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AI readiness scale for teachers: Development and validation

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Abstract
One of the most important indicators of artificial intelligence applications used to improve quality, effectiveness, and student success by optimizing instructional processes is readiness. Readiness is the cognitive, affective, and behavioral state of performing a behavior or using a technology. In this context, the development of a data collection tool for readiness in artificial intelligence applications seems necessary. In this study, a scale was developed to measure teachers' readiness for artificial intelligence applications. The sequential design model, one of the mixed research methods, was used in the research. The exploratory factor analysis (EFA) phase of this study was conducted with 616 samples while the confirmatory factor analysis (CFA) and concurrent validity phase were conducted with 345 and 128 samples, respectively. After ensuring validity and reliability in the research, the final version of the Readiness for Artificial Intelligence Applications Scale (RAIS) consisted of a total of 19 items and three dimensions. These dimensions are technology self-efficacy, interaction with students, and ethical awareness. In addition, concurrent validity was tested by examining the correlation between the General Attitudes Toward Artificial Intelligence Scale and the Artificial Intelligence Literacy Scale. The results of the analysis show that RAIS is a valid and reliable measurement tool for determining teachers' readiness for artificial intelligence applications.

Keywords Artificial intelligence · Scale development · Artificial intelligence readiness · Teacher readiness · Educational technology · Ethical awareness

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1 Introduction

Artificial intelligence (AI) has emerged as one of the most important technological developments of this era. AI refers to computer systems and algorithms with the ability to deal with new situations, perform complex tasks, and solve problems that arise by imitating human, animal, and machine intelligence (Coppin, 2004). Artificial intelligence is used to increase efficiency by analyzing more data in less time with less effort than humans (Bouhouita-Guermech et al., 2023). AI has established itself as a more reliable tool with the accuracy it achieves in the analysis of fast and comprehensive data (Chen, 2023). The effects of this technology are being felt in many sectors, from business to education, from healthcare to security. AI aims to provide personalized, adaptable, and effective learning experiences for trained students in data-driven management and decision-making (Raffaghelli et al., 2022). The impact of this technology has been felt in the great change and transformation experienced in education in recent years. It is reported that the use of AI in the educational process contributes to the optimization of the learning process, adaptive, and personalized learning, increased motivation, and automatic evaluation of knowledge and skills. It also supports the creation of virtual simulators and trainers that allow them to gain practical skills and experience without the risk of experimenting with real objects (Somenko et al., 2023). Teachers also use AI technologies to provide guidance, feedback, or support during the learning process (Hwang & Tu, 2021). AI helps to analyze learning data, generate outputs such as learning reports, and supervise, evaluate, and rank learners (Chen, 2023). The issue of preparing an effective learning environment and effective materials, which are among the most important indicators of education and training, has become even more important with the development of technologies and new pedagogical understandings (Akdeniz & Özdinç, 2021). Using artificial intelligence, teachers will be able to provide students with more personalized, flexible, inclusive, and interesting educational experiences (Luckin & Holmes, 2016).

In addition to the integration of technology, the use of artificial intelligence in education could be considered as a powerful tool to improve the quality and effectiveness of the educational process (Singh & Thakur, 2024). The successful use of artificial intelligence applications in education can be achieved by involving teachers in the creation, development, and integration of artificial intelligence (Langran et al., 2020; Qin et al., 2020). The spread and adoption of AI are closely related to how ready individuals and institutions are for this technology. Parasuraman (2000) defined technology readiness as the tendency of people to adopt and use new technologies to achieve goals. Readiness is related to how cognitively, affectively, and behaviorally prepared a person is to perform a behavior (Swearer et al., 2014). In another definition, the concept of readiness is the state of having the necessary knowledge, skills and affective characteristics to use technology (Gökçearslan et al., 2017; Senemoğlu, 2009).

Studies in the literature (Holmström, 2022; Karaca et al., 2021; Luckin et al., 2022; Wang et al., 2023b) have shown that the concept of AI readiness reveals the knowledge required to use AI-supported applications. It can be expressed as a state of skill and cognitive readiness. In this context, when considering the scales developed for AI (Table 1), it is noteworthy that they are discussed in terms of such dimensions as literacy, anxiety, attitude, awareness, and acceptance.

However, only one study on AI readiness was found in the field of health (Karaca et al., 2021). The study considered cognitive, skill, foresight, and ethical factors. Considering the measurement tools developed for readiness and technology (Table 2), it is worth noting that they are related to different technologies.

Considering the readiness measurement tools that have been developed, one can notice that the self-efficacy dimension is frequently addressed. Social Cognitive Theory emphasizes individuals' self-confidence and belief in their ability to perform certain tasks. While self-efficacy is expressed as a general belief in one's skills and abilities to cope with challenging situations (Bandura & Walters, 1977), it is also known that self-efficacy is effective in learning (Hall & Hall, 2010). This theory can also be used to assess proficiency in using technology. In the context of technological self-efficacy, this concept can be expressed as an individual's confidence in using AI technologies effectively is shaped by the individual's familiarity with these technologies, past experiences, and goals (Kraus et al., 2021). In order for instructors to use artificial intelligence to organize teaching environments and develop applications, they are supposed to be aware of the positive and negative aspects of AI (Nazaretsky et al., 2021) and have the talent and skills in this sense (Luckin et al., 2022).

In constructivist learning theory, learning occurs through an individual's experiences and social interactions (Vygotsky, 1978). This interaction is also emphasized in the social cognitive theorem. Students learn knowledge by connecting it to existing knowledge and by taking an active role in problem-solving processes. In the use of artificial intelligence in education, the issue of how to teach artificial intelligence is also important (Goel & Joyner, 2017). While organizing the teaching process, instructors can support students' learning interactively through artificial intelligence (Van Leeuwen & Rummel, 2020). In the constructivist approach, the teacher's role as a guide, facilitator of the learning process, and supporter of students' active learning experiences enables students to have deep and meaningful learning experiences (Atteh, 2023). From this perspective, it can be implied that teachers have a role in carrying out the interaction processes of students with artificial intelligence.

Ribble's (2008) definition of digital citizenship states that individuals should exhibit legal and ethical behavior while using technology. The rapid spread of artificial intelligence applications and their progress in every field has brought about concerns about moral, ethical, and legal issues (Bélisle-Pipon et al., 2021; Öztürk Dilek, 2019). The increasing amount of data, its use, regulation, processing, and dissemination of data in both public and private areas, and their involvement in decision-making mechanisms in many fields of artificial intelligence have brought about the concept of digital ethics (Floridi & Taddeo, 2016; Floridi, 2018). It is emphasized that ethical concerns regarding the collection, use, and dissemination of data in artificial intelligence need to be addressed (Pedro et al., 2019). While artificial intelligence contributes to human capabilities, it also brings challenges regarding ethical use (Holmes et al., 2019a, b). Looking at scale of artificial intelligence and the literature, it is well known that there are discussions about ethics.

Table 1 Scales developed for AI

Author	Name of the scale	Dimensions
Wang et al., (2023a)	Artificial Intelligence Literacy Scale	Awareness, Use, Evaluation, Ethics
Wang and Wang (2019)	Artificial Intelligence Anxiety Scale	Learning, Job Switching, Sociotechnical Blindness, Artificial Intelligence Configuration
Schepman and Rodway (2023)	General Attitudes Towards Artificial Intelligence	Negative Attitude Towards Artificial Intelligence, Positive Attitude Towards Artificial Intelligence
Ferikoğlu and Akgün (2022)	Artificial Intelligence Awareness Level for Teachers Scale	Ability to Relate, Belief and Attitude, Theoretical Knowledge, Application Information
Yilmaz et al. (2023)	Generative AI Acceptance Scale	Performance expectancy, Social influence, Effort expectancy, Facilitating conditions
Wang and Chuang, (2024)	Artificial Intelligence Self-Efficacy Scale	Assistance, Anthropomorphic Interaction, Comfort with AI, Technology Skills

Table 2 Some measurement tools developed for readiness and technology

Author	Name of the scale	Dimensions
Hung (2016)	Teachers' readiness for online learning	Communication Self-Efficacy, Institutional Support, Self-Learning, Learning Transfer Self-Efficacy
Lin et al. (2016)	Readiness for Mobile Learning	Mobile Learning Self-Efficacy, Optimism, Self-Directed Learning
Yurdugül and Demir (2017)	University Students' E-learning Readiness Scale	Computer Self-Efficacy, Internet Self-Efficacy, Online Communication Self-Efficacy, Self-Learning, Learner Control, Motivation for E-Learning
Youhasan et al. (2020)	Readiness for flipped classrooms	Technological Readiness, Environmental Readiness, Personal Readiness, Pedagogical Readiness, Interpersonal Readiness
Karaca et al. (2021)	Medical AI Readiness	Cognitive, Skill, Foresight, Ethical Factor
Kim and Martin, (2023)	Readiness for online learning	Course Design and Facilitation, Course Technologies, Course Expectations and Resources, Time Management
Zhong, et al. (2023)	Readiness for online learning	Technology Readiness, Student Control, Online Communication Self-Efficacy, Self-Directed Learning, Learning Motivation

Learning theories are used in the planning, execution and evaluation stages of teaching (Çakıroğlu & Kuruyer, 2016). Social learning helps individuals to act safely and responsibly in digital environments and to develop digital citizenship consciousness (Akbay, 2024). Individuals enhance their digital citizenship skills in digital environments both by observing the people around them and by defining their own experiences. As Alam and Mohanty (2023) stated that intelligent tutoring systems and ongoing technological experimentation serve as cornerstones in advancing educational journey. Thus, social learning, constructivism and digital citizenship offer important knowledge about how teachers will act in learning environments, how to construct knowledge and how to use technological tools in an ethical way.

Rapidly spreading in the field of technology, artificial intelligence has become an essential tool in the field of education as it is used by many industries. One of the most important criteria for the success of the application of these in education tools is readiness. Readiness for artificial intelligence applications is important in terms of adapting to the future needs of the education system and integrating students into developing technologies. In addition, it is necessary to take into consideration the ethical concerns which have become an important issue with artificial intelligence. In this context, for artificial intelligence applications, no previously developed readiness scale has been found in the literature that includes the dimensions of technology self-efficacy, student interaction, and ethical awareness. In this study, a scale was developed to reveal teachers' readiness for AI applications. Associating this scale to more than one theory and notion in explaining the different dimensions that emerged in its construction has established a comprehensive and detailed for us and stronger basis for your arguments.

2 Methodology

2.1 Research design

This study was designed to develop a scale to reveal teachers' readiness for artificial intelligence applications. A sequential design model, one of the mixed research methods, was used to develop teachers' readiness for artificial intelligence applications. It is reported that sequential design methods can be combined with quantitative or qualitative analysis in sequential order (qualitative > quantitative, quantitative > qualitative) (Brannen, 2017). In this study, qualitative analysis was carried out when creating the item pool, and quantitative analysis was used in the development and validation processes. In this context, the study process was carried out with (qualitative > quantitative) analyses (Creswell & Plano Clark, 2006). The RAIS scale was developed by applying the steps specified by DeVellis (2017) (Fig. 1). To test the reliability and validity features of the scale, an exploratory factor analysis was applied to the responses given by the teachers (first sample) to the RAIS scale draft form. During the validation phase, the structure that emerged after the EFA was applied to a different group of teachers (second sample). A confirmatory factor analysis was performed on the responses obtained after the application. To test concurrent validity, responses to the Attitude Towards Artificial Intelligence Scale were

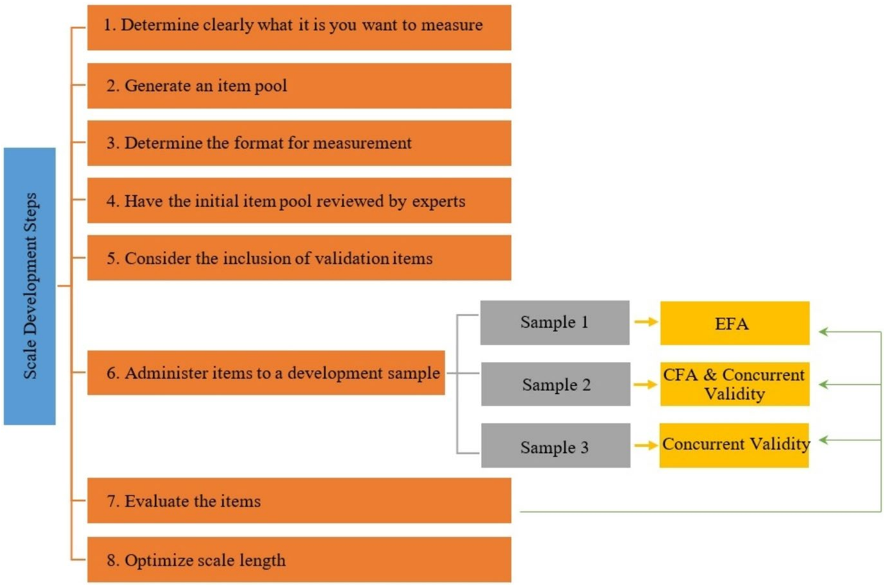

Fig. 1 RAIS scale development steps

collected with the RAIS scale applied to the second sample. In the third sample, responses to the Artificial Intelligence Literacy Scale were collected using the RAIS scale.

2.1.1 Determining clearly what it is you want to measure

This study proposes a scale development to reveal teachers' readiness for artificial intelligence applications. In this context, the scale includes the dimensions shown in Fig. 2 (Technology Self-Efficacy, Student Interaction, and Ethical Awareness).

2.1.2 Generating an item pool

By taking advantage of qualitative research methods while generating the item pool, opinions were taken from computer and instructional technology experts/academics, information technology experts/teachers, and pedagogy and ethics experts/academics with studies in artificial intelligence applications. Purposive snowball sampling method was used to form the expert group, which eventually included 67 experts. Purposive snowball sampling method is a method that allows individuals to obtain new information-laden situations by asking who else they can meet with (Patton, 2014). The expert group was asked via e-mail to list the competencies that would reveal teachers' readiness for artificial intelligence applications. A total of 179 statements or sentences were presented in the responses of a total of 54 experts from 67 expert groups. The responses obtained were subjected to descriptive analysis. After the descriptive analysis, the relevant responses were examined by the researchers

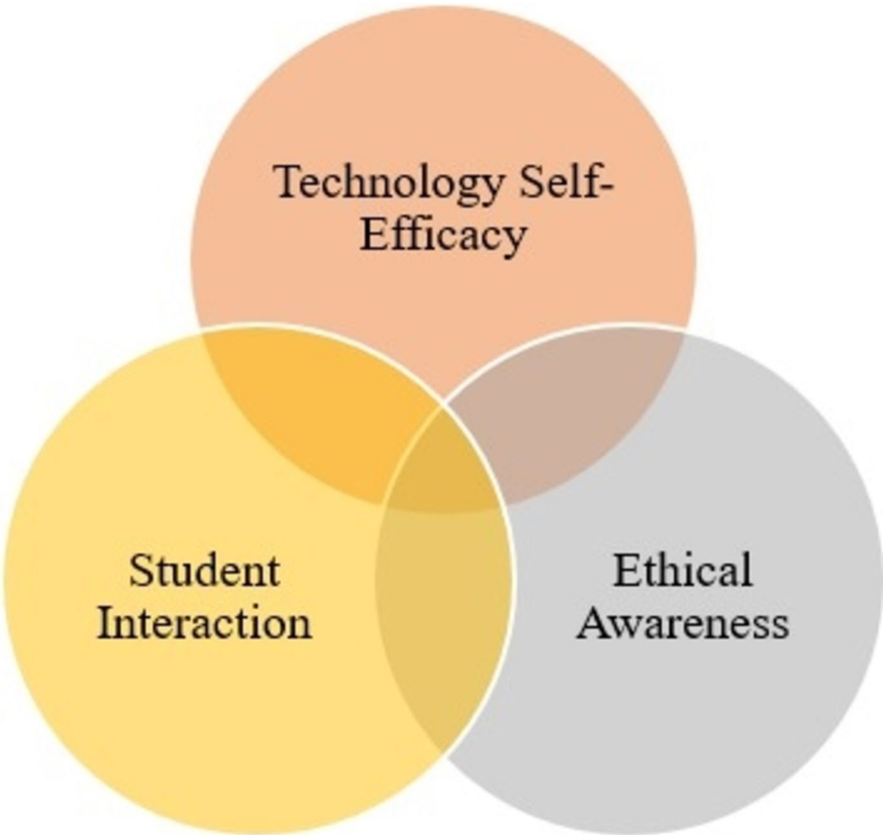

Fig. 2 RAIS dimensions

along with content revisions made for similarity. Accordingly, items with similar content were combined, and a forum consisting of three dimensions (Technology Self-Efficacy, Student Interaction, and Ethical Awareness) and 36 items was obtained as a draft. In addition, care was taken to ensure that each item was specific to the study group (DeVellis, 2017).

2.1.3 Determining the format for measurement

The measurement format of the RAIS scale is designed as a five-point Likert type and rated as "Strongly Disagree, Disagree, Undecided, Agree, and Strongly Agree". The five-point Likert type is a frequently preferred measurement format to obtain various item interaction levels of the situation to be measured (DeVeilles, 2017). It is also stated that the reliability of the measured instrument might be positively affected by the scores obtained after an increase in the number of response options (Thorndike, 2005).

2.1.4 Having the initial item pool reviewed by experts

An expert opinion form was prepared for the suitability of the 36-item form created for the RAIS scale, with the options ("Suitable", "Must be corrected", "Unsuitable" and "Your Opinion and Additions") for each item. The expert opinion form prepared for the RAIS scale was presented to the experts in a series of stages. In the first stage, 12 experts/academics in the field of computer and instructional technologies education were consulted. As a result of the experts' opinion form, 13 out of 46 items in the original form were found to be inappropriate and were removed from the scale form with consensus. The remaining 33 items in the form were listed according to their numbers (Item 1, Item 2, Item 3 … Item 23). In addition to the extracted items, corrections were made to 10 items based on expert opinions, (Item 1, Item 2, Item 3, Item 5, Item 9, Item 11, Item 13, Item 14, Item 16, Item 18, Item 19, Item 20, Item 21, Item 23). As a result of the opinion of experts in the field, Item 18 was divided into two items (Item 18 and Item 22) and an Item (Item 25) was added to the scale form. The experts reported that adding the word artificial intelligence application/s to the beginning of the scale form could eliminate misconceptions. As a result, and together with the suggestions, the RAIS scale form consisting of three dimensions (Technology Self-Efficacy, Student Interaction, and Ethical Awareness) and 25 items was created.

In the next stage, the 25-item form of the scale was presented to the opinion of two experts in the field of Turkish language. The sentence structure of the total 4 items (Item 12, Item 14, Item 21, and Item 23) was corrected in response to the opinions of experts in the field of Turkish language. In the final stage, two measurement and evaluation experts were consulted for their opinions. With a common opinion of the measurement and evaluation experts, words in two items (Item 6 and Item 7) were corrected and one item (Item 5) was removed from the scale form as it was found to measure a similar structure. All changes made to the RAIS scale form (items to keep, corrections, removals, and additions) were made following the absolute majority of the expert opinions at each stage. The final version of the RAIS scale form consisted of 24 items (a total of 9 items for the Technology Self-Efficacy dimension, a total of 7 items for the Student Interaction dimension, and a total of 8 items for the Ethical Awareness dimension). At this stage, the order of the RAIS scale form was rearranged (Item 1, Item 2, Item 3, …, Item 24).

After the final form of the 24-item RAIS scale was created, a cognitive interview was conducted with 21 teachers from different departments (nine information technology teachers, seven English teachers, and five mathematics teachers) to check the suitability of the scale. In this process, three teachers were interviewed regarding each dimension of the RAIS scale. For the entire scale interviews were held with 12 teachers. Interviews regarding the dimensions lasted on average (20–35) minutes. Interviews for the entire RAIS scale lasted approximately 60 min. Notes were taken for the interviews throughout the entire cognitive interview process.

2.1.5 Considering the inclusion of validation items

No specific validation items were included in the RAIS. This method may pose potential biases and limitations, but care was taken during the data collection process to identify forms in which missing responses were inadvertantly observed. In this regard, attention was paid to the inadequacy of the responses and thus the responses given by individuals showing similar situations (consecutive responses) were taken into consideration (Tabachnick & Fidell, 2013). For this reason, 53 data in the exploratory factor analysis sample and 36 data in the confirmatory factor analysis and concurrent validity sample were not evaluated due to careless responses.

2.1.6 Administering items to a development sample

During the fall semester of the 2023–2024 academic year, a pilot study was conducted to examine the reliability and validity structures of the RAIS scale with a total of 63 teachers (30 female; 16 male) teaching in different branches in Siirt Province, Türkiye. As part of the pilot study, the participants' response times to unclear terms and items were examined in detail. As a result, no unclear terms were found and the general applicability of the form was found to be positive depending on the interest and general opinion. The average duration of participants' responses to the items ranged from 7 and 10 min. In light of these findings, the researchers took precautions by setting 10 min to prevent the time factor from hurting reliability in the validity structure application of the scale. In order to determine the validity structure of the RAIS scale, the development stage was performed together with two different sample groups. Exploratory factor analysis procedures were applied to the responses obtained from the first sample group. Convergent and divergent validity as well as confirmatory factor analysis procedures were applied to the responses obtained from the second sample group. The responses obtained at different time intervals (EFA—CFA & Concurrent Validity, respectively) were collected through non-probability convenience sampling techniques on Google Form during the fall semester of the 2023–2024 academic year on a voluntary basis. Since there is a common generalizability concern in quantitative research, probability sampling techniques are more preferred. However, the reason for choosing the non-probability sampling technique in this study is to test that the RAIS scale is a safe and valid tool rather than generalizability.

It is vital to reach an appropriate sample size to obtain reliable and valid results from the development of the RAIS measurement tool. Otherwise, negative structures may be obtained during the development stages. It is possible to find suggestions in the literature regarding the decision of the appropriateness of the sample size. Considering the majority of such suggestions, a sample size of 300–500 is found to be good (Comrey & Lee, 1992; Tabachnick & Fidell, 2013). In addition, it is reported that it would be preferable to measure items five or tenfold (Bentler & Chou, 1987; Kass & Tinsley, 1979). In this context, it is further suggested that the factor loadings of good sample size (>0.40) would result in appropriate items with unbiased estimation (Forero et al., 2009). Moreover, it has also been stated that a sample size of 100–200 is acceptable (Kline, 2011). Within the scope of this study, a sample size of

616 was obtained for the exploratory factor analysis phase, and a sample size of 345 and 128 for the confirmatory factor analysis and Concurrent Validity phases, respectively. Therefore, the sample size for this study can be described as good for the first stage and very good and acceptable for the second stage. However, it can be said that it is limited in terms of demographic diversity. The demographic characteristics of the sample are shown in Table 3.

2.1.7 Evaluating the items

In order to reveal the validity and reliability structures of the RAIS scale, construct validity (exploratory factor analysis, confirmatory factor analysis, convergent and divergent validity analysis) and concurrent validity were gradually conducted. Before the exploratory factor analysis, some procedures were carried out, and the results of Kaiser Meyer Olkin (KMO) and Bartlett's tests were examined for the appropriateness of the sample size. The Kaiser Meyer Olkin (KMO) value (≥) 60 and the significance of Bartlett's test ($p < 0.01$) indicate the appropriateness of the sample size (Tabachnick & Fidell, 2013). However, the item-total correlation values of the item in the RAIS scale were examined to be ≥ 0.30 (De Vaus, 2004; Field, 2017; Neale & Liebert, 1980; Pallant, 2016) and the kurtosis and skewness values for the normality distribution of the first sample ranged between ± 2 (Bachman, 2004).

After completing the procedures in question, the exploratory factor analysis was applied to the first sample (616) obtained in the first stage, using the SPSS program. In this stage of determining the dimensions of the RAIS scale, the factors with an eigenvalue ≥ 1.00, the explanation of the total variance of each factor at least ≥ 5%, and the flattening slope of the scree plot were taken into consideration (Cattell, 1966; Guttman, 1954; Kaiser, 1960). There are different approaches in the literature regarding the absolute value of the items, but it is important that the value be (≥) 0.40 to reveal the relationship between the dimension and the items (Matsunaga, 2010). Regarding the explanation of the total variance, it is reported that a percentage of 40% to 60% is acceptable in social science fields (Netemeyer et al., 2003; Pallant, 2016; Scherer et al., 1988).

The normal distribution given by the scope of the procedures specified before exploratory factor analysis was examined and the maximum likelihood method was used when CFA was applied. Accordingly, since there might be a relationship between the factors, Direct Oblimin was applied to the data (Pedhazur & Schmelkin, 1991). In addition to the factor on which the items in the factors that emerged after all these applications at this stage should be loaded, the item-total correlations (corrected item-total correlation) were also calculated. On the other hand, the reliability coefficients of the resulting factors (acceptable reliability coefficient for ≥ 0.70, good reliability coefficient for ≥ 0.80, and excellent reliability coefficient for ≥ 0.90) were examined (Cronbach, 1951). Then, the r effect value (small effect value for 0.1, medium effect value for 0.3, and large effect value for 0.5) was calculated after the correlations between the factors were checked (Field, 2017).

In the second stage, confirmatory factor analysis was applied to the second sample (345) using the Mplus program to confirm the internal structure obtained from

Table 3 Demographic characteristics of participants

1st Sample (N = 616)			2nd Sample (N = 345)			3rd Sample (N = 128)		
City	**F**	%	**City**	**f**	%	**City**	**f**	%
Ankara	152	25	Diyarbakır	97	28	Siirt	29	13.3
İstanbul	143	23	Kastamonu	88	26	Aydın	17	7.8
Siirt	98	16	Niğde	86	25	Batman	12	5.5
Batman	86	14	Bolu	74	21	Sakarya	8	3.7
Muğla	79	13				İstanbul	9	4.1
Eskişehir	58	9				Diyarbakır	9	4.1
						Şırnak	9	4.1
						Kırıkkale	9	4.1
						Bitlis	4	1.8
						Adana	4	1.8
						Bolu	4	1.8
						Mersin	4	1.8
						Van	5	2.3
						Artvin	5	2.3
Gender	**F**	%	**Gender**	**f**	%	**Gender**	**f**	%
Female	381	61.9	Female	233	67.5	Female	87	68
Male	235	38.1	Male	112	32.5	Male	41	32
Department	**F**	%	**Department**	**f**	%	**Department**	**f**	%
Information Technologies	164	26.6	Information Technologies	105	30.4	English Language Teaching	22	17.2
Turkish Language Teaching	84	13.6	Pre-school Teaching	85	24.6	Classroom Teaching	21	16.4
Elementary Mathematics Teaching	78	12.7	English Language Teaching	44	12.8	Elementary Mathematics Teaching	16	12.5
Psychological Counseling and Guidance	76	12,3	Classroom Teaching	35	10.1	Physics Teaching	14	10.9
Science Teaching	61	9.9	Turkish Language Teaching	33	9.6	Preschool Teacher	12	9.4
English Language Teaching	55	8.9	Science Teaching	17	4.9	Turkish Language Teaching	12	9.4

Table 3 (continued)

1st Sample (N = 616)			2nd Sample (N = 345)			3rd Sample (N = 128)		
City	**F**	%	**City**	**f**	%	**City**	**f**	%
Classroom Teaching	53	8.6	Social Sciences Teaching	15	4.3	Science Teaching	10	7.8
Social Sciences Teaching	45	7.3	Elementary Mathematics Teaching	11	3.2	Social Sciences Teaching	7	5.5
						Psychological Counseling and Guidance	2	1.6
						Philosophy Teaching	2	1.6
						Physical Education and Sports Teacher Education	2	1.6
						Information Technologies	1	0.8
						Special Education Teaching	1	0.8

EFA. In this context, the model's χ2/sd (chi-square goodness of fit), CFI (comparative fit index), TLI (Tucker–Lewis index), RMSEA (root mean square error of approximation), and SRMR (standardized root mean square residual) data compliance goodness indices were examined. Acceptable values of model-data fit indices are presented in Table 4.

After the model-data fit indices were identified, the load values of the items in the factors, the Cronbach's alpha reliability coefficients of the factors, and the correlation coefficients (r) between the factors were calculated.

In the next stage, convergent and divergent validity analysis was performed. In this context, the criteria of average variance extracted (AVE) value ≥ 0.50 and composite reliability (ω) value ≥ 0.70 were taken as a basis (Fornell & Larcker, 1981; Hu & Bentler, 1999; Nunnally, 1978).

In the last stage, a concurrent validity test was performed by calculating Pearson correlation coefficients with a similar scale. In this context, the general attitudes towards the artificial intelligence scale, developed by Schepman and Rodway (2020) and adapted to Turkish culture by Kaya et al. (2022), and the Artificial Intelligence Literacy Scale developed by Wang et al., (2023a) and adapted to Turkish culture by Çelebi et al. (2023) was used since it is a suitable measurement tool for teachers and contains items similar to the RAIS scale. Details of the scale are included in the literature review.

2.1.8 Optimizing scale length

The length of the RAIS scale was optimized according to the results of construct and concurrent validity. The RAIS scale initially consisted of 36 items, and then the number of items was reduced based on expert opinion. As a result of the EFA and CFA analyses for the RAIS scale, a final length of 19 items was decided.

3 Findings

Findings based on the construct validity and concurrent validity analyses of the scale development study are presented in this section.

3.1 Construct validity

In the study, Kaiser Meyer Olkin (KMO) and Bartlett's tests were used to test the appropriateness of the sample size before EFA. In the study, the Kaiser Meyer Olkin (KMO) value was found to be $= 0.903$, and Bartlett's test as ($\chi 2$: 5359.246, $P = 0.000$) (Table 5). Therefore, it can be claimed that the sample size is adequate.

The Cronbach's alpha reliability coefficient of the RAIS scale, which consists of 24 items, was found to be 0.892. In addition, the kurtosis and skewness values of the data obtained were found to range between ± 2. This result indicates that the RAIS scale has high reliability and the data show a normal distribution. The Corrected Item-Total Correlation of the RAIS Scale was found to be < 0.30 (Item1 $r = 0.20$).

Table 4 Model-data fit indices

Item fit indices	Acceptable fit	Source
χ^2/sd	<4	(Kline, 2011; Schermelleh-Engel et al., 2003; Baumgartner & Homburg, 1996; Bentler, 1980; Bentler & Bonett, 1980; Marsh et al., 2006; Browne & Cudeck, 1993; Hu & Bentler, 1999; MacCallum et al., 1996)
CFI	≥0.90	
TLI	≥0.90	
RMSEA	≤0.08	
SRMR	≤0.08	

Table 5 RAIS KMO and Bartlett's test

KMO		0.903
Bartlett's Test of Sphericity	Approx. Chi-Square	4837.838
	Df	171
	p	0.000

*p < 0.001

Therefore, this item was removed from the scale form. It was observed that the item-total correlations of the RAIS scale varied between r (Item 7) = 0.320 and r (Item 10) = 0.612 (Table 6). According to this result, it can be suggested that item-total correlations are sufficient and readiness for artificial intelligence can be measured with the remaining 23 items.

3.1.1 Exploratory Factor Analysis (EFA)

As a result of the adequacy of the sample size, EFA was performed to determine the factor structure of the RAIS scale. Since there might be a relationship between factors in EFA, the Maximum Likelihood method was used by applying Direct Oblimin to the data. Load values on the factors were examined as (≥) 0.40. In the first EFA application, the RAIS scale was found to have a four-factor structure with an eigenvalue ≥ 1. It was also observed that the four-factor structure explained 47.646% of the total variance. However, some items were included in different factors (Item 5, Item 17, Item 24) and the load values of Item 7 were below 0.40. These items were removed from the scale form and EFA was applied again. As a result of the application, a three-factor structure with an eigenvalue ≥ 1 was obtained in the RAIS scale. Additionally, the scree plot graph highlighted that the horizontal slope continued after the third factor (Fig. 3).

The three-factor structure explains 50.563% of the total variance, indicating that the total variance explained is acceptable. The eigenvalues of the factors were determined as (30.653) for the first factor, (12.630) for the second factor, and (7.279) for the third factor. Then, the Cronbach's alpha reliability coefficients of the RAIS scale were calculated, and the first-factor reliability coefficient was found to be 0.833, the second-factor reliability coefficient 0.835, and the third-factor reliability coefficient 0.8885. This indicates that the internal consistency of the RAIS scale is acceptable. Regarding the calculation of the correlation coefficients (r) between the factors of the RAIS scale, there was a moderate and positive correlation between the first factor and the second factor (r = 0.307), the first factor and the third factor (r = 0.437), and the second factor and the third factor (r = 0.445). EFA results of the RAIS Scale are presented in Table 6.

3.1.2 Confirmatory Factor Analysis (CFA)

As a result of EFA, the RAIS scale was found to have a structure of three factors and 19 items. To verify the relevant structure, data were collected a second time

Table 6 EFA values of the RAIS scale

Items	Factor 1	Factor 2	Factor 3	Mean	Std. Deviation	Corrected Item-Total Correlation
Item1*				2.41	1.23	**Correlations of the items < 0.30**
Item2	-0.496			3.51	1.25	0.470
Item3	-0.601			3.78	1.22	0.546
Item4	-0.654			3.40	1.26	0.565
Item5*				2.70	1.28	**Involved in different factors**
Item6	-0.655			3.28	1.16	0.415
Item7*				3.05	1.34	**loading value of < 0.40**
Item8	-0.817			3.63	1.21	0.572
Item9	-0.743			3.59	1.27	0.482
Item10		0.48		3.31	1.27	0.612
Item11		0.46		3.42	1.29	0.543
Item12		0.61		2.85	1.22	0.485
Item13		0.73		2.71	1.30	0.390
Item14		0.73		3.21	1.27	0.567
Item15		0.68		2.93	1.29	0.512
Item16		0.57		2.92	1.22	0.548
Item17*				3.35	1.22	**Involved in different factors**
Item18			0.61	3.67	1.26	0.527
Item19			0.57	3.35	1.26	0.437
Item20			0.90	3.67	1.23	0.498
Item21			0.91	3.87	1.13	0.511
Item22			0.88	3.70	1.20	0.546
Item23			0.64	3.89	1.17	0.472
Item24*				2.43	1.19	**Involved in different factors**
19 Items	**6 Items**	**7 Items**	**6 Items**			
%50.563	%30.653	%12.630	%7.279		% of Variance	
a = 0.892	a = 0.833	a = 0.835	a = 0.885		Cronbach's alpha	
Faktör	F1**	F2**	F3**	Correlations among dimensions		
F1**	1.000	-	-			
F2**	0.307	1.000	-			
F3**	0.437	0.445	1.000			
Extraction Method: Maximum Likelihood						
Rotation Method: Oblimin with Kaiser Normalization						

*Removed items, **F1 = Technology Self-Efficacy, **F2 = Student Interaction, **F3 = Ethical Awareness

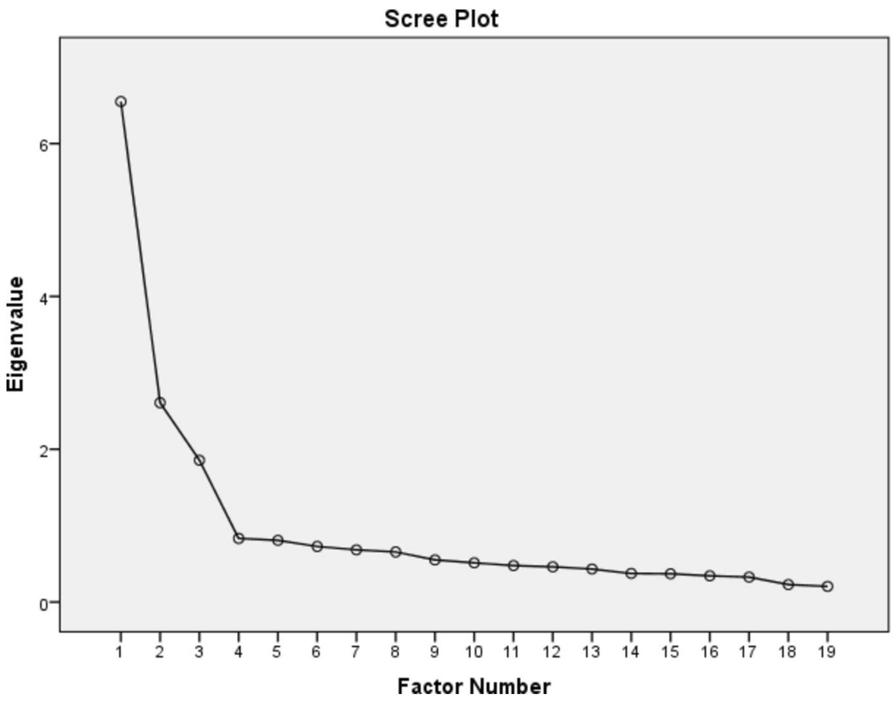

Fig. 3 Scree plot

Table 7 Model-data fit indices of the RAIS scale

Item fit indices	Before modification	After modification	Acceptable fit
χ^2/df	526.902	455.991	<4
CFI	0.924	0.938	≥ 0.90
TLI	0.913	0.928	≥ 0.90
RMSEA	0.086	0.078	≤ 0.08
SRMR	0.049	0.044	≤ 0.08

and CFA was applied. The model-data fit indices of the applied CFA were found to be $\chi 2/df$ (148,345) = 455.991, CFI = 0.938, TLI = 0.928, RMSEA = 0.078, and SRMR = 0.044. According to the relevant data, the model-data index fit is very good, which indicates that the 3-factor, 19-item structure of the RAIS scale was confirmed. The model-data fit indices of the RAIS scale are presented in Table 7.

It can be observed that the factor load values of the items under the Technology Self-Efficacy factor (Item 2, Item 3, Item 4, Item 6, Item 8, Item 9) range between 0.60 and 0.83, the items under the Student Interaction factor (Item 10, Item 11, Item 12, Item 13, Item 14, Item 15, Item 16) range between 0.78 and 0.90, and the factor load values of the items under the Ethical Consciousness

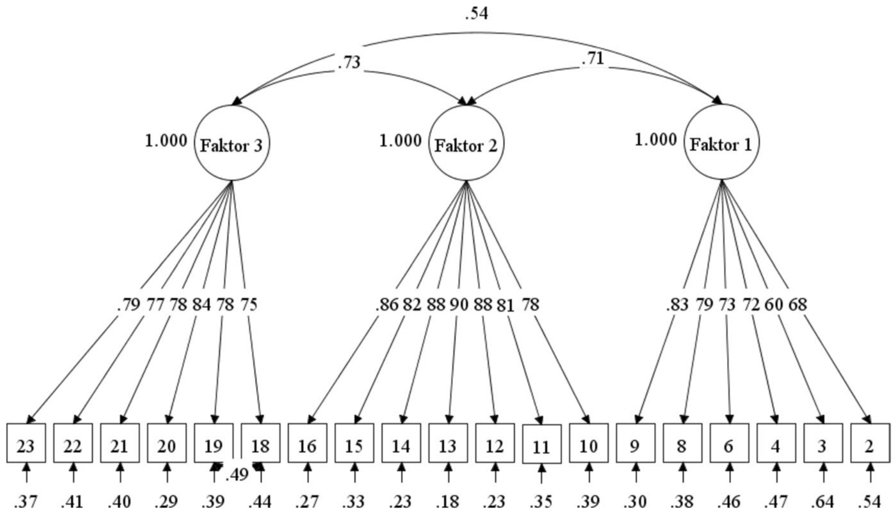

Fig. 4 RAIS scale diagram. F1 = Technology Self-Efficacy, F2 = Student Interaction, F3 = Ethical Awareness

factor (Item 18, Item 19, Item 20, Item 21, Item 22, Item 23) range between 0.75 and 0.84.

The correlation coefficients (r) of the RAIS scale were found to be r value = 0.71 for the Technology Self-Efficacy factor and Student Interaction factor, r value = 0.54 for the Technology Self-Efficacy factor and Ethical Awareness, and r value = 0.73 for the Student Interaction factor and Ethical Awareness. As a result, it can be suggested that the RAIS scale is reliable along with a high level of positive relationship between its factors. The diagram of the RAIS scale is presented in Fig. 4 and the CFA results are presented in Table 8.

3.1.3 Convergent and divergent validity

After the EFA and DFA analyses, convergent and divergent validity analyses were conducted by calculating the average variance extracted (AVE) of the RAIS scale. Considering the convergent analysis values of the RAIS scale, the average variance extracted (AVE) ranges between (0.53–0.70) and the composite reliability coefficients range between (0.87–0.95), Cronbach's alpha reliability coefficients are 0.868 for the Technology Self-Efficacy factor, 0.946 for the Student Interaction factor, and 0.909 for the Ethical Awareness factor, respectively. Accordingly, it can be observed that the RAIS scale provides convergent validity. AVE, composite reliability, and Cronbach's alpha reliability coefficients of the RAIS scale are presented in Table 9.

As part of the Divergent Validity analysis of the RAIS scale, the square roots of AVEs and correlation coefficients among latent variables were examined. Correlation coefficients between latent variables are expected to be lower than the square roots of the AVEs. The values of the divergent validity analysis showed that the correlation coefficients (0.71, 0.54, and 0.73) were among the factors

Table 8 CFA results of RAIS

No	Item	Factor Loading	Standard Error	t	P
Technology Self-Efficacy					
	I can learn a programming language at a level that can create an artificial intelligence product	0.68	0.030	20.67	< 0.0001
	I can use artificial intelligence applications (such as ChatGPT, Chatboot, Bing, Dall-e, …)	0.60	0.04	15.90	< 0.0001
	I can analyze artificial intelligence data	0.73	0.03	24.36	< 0.0001
	I can solve the problems of artificial intelligence applications	0.73	0.03	25.40	< 0.0001
	I can develop artificial intelligence projects	0.79	0.03	31.88	< 0.0001
	I can manage artificial intelligence projects	0.83	0.02	38.94	< 0.0001
Student Interaction					
	I can lead classroom discussions on artificial intelligence topics with students	0.78	0.02	34.80	< 0.0001
	I can encourage students to learn artificial intelligence topics	0.81	0.02	39.73	< 0.0001
	I can help students develop collaborative projects on artificial intelligence	0.88	0.01	61.22	< 0.0001
	I can design activities that encourage student interaction regarding artificial intelligence	0.90	0.01	76.92	< 0.0001
	I can help students critically evaluate AI projects	0.88	0.01	62.29	< 0.0001
	I can mentor students for artificial intelligence projects	0.82	0.02	43.07	< 0.0001
	I can help students discover their talents in the field of artificial intelligence	0.86	0.02	53.83	< 0.0001
Ethical Awareness					
	I pay attention to data privacy in artificial intelligence applications	0.75	0.03	27.11	< 0.0001
	I exhibit ethical behavior in the use of artificial intelligence applications	0.78	0.03	31.55	< 0.0001
	I can take precautions against unethical artificial intelligence practices	0.84	0.02	42.84	< 0.0001

Table 8 (continued)

No	Item	Factor Loading	Standard Error	t	P
I can detect unethical AI practices		0.78	0.03	30.89	< 0.0001
I can ensure personal data security in artificial intelligence applications		0.77	0.03	30.25	< 0.0001
I am aware of my ethical responsibilities in artificial intelligence applications		0.79	0.02	33.55	< 0.0001
Correlations among dimensions	Technology Self-Efficacy	Student Interaction		Ethical Awareness	
Technology Self-Efficacy	1.000	-		-	< 0.0001
Student Interaction	0.71	1.000		-	< 0.0001
Ethical Awareness	0.54	0.73		1.000	< 0.0001

Table 9 AVE and reliability coefficient values of the dimensions of RAIS

Dimension	AVE	Composite Reliability (ω)	Cronbach (α)
Technology Self-Efficacy	0.53	0.87	0.86
Student Interaction	0.70	0.95	0.94
Ethical Awareness	0.60	0.91	0.90

Table 10 AVE AVE and correlation coefficient values between factors

Dimension	Technology Self-Efficacy	Student Interaction	Ethical Awareness
Technology Self-Efficacy	**0.73***		
Student Interaction	0.71	**0.85***	
Ethical Awareness	0.54	0.73	**0.79***

*The diagonal elements of the matrices are the divergent validity coefficients, which were obtained through the calculation of the square root values of the AVE

lower than the square roots of AVEs (0.73, 0.85, and 0.79). These results provide evidence for the divergent validity of the RAIS. The correlation coefficient values between factors are shown in Table 10.

3.2 Concurrent validity

To prove the concurrent validity of the RAIS scale, the General Attitudes Towards the Artificial Intelligence Scale, consisting of two factors (positive attitudes—negative attitudes), was used with the second sample (N = 345). In this study, the Cronbach alpha value of the positive attitudes factor was = 0.93 and the Cronbach Alpha value of the negative attitudes factor was = 0.85. In the third sample (N = 128), the Artificial Intelligence Literacy scale consisting of four dimensions (awareness, use, evaluation, ethics) was used. In this study, the Cronbach alpha value of the awareness dimension was = 0.75, the Cronbach alpha value of the use dimension was = 0.73, the Cronbach alpha value of the evaluation dimension was = 0.86 and the Cronbach alpha value of the ethics dimension was = 0.73. The examination of the Pearson correlation values (r) between the sub-dimensions of the scales revealed a medium and positive relationship between all the dimensions of the RAIS scale and the positive attitude dimension, with no significant relationship with the negative attitude dimension, a small and medium level positive relationship with the awareness dimension, a medium and high-level positive relationship with the use and evaluation dimension, and a medium level positive relationship with the ethical dimension. All these results show the concurrent validity of the RAIS scale. The Pearson correlations between the factors are shown in Table 11.

Table 11 Pearson correlation values between factors

Correlation	RAIS Sub-factors		
	Technology Self-Efficacy	**Student Interaction**	**Ethical Awareness**
Positive Attitude	**0.393***	**0.484***	**0.452***
Negative Attitude	- 0.051	- 0.082	- 0.077
Awareness	**0.341***	**0.354***	**0.242***
Use	**0.503***	**0.519***	**0.386***
Evaluation	**0.462***	**0.526***	**0.463***
Ethics	**0.408***	**0.426***	**0.499***

*$p < 0.001$

4 Discussion

This study was designed to develop a scale in an attempt to reveal teachers' readiness for artificial intelligence applications. During the development stage of the RAIS measurement tool, a scale form was created based on the mixed method. In creating the scale form, an expert group consisting of 67 panelists with expertise in artificial intelligence was selected through snowball sampling. The item pool obtained in the panelist expert group was presented to the field experts again and the RAIS scale took its final form. Various approaches were adopted to examine the validity and reliability of the resulting scale. For the data obtained within the framework of these approaches, the SPSS program was used for EFA, the Mplus program for CFA, and the Excel program for convergent and divergent validity.

Within the scope of validity and reliability, as a result of EFA, the RAIS scale consisting of three dimensions (Technology Self-Efficacy, Student Interaction, and Ethical Awareness) and 19 items emerged. The eigenvalues of the factors as a result of EFA were found to be 30.653% for the first factor, 12.630% for the second factor, and 7.279% for the third factor with the three-factor structure explaining 50.563% of the total variance. The model-data fit indices of CFA were found to be $\chi2/df\ (148,345) = 455.991$, $CFI = 0.938$, $TLI = 0.928$, $RMSEA = 0.078$, and $SRMR = 0.044$. As a result, the data obtained from both EFA and CFA revealed that the RAIS scale is a valid and reliable measurement tool. Later, concurrent validity was tested by examining the correlation between the RAIS, whose validity and reliability were determined, general attitudes towards artificial intelligence, and the Artificial Intelligence Literacy Scale. Finally, concurrent validity between the scales was achieved.

The contribution of the RAIS to the literature is thought to be important in several aspects. First, it was developed by taking into account the experience and knowledge of teachers in different branches working in Turkey. Secondly, the existing measurement tools in the literature have demonstrated that no RAIS scale has been developed for teachers. In this sense, it is claimed that the RAIS scale would fill the relevant gap. Third, RAIS with the technology self-efficacy dimension and student interaction dimension contains sub-factors that are similar to other scales. Similarities have been observed with the self-efficacy skills and student interaction dimensions in many scales developed in the context of readiness (Hung, 2016; Karaca et al., 2021; Kim & Martin, 2023; Lin et al., 2016; Youhasan et al., 2020; Yurdugül & Demir, 2017; Zhong et al., 2023). However, the RAIS is different from other scales because the ethical awareness dimension seems to be a new dimension among other readiness scales. Karaca et al. (2021) stated that the ethical factor of the study titled "Medical artificial intelligence preparation scale for medical students (MAIRS-MS)" was addressed from a health ethics perspective. Finally, the RAIS scale can provide information for the design and implementation of effective learning environments.

At the end of the research, the Readiness for Artificial Intelligence Scale was developed. The development stages of the scale were carried out sequentially, and its validity and reliability were proven by conducting validity and reliability tests with different sample groups. This finding allows researchers to use the RAIS in both face-to-face learning and online learning processes.

5 Conclusion

In conclusion, the Readiness for Artificial Intelligence Scale, consisting of three dimensions (Technology Self-Efficacy, Student Interaction, and Ethical Awareness) and 19 items, is recommended in the study. The high score obtained from the scale, which is designed as a five-point Likert measurement format, indicates that the teachers' level of readiness is high. The high score obtained in the context of the dimensions indicates that technology self-efficacy, student interaction, and ethical awareness are all high and at similar levels. Another result is that the reliability coefficients of the scale were above the acceptable level and the construct validity tests showed that the relevant items adequately represented the constructs. In conclusion, it can be noted that the RAIS scale is a safe and valid tool for measuring the intended constructs.

6 Recommendations for research

Correlational comparison and prediction studies with the Readiness for Artificial Intelligence Scale and similar scales that are thought to be related are recommended. However, studies can be conducted to reveal the differences in RAIS in the context of a variety of different variables. RAIS has been applied in the Turkish culture, while studies on reliability and validity analyses can be conducted to adapt it to new cultures. It is also stated that the RAIS is aimed at teachers; however, the readiness of individuals providing training on artificial intelligence applications in different fields can be examined. In addition, it can be applied to teacher candidates who teach in internship schools as part of their teaching practice. Similar studies can be conducted with a group with a demographically diverse sample regarding the demographic diversity, which is a limitation of the study.

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Data availability The datasets generated during and/or analysed during the current study are not publicly available but are available from the corresponding author on request.

Declarations

Conflict of interest None.

Ethical approval The design of the study and the data collection procedures are approved by Siirt University Directorate of Ethics Committee (2023–6042). The study followed all protocols required to research in an ethical manner.

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