figure 2). Parallel analysis supported the retention of four factors because only the first four observed eigenvalues exceeded the corresponding simulated eigenvalues. The results, summarized in Table 1, show that the scale items had mean scores ranging from 2.83 to 4.41 and standard deviations between 0.672 and 1.017. A four-factor structure was identified, and the factors contributed more than 5% to the explained variance.

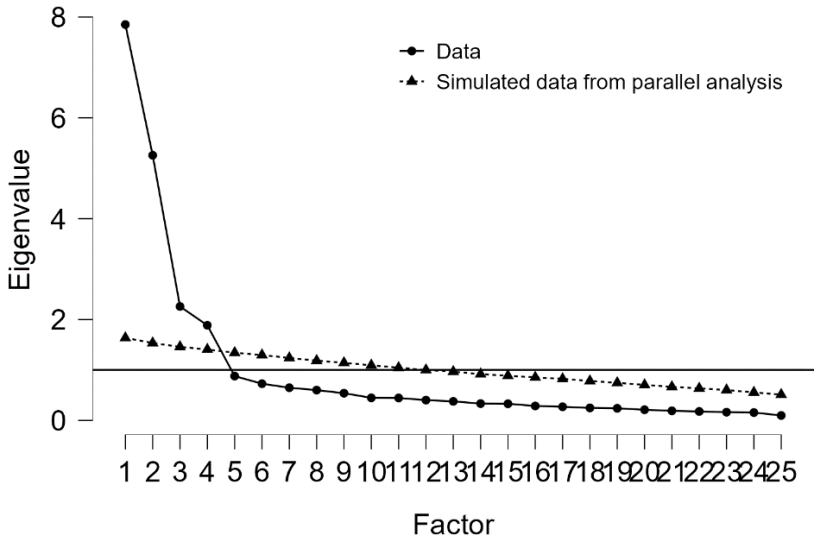


Figure 2. Parallel analysis scree plot

Table 1. Factor loadings, eigenvalues, explained variances, and descriptive statistics results

Items	N	Item Mean	Standard Deviation	AI knowledge	AI skills	Attitude towards AI	Ethics in AI usage		
								h^2	u^2
				Factor loading				Communalities	Uniqueness
1	268	2.83	0.987	0.837				0.673	0.327
2	268	3.25	0.972	0.851				0.706	0.294
3	268	2.96	0.965	0.733				0.632	0.368
4	268	3.15	1.001	0.908				0.788	0.212
5	268	3.06	0.956	0.734				0.729	0.271
6	268	3.48	0.981	0.710				0.777	0.223

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7	268	3.41	0.909		0.753			0.645	0.355
8	268	3.36	0.943		0.746			0.786	0.214
9	268	3.44	1.017		0.794			0.698	0.302
10	268	3.50	0.958		0.700			0.516	0.484
11	268	3.37	0.960		0.827			0.740	0.260
12	268	3.18	0.981		0.782			0.638	0.362
13	268	3.24	0.969		0.795			0.705	0.295
14	268	3.45	0.976		0.899			0.768	0.232
15	268	3.39	1.005		0.856			0.685	0.315
16	268	4.20	0.813			0.780		0.623	0.377
17	268	4.19	0.796			0.823		0.798	0.202
18	268	4.09	0.777			0.868		0.801	0.199
19	268	4.07	0.806			0.965		0.925	0.075
20	268	4.04	0.860			0.965		0.901	0.099
21	268	4.10	0.727			0.875		0.825	0.175
22	268	4.26	0.723				0.897	0.827	0.173
23	268	3.93	0.802				0.890	0.834	0.166
24	268	4.41	0.672				0.842	0.874	0.126
25	268	4.15	0.748				0.808	0.796	0.204
Variance explained				38.080	23.040	9.120	6.780		
Total variance explained							**77.030**		

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The factor loadings of the items ranged as follows: for the AI knowledge dimension, between .710 and .908; for the AI skills dimension, between .700 and .899; for the attitudes toward AI dimension, between .780 and .965; and for the ethics in AI use dimension, between .808 and .897. Collectively, the 25 items accounted for 77.030% of the total variance. The communalities (h^2) ranged from .516 to .925, and uniqueness values (u^2) ranged from .075 to .484. Since all communalities exceeded .50, the items were adequately represented by the four-factor solution, supporting the adequacy of the factor structure (MacCallum et al., 1999).

The results of the item analyses and internal consistency coefficients are presented in Table 2. When comparing the mean scores of the lowest and highest 27% groups, the t-values for all items were statistically significant ($p < .001$). Items with corrected item-total correlations below .20 reduce internal consistency (Streiner et al. 2015). In this study, the corrected item-total correlations for the scale items ranged between .30 and .77. Cronbach's Alpha internal consistency coefficients were calculated as follows: .91 for the AI knowledge dimension, .94 for the AI skills dimension, .92 for the attitudes toward AI dimension, .84 for the ethics in AI use dimension, and .93 for the overall scale.

Table 2. Item analysis and internal consistency values

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Dimensions	Items	t	Corrected Item-Total Correlation	Cronbach's Alpha
AI knowledge	1. I know how to use artificial intelligence-based tools to support children's development and learning.	13,607**	0,620	.91
	2. I can select artificial intelligence-based tools to support children's development and learning.	13,83**	0,672	
	3. I know the basic principles and application areas of artificial intelligence-based tools.	11,918**	0,566	
	4. I can choose suitable artificial intelligence-based tools to monitor children's development.	17,188**	0,734	
	5. I know how to integrate artificial intelligence-based tools into the teaching program.	15,987**	0,661	
	6. I am aware of artificial intelligence-based applications that can support children's development and learning.	12,024**	0,633	
AI skills	7. I can use artificial intelligence-based tools in children's developmental assessments.	15,678**	0,693	.94
	8. I can effectively guide children using artificial intelligence-based tools.	15,997**	0,712	
	9. I can develop problem-solving and creative thinking skills in children by creating scaffolds with artificial intelligence-based tools.	16,269**	0,739	
	10. I can concretize abstract concepts for children using artificial intelligence-based tools.	14,538**	0,693	
	11. I can develop projects with children using artificial intelligence-based tools.	15,197**	0,688	
	12. I can design games and activities supporting children's development using artificial intelligence-based tools.	17,496**	0,736	
	13. I can prepare suitable learning materials for children with artificial intelligence-based tools.	16,613**	0,702	
	14. I can support children's learning objectives with game-based artificial intelligence applications.	18,786**	0,776	
	15. I can ensure students' active participation in activities with artificial intelligence-based tools.	18,837**	0,757	
attitude towards AI	16. Artificial intelligence-based tools can be used to develop 21st-century skills in children.	7,177**	0,508	.92
	17. Artificial intelligence-based tools make children's learning processes fun.	6,854**	0,462	

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	18. I believe using artificial intelligence-based tools in teaching and learning processes is enjoyable.	7,386**	0,505	
	19. I participate in courses, seminars, etc., focused on the effective use of artificial intelligence-based tools in teaching and learning processes.	7,264**	0,468	
	20. I am eager to research and learn about unfamiliar artificial intelligence-based tools.	9,289**	0,490	
	21. Using artificial intelligence-based tools in early childhood education encourages active participation in the learning process.	6,474**	0,430	
ethics in AI usage	22. When using artificial intelligence-based tools, I take care to protect the personal information of students.	6,207**	0,412	.84
	23. I am aware of ethical issues related to artificial intelligence-based tools and am sensitive to these issues.	4,959**	0,313	
	24. I respect students' privacy (such as sharing photos, voice, video, etc.) when using artificial intelligence-based tools.	7,291**	0,447	
	25. I constantly ensure compliance with ethical principles in using artificial intelligence-based tools.	5,524**	0.30	
Cronbach's Alpha for the overall scale				.939

**p<.001

Based on the evaluation of item analyses and internal consistency, no items were removed from the scale. CFA was conducted to confirm the factor structure. Because the ACES items were rated on a 5-point Likert scale, they were treated as ordered categorical indicators in the CFA. Therefore, the confirmatory factor analysis was re-estimated using the WLSMV estimator, which is more appropriate for ordinal data than maximum likelihood estimation. Under WLSMV estimation, model evaluation relied primarily on CFI, TLI, RMSEA, and SRMR. The CFA results indicated that standardized factor loadings ranged from .71 to .96 (see Figure 3 and Table 4). The goodness-of-fit indices for the four-factor structure (Table 3) demonstrated robust model fit: $\chi^2/df = 3.90$, CFI = .97, TLI = .97, SRMR = .041, and RMSEA = .065.

Table 3. Goodness of fit values as a result of confirmatory factor analysis

χ2	df	χ2/df	CFI	TLI	SRMR	RMSEA
1050.263	269	3.90	.97	.97	.041	.065

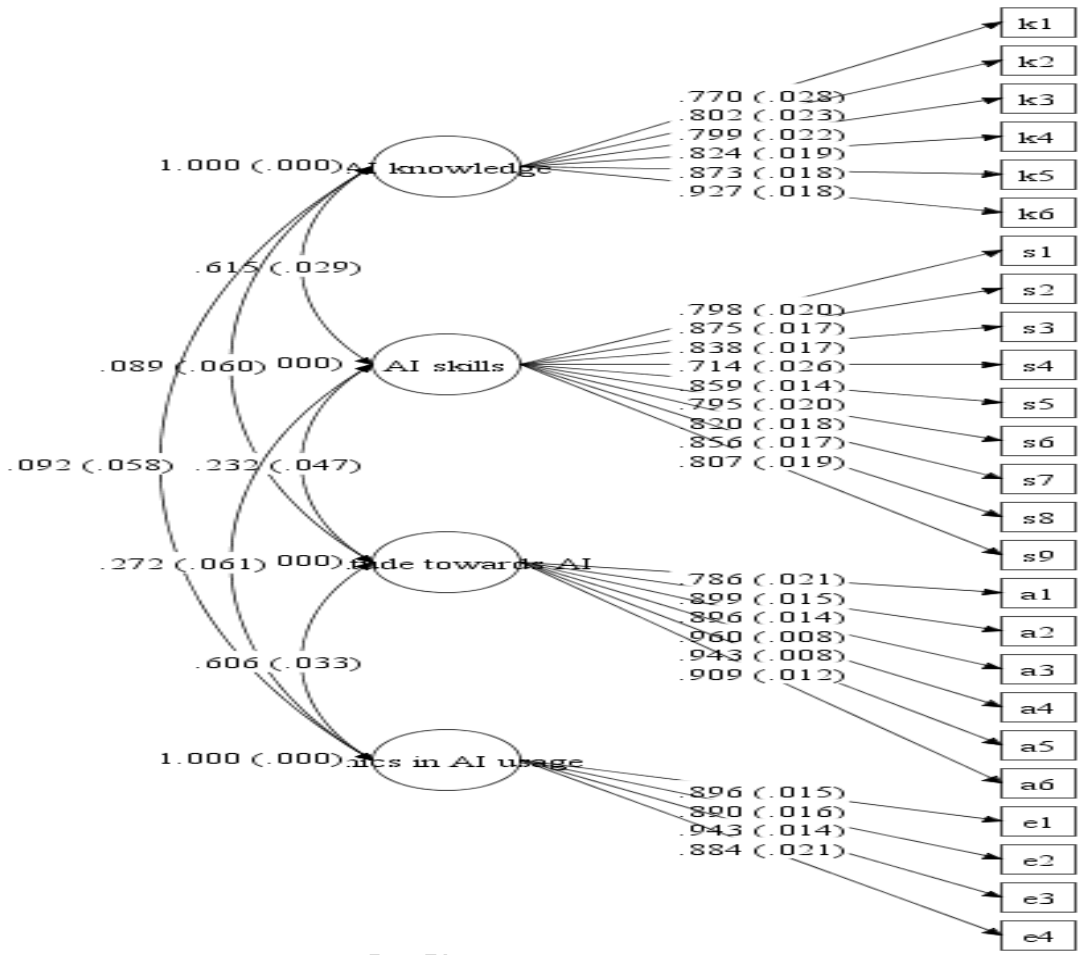


Figure 3. Path diagram of CFA

The consistency of the scale items and their respective factors, or convergent validity, was tested by calculating CR and AVE (see Table 4). A CR value of .70 or higher and an AVE value of .50 or higher are recommended as acceptable thresholds (Hair, 2014). As shown in Table 4, CR values ranged from .84 to .94, while AVE values ranged from .57 to .65, indicating that the scale meets the criteria for convergent validity.

Table 4. Convergent validity of the scale

Dimensions	Factor Loading	CR	AVE
AI knowledge	.77-.92	0.91	0.65
AI skills	.71-.87	0.94	0.64
attitude towards AI	.78-.96	0.92	0.66
ethics in AI usage	.88-.94	0.84	0.57

HTMT was calculated to assess discriminant validity further. The relationship between the dimensions was also assessed by calculating Pearson correlation coefficients (see Table 5). Our

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results showed that the HTMT values were lower than the threshold values (Henseler et al., 2015). However, our results showed significant positive correlations between all dimensions. A high correlation was found between AI knowledge and AI skills (r= .622). Similarly, there is a high correlation between Attitude towards AI and Ethics in AI usage (r= .612). There is also a low level relationship between AI knowledge and Attitude towards AI (r= .086) and Ethics in AI usage (r= .091). Similarly, there is a low level relationship between AI skills and Attitude towards AI (r= .232) and Ethics in AI usage (r= .272).

Table 5. Heterotrait-Monotrait Ratio (HTMT) and correlation analysis results

Dimensions	AI knowledge	AI skills	Attitude towards AI	Ethics in AI usage
AI knowledge	-	**0.691**	**0.112**	**0.130**
AI skills	0.622**	-	**0.283**	**0.320**
Attitude towards AI	0.086*	0.232**	-	**0.740**
Ethics in AI usage	0.091*	0.272**	0.612**	-

*Note; The values shown in bold in the upper right corner show the HTMT rates. Values shown in the lower left corner indicate Pearson correlation coefficients (*p<.05; **p<.001).*

Test-retest reliability shows the stability of ACES against time. ACES was administered to ECE teachers in two different time periods and Intraclass Correlation Coefficient (ICC) values are presented in Table 6. ICC values for the items ranged from moderate (.512) to good (.721). In addition, ICC values for the overall scale (.683), AI knowledge (.651), AI skills (.602), Attitude towards AI (.643) and Ethics in AI usage (.648) were found to be at good level.

Table 6. Test-retest reliability of ACES

ACES, dimensions, and items	**Intraclass Correlation Coefficient(ICC)**
ACES total score	0.683**
AI knowledge	0.651**
Item1	0.718**
Item2	0.701**
Item3	0.670**
Item4	0.571**
Item5	0.705**
Item6	0.719**
AI skills	0.602**
Item7	0.665**
Item8	0.518**
Item9	0.662**
Item10	0.561**
Item11	0.512**
Item12	0.568**
Item13	0.698**
Item14	0.587**
Item15	0.564**
Attitude towards AI	0.643**
Item16	0.551**
Item17	0.612**

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Item18	0.601**
Item19	0.702**
Item20	0.713**
Item21	0.721**
Ethics in AI usage	0.648**
Item22	0.687**
Item23	0.556**
Item24	0.631**
Item25	0.652**

**p<.01

Discussion

This study evaluated the validity and reliability of the self-report-based ACES Scale, designed to measure the AI competencies of ECE teachers. EFA revealed a four-factor structure comprising 25 items, explaining approximately 77% of the variance. Item analyses and internal consistency coefficients provided evidence that the items had acceptable reliability within the present sample. The comparison of lower and upper groups indicated that the items showed statistically significant discriminatory capacity. CFA was conducted to examine the relationships between observed variables and the underlying constructs. The results yielded acceptable-to-good fit indices, providing support for the proposed four-factor structure of the ACES Scale. Finally, convergent validity analyses indicated that the scale items are consistent with one another and aligned with their respective factors. While the HTMT rates provided additional evidence for the discriminant validity of the ACES scale, the test-retest results supported the consistency of the scale over time.

AI has become the center of digital transformation in the last few years. AI is expected to transform learning and teaching as educational technology in medicine, engineering, science, and law. AI is both a field of competence and a tool to enrich educational processes. AI can teach children high-level skills, constructivist learning experiences, and motivation. A recent field study on using AI in ECE revealed that AI develops children's computer science concepts, collaborative inquiry, and computational thinking (Su and Yang, 2022). However, children are expected to have skills in digital literacy and how to mitigate the harms of digital technologies (Ali et al. 2021). At this point, teacher competencies are an essential area to be considered to provide children with these skills in the early years.

AI research in ECE has generally focused on curriculum (Chiu, 2021), young children's AI literacy (Ng et al. 2021; Su et al. 2023), AI content, and outcomes (Yau et al. 2023). Some research discusses integrating AI education into ECE (Su and Zhong, 2022; Yang, 2022). However, a more pressing issue is the teacher competencies for this integration and whether teachers are ready for this transformation. In this context, little is known about teacher competencies and how to integrate AI into classroom activities. The impact of teachers on educational outcomes is well-known by policymakers, school administrators, and parents. The use of AI tools in early childhood education also largely depends on teachers' competence (Lim, 2023). To develop children's higher-order skills, ECE teachers need to have the skills to provide opportunities for children (Kewalramani et al. 2021). Teachers who lack basic competencies in AI may have a negative attitude toward developing activities for children (Su et al. 2023).

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In our study, we focused on the AI competencies of ECE teachers, conceptualizing these competencies within the framework of AI literacy as a four-factor structure. A pool of items aligned with the conceptual definition of the ACES Scale was created, and the proposed structure was examined using empirical data. During the EFA process, items were removed, and the CFA results supported a four-factor structure consisting of 25 items. The model fit was evaluated with a large number of goodness-of-fit indices. Good fit (TLI CFI, SRMR and RMSEA) values were obtained when compared with the cut-off values suggested in the literature (Byrne, 2010; Hu and Bentler, 1999; Schumacker and Lomax, 2004; Tabachnick and Fidell, 2007). Fit is defined as the ability of a model to reproduce the data, i.e., the variance-covariance matrix. The good fit values indicate that the proposed conceptual model was compatible with the observed data in the present sample (Erkorkmaz et al., 2013). In this context, the goodness-of-fit results provide strong evidence for the validity of the four-factor structure of ACES. This multi-factor structure of ACES supports previous studies that address AI competences as a multidimensional structure (Çelik, 2023; Delcker et al., 2024). However, in the six-factor model of Delcker et al. (2024), professionalisation and attitude dimensions were removed from the model to improve the goodness of fit values. In our study, professional development in the context of professionalisation was considered as an indicator of attitude towards AI. We assumed that ECE teachers with positive attitudes towards AI would exhibit behaviours towards professionalisation to use AI effectively in their classrooms. Our validity analyses also supported this view.

The dimensions of the ACES Scale are aligned with AI literacy frameworks (Ding et al. 2024; Wang et al. 2023) and broadly overlaps with existing frameworks for digital and AI competencies (Chiu et al. 2024; Delcker et al. 2024; Kim and Kwon, 2023; Vuorikari et al. 2022). Additionally, ACES is compatible with the core domains outlined in UNESCO's (2024) draft AI competency framework for teachers. It integrates knowledge, skills, and attitudes as foundational areas within its five key competency domains.

Among the dimensions of ACES, the knowledge dimension contributed most significantly to the explained variance. However, this finding should be interpreted as an empirical feature of the factor solution rather than as evidence that knowledge is necessarily the most important component of AI competence. To enhance and support their instructional practices, teachers must possess AI knowledge, update it regularly, and utilize it to promote personalized learning experiences (Ng et al. 2021). The skills dimension refers to teachers' ability to apply their AI knowledge in educational contexts, mainly through classroom activities to support student development. In addition to knowledge and skills, teachers are expected to hold positive attitudes toward AI. Teachers lacking sufficient knowledge and skills may develop negative attitudes toward using AI in classroom processes. As a matter of fact, our correlation analysis results revealed that there are positive relationships between attitude towards AI and AI knowledge and AI skills. They may perceive AI as a threat or fail to recognize its potential as an effective educational tool. Thus, attitudes toward AI form a critical component of AI competency. In previous studies on digital or AI competencies (Chiu et al. 2024; Economou, 2023), professional engagement has been considered a fundamental competency component. However, in the ACES framework, professional development is conceptualized as an indicator of attitudes toward AI. Teachers with positive beliefs and values regarding AI are more likely to participate in AI-based

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professional development activities. In this sense, attitude toward AI was conceptualized broadly to include not only affective evaluations of AI, but also teachers' willingness to engage in AI-related professional learning and practice. Finally, ethics in AI use is a critical dimension, as it encompasses privacy concerns (Zhang and Aslan, 2021). While AI drives innovation, it threatens children's rights, such as privacy, safety, and security (Su and Zhong, 2022). In ECE settings, where teachers largely guide children, ethical considerations in the use of AI depend on teachers' awareness and competencies.

Our analyses provided additional evidence regarding the psychometric properties of the scale. The Cronbach alpha reliability coefficient of the scale for the dimensions was between .84 and .94. Pallant (2007) states that Cronbach alpha for each factor should be at least .70. AVE and CR values were calculated to evaluate convergent validity. The calculated AVE and CR values were found to be at acceptable threshold values (Hair, 2014). These results suggest that the items in the scale dimensions measure similar constructs and can adequately represent the relevant dimensions. In addition, discriminant validity was analysed by calculating the HTMT ratios. Our analyses showed that the HTMT values were below the threshold values (Henseler et al., 2015). These findings provide evidence that the scale dimensions are empirically distinguishable from one another. ACES showed good test-retest reliability results. However, future studies with larger samples are needed to further examine the stability of the scale over time.

Implications and Contributions

Unlike previous scales focusing on technical AI competencies (Brauner et al. 2023), ACES targets more foundational competency areas for ECE teachers. As Mikaladze et al. (2024) highlighted in their review of AI competency frameworks for educators, it is essential to acknowledge that no AI competency framework is perfect. Teachers may lack sufficient experience and understanding to implement AI effectively in educational settings, mainly as AI is still in its developmental stage. As AI competencies evolve, the ACES framework can contribute to broadening discussions in this domain.

The 25-item ACES scale can be used as a reliable tool to measure ECE teachers' AI competencies. However, our framework and research results on ECE teachers' AI competences have important implications for teachers' professional development and teacher education. It is well known that improving teachers' theoretical and practical knowledge about AI addresses their concerns and supports their confidence towards AI (Nazaretsky et al., 2022). In this context, structuring professional development programmes for ECE teachers within the framework of our proposed AI competencies can support both teachers' positive attitudes towards AI and their professional practices. In addition, we did not define AI competencies as a complex construct based on computer and engineering science terminology. We took into account the ECE context and classroom practices. In this context, we suggest that instead of teaching the complex background of AI in professional development programmes, we suggest focusing on what teachers should know and how they should apply AI in order to support children's development while adhering to ethical considerations. In addition, although the impact of AI is rapidly expanding, our understanding of its effective use in educational settings is still limited. Professional development programmes on the use of AI in ECE settings may help address some of these challenges and

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support more informed pedagogical practices. Furthermore, the four-factor framework we propose can be integrated into ECE pre-service teachers' education programmes. Indeed, numerous studies (Ma and Lei, 2024; Sanusi et al., 2024) have shown that supporting pre-service teachers' knowledge and skills about AI promotes their usage intentions and positive attitudes. The inclusion of AI competencies in teacher education programmes as a core stage of professional development may support opportunities for the use of AI in the ECE context from a pedagogical and ethical perspective. Finally, the ACES scale may contribute to future research examining the antecedents, correlates, and outcomes of ECE teachers' perceived AI competencies.

Limitations

Several limitations should be considered when interpreting the findings of this study. Firstly, ethical risks (e.g. data privacy, biased algorithms), implementation difficulties (lack of infrastructure, classroom adaptability) and teacher resistance (perceived threat, increased workload) that may arise in the integration of AI-based tools into ECE should be included in the discussion and concrete solutions should be developed for these issues. Secondly, collecting data with a self-report scale may lead to biases such as social desirability bias and recall errors; therefore, in the future, mixed designs including methods such as observation, performance-based assessment, and qualitative interviews should be used to increase the reliability of the results. Another limitation concerns the sample size. Although the sample was sufficient for the psychometric analyses conducted, a larger and more diverse sample would provide stronger evidence for the stability, generalizability, and replicability of the factor structure. Furthermore, testing the adaptability of the scale in different educational levels or disciplines, testing cross-cultural validity, and monitoring the development of teacher AI competences over time with longitudinal designs will provide theoretical and practical contributions to the literature. Third, participation in the study required teachers to have attended an AI-focused training. This inclusion criterion was used to ensure that participants were at least basically familiar with AI-based tools, which represent a current phenomenon, and that they could respond to the scale items based on concrete experiences or informed awareness. However, this choice may have resulted in a sample consisting of teachers with relatively higher AI awareness. Therefore, the generalizability of the findings to teachers who have not received any training on artificial intelligence may be limited. Accordingly, future validation studies of the scale are recommended to use stratified or random sampling designs that include both teachers who have and have not received AI training. Finally, the fact that the participants were largely reached through the institutions that the researchers had access to can be considered as a situation that may limit the geographical and institutional diversity of the sample. This should be interpreted with caution regarding the generalisability of the findings.

Conclusion

We developed the 25-item ACES scale to measure ECE teachers' perceived competencies in using AI-based tools in educational settings. The scale comprises four sub-dimensions: AI knowledge, AI skills, attitude towards AI, and ethics in using AI. The increase in the scores obtained from the scale means that the competencies of ECE teachers towards using AI tools in educational environments increase. To our knowledge, validated self-report instruments

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specifically designed to assess early childhood educators' AI competencies remain limited. The ACES scale may contribute to expanding the research agenda in this field. In addition, it can contribute to identifying and assessing teachers' professional development needs using AI.

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Data availability

The datasets generated during and/or analysed during the current study are not publicly available due to data protection and the policy of the ethics committee, but are available from the corresponding author on reasonable request.

Funding

The authors have not declared a specific grant for this research from any funding agency in the public, commercial or not-for-profit sectors.

Competing interests

The authors declare no competing interests.

Ethical approval

This study was conducted in accordance with the Declaration of Helsinki. Ethical approval for this study was obtained from the Bingöl University Scientific Research and Publication Ethics Committee of Social and Human Sciences (Date: 16.06.2023, No: E.108984).

Informed consent

Before the data collection, all participants were informed of the purpose and scope of the study and how the data would be used. They all signed the informed consent and agreed to participate in this research, data use, and consent to publish.

Appendix 1

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Appendix 2

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