RESEARCH ARTICLE WWW.PEGEGOG.NET

# From Classrooms to Codes: Measuring the Perceptions of School Administrators and Teachers Towards Artificial Intelligence

**MUSTAFA TAKTAK**

mtaktak@gelisim.edu.tr

**ABSTRACT**

Technology is not just a tool, but a reflection of the relationship that humans establish with the knowledge they produce. In this context, a scale was created to measure educators' perception of artificial intelligence in Turkey and validity and reliability analyses were conducted. The research was conducted with three independent sample groups. In the first stage, the 12-item draft scale was applied to 233 participants and reduced to 8 items[1] as a result of EFA. In the second stage, the scale was applied to 153 participants and CFA was performed, confirming a one-dimensional structure, and acceptable fit indices were reached. In the third stage, the temporal stability and criterion validity of the scale were evaluated with 48 participants using the test-retest method. The reliability of the scale was determined by Cronbach's Alpha coefficient being 0.62 and KMO value being 0.90. Additionally, various statistical analyses, including item-total correlation, item-residual analysis, and test-retest correlation analysis, were conducted to ensure the validity and reliability of the scale.

**Keywords:** Artificial intelligence, school administrator, teacher, perception, scale

## Introduction

The concept of artificial intelligence (AI) was first introduced to the literature by John McCarthy in 1956. The Turing test developed by Alan Turing in the 1950s is considered as an important turning point in the field of AI (Arslan, 2020). The Turing test is a measurement tool developed to determine whether a machine has cognitive competence like humans (Muggleton, 2014). Over time, concepts such as "expert systems", "machine learning", "data mining" and "deep learning" have revolutionised AI research ((Coppin, 2004). The popularity of artificial intelligence has gained a great momentum with the introduction of AI applications such as ChatGPT developed by OpenAI. ChatGPT is a chatbot that compiles information from the Internet and provides users with logical and satisfying answers (Lo, 2023). Thanks to its ability to make logical predictions and quickly adapt to different languages and experiences, ChatGPT-like applications have been widely used in various fields (Akiba & Fraboni, 2023). It has assumed an important role especially in sectors such as health, finance, education, communication and transport (Taktak et al., 2024). However, the impact of artificial intelligence in education is still in its infancy compared to other fields (Singh & Thakur, 2024; Langran et al., 2020).

**Corresponding Author mail :** mtaktak@gelisim.edu.tr

**How to cite this article:** MUSTAFA TAKTAK. From Classrooms to Codes: Measuring the Perceptions of School Administrators and Teachers Towards Artificial Intelligence, Vol. 15, No. 4, 2024, 846-860

**Source of support:** Nil **Conflicts of Interest:** None. **DOI:** 10.48047/pegegog.15.04.42

**Received:** 12.03.2024

**Accepted:** 12.04.2024 **Published:** 05.06.2024

[1] Scale items were given at the end of the study

Artificial intelligence is a rapidly developing discipline that has the potential to provide innovative solutions to the problems of societies in different fields. Thanks to this potential, AI is used in many fields today, facilitating and improving human life (Qin et al., 2020). Artificial intelligence is defined as the ability to solve problems by imitating the thinking and learning functions of the human brain (Russell & Norvig, 2010). Nabiyev (2016) defines this ability as the capacity of machines to fulfil human-specific cognitive functions. Obschonka and Audretsch (2020) define artificial intelligence as humanoid intelligence exhibited by machines. These definitions show that artificial intelligence gives machines the ability to perform basic tasks that require human intelligence such as reasoning, learning, perception and problem solving (Loos et al., 2023; Luckin et al., 2022).

Artificial intelligence applications in education started in the 1970s with expert systems developed to facilitate learning (Jaakkola et al., 2019). There are various applications where data and logic-based artificial intelligence technologies are used in education (Roll & Wylie, 2016). Examples of such applications are dialogue-based teaching systems, intelligent teaching systems, intelligent tutoring systems, and autonomous learning systems. There are also applications developed for providing meaningful experiences, accessing information effectively, and supporting students to learn at their own pace ((Ruiz-Rojas et al., 2023; Nabiyev et al., 2020). These applications offer various advantages such as increasing students' academic achievement and reducing teachers' workload by making learning processes more effective, efficient and interesting through data analysis of student performance and behaviours (Ouyang & Jiao, 2021). In addition, it offers important benefits such as creating personalised learning environments according to the needs of individuals (Taktak et al., 2024), providing instant feedback and promoting comprehensive learning (Li et al., 2023), helping grading by automating objective assessment (Lo, 2023), improving students' language and writing skills (Jeon et al., 2023), and providing more appropriate suggestions for career goals (Akiba & Fraboni, 2023).

When educational artificial intelligence applications on a global scale are examined, it is seen that there are countries that have made these technologies an important part of their education systems. For example, Squirrel AI, based in China , provides educational services according to the individual differences of students, while the US-based adaptive artificial intelligence called Watson provides services according to the learning potential of students. Similarly, Third Space Learning in the UK and Sana Labs in Sweden are widely used. In Turkey, artificial intelligence education and training projects are carried out under the supervision of the Ministry of National Education. A study by Zawacki-Richter et al. (2019) shows that Turkey is the fourth country in the ranking of scientific studies on artificial intelligence in education.

There are various artificial intelligence tools and platforms used for educational purposes worldwide. ChatGPT, Calscraft, Aleks, Copilot, Coursera, Quiziz and Utifen are some of these tools and platforms. However, studies reveal that AI applications for educational purposes are still in the development stage and need to be further sophisticated (Atteh, 2023; Guan et al., 2020; Tang et al., 2021). Teachers are key determinants of how and when to use AI and at what stage of the learning process (Zawacki-Richter et al., 2019). Therefore, teachers are expected to assume critical roles for the effective use of AI in education. Teachers' perceptions towards the use of AI directly affect the quality of the current AI- supported curriculum and the thoughts and plans of decision makers (Kalafat, 2022). The concept of perception refers to the process of transferring the objective world to the subjective consciousness of the individual and giving meaning to the stimuli in the environment (Collins, 1967). According to the Turkish Language Association, perception is the process of becoming conscious of something by drawing attention to it. Teachers' perceptions about the use of artificial intelligence can provide important clues in the process of understanding, interpreting and managing artificial intelligence. Thus, it can enable the evaluation of AI applications from different perspectives, including ethical implications and potential effects on the learner and the teacher. In addition, it can help teachers to make more effective decisions and act more consciously by taking into account ethical consequences as well as learning and teaching perception in their decisions.

## Literature Review

In the literature, many studies have been conducted to develop artificial intelligence (AI) scales and these studies have created various scales. For example, "General Attitudes towards Artificial Intelligence Scale" (Kaya et al., 2022; Schepman & Rodway, 2023), "Artificial Intelligence Attitude Scale" (Grassini, 2023; Jang et al., 2022; Sindermann et al., 2021), "Threats of Artificial Intelligence Scale" (Kieslich et al, 2021), "Productive AI Acceptance Scale" (Karaoğlan Yılmaz et al., 2023), "Artificial Intelligence Literacy Scale" (Wang et al., 2023), "Artificial Intelligence Readiness Scale for Medical Students" (Karaca et al., 2021) and "Artificial Intelligence Self-Efficacy Scale" (Wang & Chuang, 2023) are some of these scales. In Turkey, it is seen that most of the studies on artificial intelligence in education in recent years have qualitative research designs and therefore mixed and efficient research is limited (Meço & Coştu, 2022). Studies generally focus on teachers' tendencies towards the use of artificial intelligence (Sanlı et al., 2023), pre-service teachers' awareness of artificial intelligence technologies (Çam et al., 2021; Ferikoğlu & Akgün, 2022), teachers' views on the use of artificial intelligence in schools (Özer et al., 2023) and teachers' perspectives on the importance of artificial intelligence in education (Köse et al., 2023). These studies provide important contributions to the perceptions and applications of artificial intelligence in the field of education both in Turkey and internationally. Schleicher (2012) states that innovation in education does not only consist of technology integration, but also includes the transformation of teaching approaches so that students can compete on a global scale. In this context, examining teachers' perceptions of AI technologies can provide valuable data for the development and implementation of AI-supported curricula by contributing to the understanding and effective management of these technologies in the educational ecosystem. In addition, recognising teachers' perceptions towards AI will support understanding their interest and motivation towards technology, making their teaching processes more interesting and equipping their students with knowledge and skills in line with the requirements of the age such as artificial intelligence. Analysing the perceptions of teachers, who are responsible for predicting, adopting and developing the future role of artificial intelligence in education, will be a critical data source in the process of integration and diffusion of this technology into education. Therefore, the need for a valid and reliable measurement tool to measure teachers' perceptions of artificial intelligence becomes evident. In this context, the current study focuses on determining the perceptions towards the use of artificial intelligence in education and includes validity and reliability analyses for the development of this measurement tool.

## Method

### Research model

The main purpose of this study is to develop a Likert-type scale that can validly and reliably evaluate teachers' perceptions of the use of artificial intelligence in education. The study was conducted within the framework of survey design, which is a quantitative research method. Cohen and colleagues (2021) state that survey design is a frequently preferred method in the data collection process in order to identify certain characteristics of a group.

### Working Group

Within the scope of the research, data were obtained from three different study groups. These groups consisted of school administrators and teachers working in public and private schools in Turkey in the 2024-2025 academic year. In order to achieve reliable and valid results in the scale development process, it is stated that the number of individuals in the study group should be at least 10 times the number of items in the pre-application form of the scale (Kline, 2016). On the other hand, Cohen and colleagues (2021) stated that a sample size of 150 to 200 people is sufficient regardless of the number of variables. In this framework, data were collected from 233 participants for Exploratory Factor Analysis (EFA) and 153 participants for Confirmatory Factor Analysis (CFA). In addition, for test-retest and criterion validity analyses, data were obtained from 48 school administrators and teachers who constituted the third study group. In order to perform exploratory and confirmatory factor analyses, this study was conducted in two different time intervals and on independent study groups. Detailed information about the study groups in the study is given in Table 1.

**Table 1.** *Demographic information on the study groups.*

| Variable | | EFA | | CFA | | Criterion validity & Test-retest | |
|---|---|---|---|---|---|---|---|
| | | F | % | F | % | F | % |
| Gender | Woman | 158 | 67.9 | 91 | 59.6 | 27 | 55.7 |
| | Male | 75 | 32.1 | 62 | 40.4 | 21 | 44.3 |
| Age | 25 years old and under | 12 | 0.6 | 1 | 0.9 | 0 | 0 |
| | 26-35 years old | 73 | 34.5 | 52 | 33.5 | 17 | 36.7 |
| | 36-45 years old | 101 | 47.6 | 88 | 56.8 | 24 | 49.2 |
| | 46-55 years old | 35 | 16.7 | 10 | 7.1 | 7 | 14.1 |
| | Ages 56 and over | 12 | 0.6 | 2 | 1.7 | 0 | 0 |
| Duty | Executive | 29 | 12.3 | 24 | 15.7 | 10 | 21 |
| | Teacher | 204 | 87.7 | 129 | 84.3 | 38 | 79 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Field | Kindergarten | 51 | 22 | 27 | 18.1 | 0 | 0 |
| | Primary school | 13 | 5.4 | 32 | 21.3 | 18 | 38.1 |
| | Middle school | 38 | 16.1 | 57 | 36.7 | 14 | 29.1 |
| | High school | 131 | 56.5 | 37 | 23.9 | 16 | 32.8 |
| Does it use AI? | Yes | 132 | 56.5 | 90 | 59.2 | 40 | 50.1 |
| | No | 101 | 43.5 | 63 | 40.8 | 8 | 49.9 |
| | ***Total*** | ***233*** | | ***153*** | | ***48*** | |

Upon examining Table 1, it is observed that the number of female participants is higher than that of male participants in the study group. Regarding the age distribution of the participants, the most prevalent age range is between 36 and 45, with a significant portion of this group consisting of teachers. In terms of educational levels, the majority of participants are teachers in high schools and kindergartens. Furthermore, more than half of the participants reported using artificial intelligence applications, indicating the increasing adoption of this technology in the field of education. However, the fact that some participants have never used any artificial intelligence applications is crucial for obtaining more objective data regarding the perceptions of school administrators and teachers about artificial intelligence. This situation provides an opportunity for a more comprehensive and balanced analysis of artificial intelligence applications by reflecting the diverse experiences and perspectives of the participants.

### Scale Development Process

Scale development is a process that involves defining, classifying and grading the qualities to be measured, as well as establishing the appropriate methodology (Büyüköztürk, 2012). In this context, the process was designed by considering the steps suggested by DeVellis (2017) in scale development processes. Scale development processes are given in Figure 1 below.

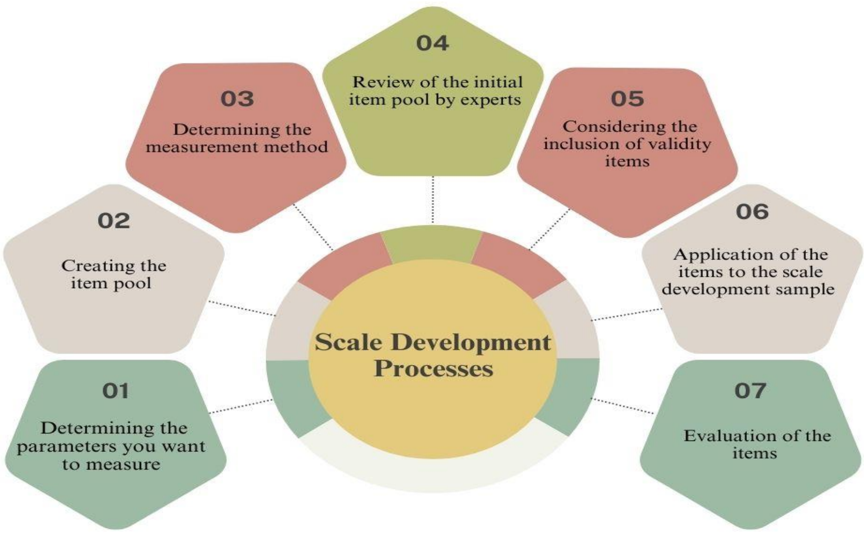


**Figure 1.** *Scale Development Processes*

The scale development process first started with a clear and explicit definition of the concept to be measured. Following this definition, national and international literature was extensively reviewed and an item pool consisting of 16 items was created. In the fourth stage of the process, expert opinions were sought and a two-stage expert evaluation process was meticulously carried out in this direction. These expert evaluations are as follows:

- The scale was reduced to 12 items and reshaped by taking into account the evaluations *(in terms of language and expression, spelling rules, clarity and comprehensibility, etc.*) of three different teachers working at primary, secondary and high school levels who had used various artificial intelligence applications.

- In the second stage, based on the opinions of 4 expert researchers who have scientific research on the use of artificial intelligence in the field of education, the pre-application form of the scale was reduced to 11 items and reorganised. (The experts were asked to evaluate each item as "Appropriate, Should be Corrected, Should be Removed" and a special section was added to the form for them to write their opinions).

In order to determine the opinions on the items in the scale, a 5-point Likert form as "Strongly Agree (5)," "Agree (4)," "Partially Agree (3)," "Disagree (2)" and "Strongly Disagree (1)" was preferred. The draft form was made ready for use.

**Data collection**

The data collection process was initiated after obtaining ethics committee approval and necessary permissions from school administrations. The data were collected in two different stages and the schools were randomly divided into two groups for Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). In the literature, it is stated that it is not recommended to conduct both EFA and CFA in the same study group (Erkuş, 2012). This approach aims to prevent data integrity and overlaps. In the study, written forms were sent to the school administrators determined for factor analyses by the researcher and the data were collected with the voluntary consent of the participants.

**Data analysis**

During the Exploratory Factor Analysis (EFA) process, descriptive statistics of the scale were calculated and the suitability of the data to normal distribution was evaluated. In addition, visual evaluation of the factor structure was made using scree plot. Within the scope of validity analyses, Kaiser-Meyer-Olkin (KMO) test and Bartlett's test results were examined in detail to evaluate the suitability of the factor structure and the total variance explained by the scale. After the EFA was completed, Confirmatory Factor Analysis (CFA) was conducted to evaluate the model fit of the unidimensional structure and eight items of the scale. CFA analyses were conducted using SPSS AMOS software. In order to evaluate the reliability of the scale over time, the test-retest method was used, the scale was applied to the same participants twice with a 25-day interval and the results were compared. The test-retest correlation coefficient was found to be r=0.63, indicating that the scale provides consistent measurements over time. In addition, concurrent (criterion) validity, which is an important parameter in determining the validity of the scale, was examined and detailed findings are presented in the results section.

## Findings

This section presents the results of both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) conducted on two distinct sample groups. Additionally, the reliability of the scale and the analysis of each item are discussed to evaluate the psychometric properties of the scale.

### Exploratory factor analysis

Exploratory factor analysis (EFA) was performed on the data collected from 168 teachers to determine the structure of the scale and to evaluate its construct validity. KMO value and Bartlett's Test of Sphericity were applied to evaluate the suitability of the data for EFA. The related results are shown in Table 2. In addition, principal component analysis was applied to determine the factor structure of the scale and Varimax rotation technique was preferred for better interpretation of the factors. As stated by DeVellis (2017) and Field (2018), in order for an item to be included in the relevant factor in factor analysis, the factor loading must be higher than .30. As a result of the exploratory factor analysis (EFA) conducted in this direction, items with factor loadings below .30 were removed from the scale. According to the findings of the analysis, items 2, 5 and 9 with factor loadings below .30 were eliminated from the scale respectively. The Scree Plot graph of the scale is presented in Figure 2 and the CFA results are presented in detail in Table 2.

Cronbach's Alpha coefficient was calculated to determine the internal consistency level of the scale and this coefficient was found to be .862. This value is within the acceptable reliability limits recommended by Çokluk, Şekercioğlu, and Büyüköztürk (2018) and indicates a satisfactory level in terms of the overall reliability of the scale. In addition, it was determined that the item-total correlation coefficients of the scale items ranged between .51 and .80. In terms of psychometric properties of the measurement tool, item-total correlations above .20 indicate that the relevant items adequately represent the construct they measure (Büyüköztürk, 2012; Tabachnick & Fidell, 2015). The fact that all scale items have a correlation coefficient above .51 reveals that the items have a high discrimination level. In this direction, the findings obtained show that the reliability of the developed scale is at a high level and construct validity is provided. In the final stage, the final version of the scale, which consists of a single factor and contains a total of 8 items, is presented in detail in Table 2.

**Table 2.** *EFA results related to the scale*

| Draft scale items | Final scale | Factor Loading | Mean | SD | Explained Variance | Cronbach alfa |
|---|---|---|---|---|---|---|
| Item-1 | Item-10 | 0.801 | 3.89 | .929 | 53.244 | 0.862 |
| Item-2* | Item-11 | 0.799 | 3.63 | .958 | | |

| | | | | |
|---|---|---|---|---|
| Item-3 | Item-8 | 0.768 | 3.51 | 1.07 |
| Item-4 | Item-3 | 0.732 | 3.58 | .924 |
| Item-5* | Item-7 | 0.721 | 3.32 | .943 |
| Item-6 | Item-6 | 0.666 | 3.61 | .890 |
| Item-7 | Item-1 | 0.651 | 4.05 | .810 |
| Item-8 | Item-4 | 0.519 | 3.83 | .640 |
| Item-9* | | | | |
| Item-10 | | **KMO** | 0.90 | |
| Item-11 | | Approx. Chi-Square | 494,493 | |

*Removed items

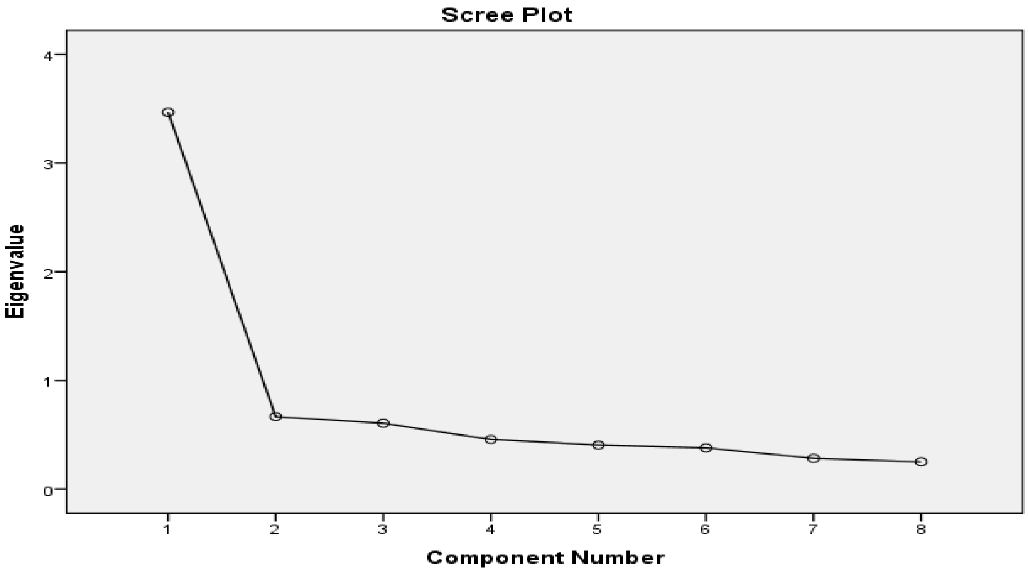


**Figure 2.** *Scree plot*

Upon examining Table 2, a KMO (Kaiser-Meyer-Olkin) value of 0.901 is obtained. According to Kaiser and Rice (1974), KMO values of 0.90 and above are considered excellent. In this context, the obtained KMO value of 0.901, combined with the significant result of the Bartlett test ($\chi^2$ = 494.493; $p < 0.01$), indicates that the sample size is highly suitable for factor analysis. These findings suggest that the data is appropriate for factor analysis. Furthermore, the unidimensional structure of the scale is clearly demonstrated in both Figure 2 and Table 2. An important parameter in exploratory factor analysis (EFA) is the percentage of total variance explained by the scale. In this case, the explained variance is 53.24%. According to Hair et al. (2014), when the explained variance ratio is 50% or higher, it is considered that the sub-factors adequately explain the structure of the scale. In this regard, the 53.24% explained variance indicates that the factor structure of the scale is valid and meaningful. Finally, Table 3 presents the correlation coefficients of the scale items, which serve as an additional indicator of the scale's reliability

.

**Table 3.** *Scale İtems Correlation Coefficient*

| | Item-1 | Item-3 | Item-4 | Item-6 | Item-7 | Item-8 | Item-10 | Item-11 |
|---|---|---|---|---|---|---|---|---|
| Item-1 | 1 | .454** | .400** | .387** | .331** | .564** | .364** | .455** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Item-3 | 1 | .361* | .451** | .441** | .455** | .536** | .489** |
| Item-4 | | 1 | .335** | .330** | .327** | .416** | .391** |
| Item-6 | | | 1 | .514** | .433** | .385** | .429** |
| Item-7 | | | | 1 | .489** | 429** | .477** |
| Item-8 | | | | | 1 | .518** | .533** |
| Item-10 | | | | | | 1 | .669** |
| Item-11 | | | | | | | 1 |

**p<0,001.

Upon examining Table 3, it is observed that the item-total correlation coefficients of the scale items range from 0.33 to 0.66. From a psychometric perspective, item-total correlation coefficients above 0.20 indicate that the items adequately represent the construct being measured (Büyüköztürk, 2012; Tabachnick & Fidell, 2015). The fact that all items have a correlation coefficient greater than 0.33 suggests that the items possess a high level of discriminative power. These results support the conclusion that the scale has a robust psychometric structure.

## Confirmatory Factor Analysis

Following the completion of the exploratory factor analysis, confirmatory factor analysis was conducted using data from an independent sample group to rigorously assess the validity of the identified construct consisting of eight items combined under a single latent dimension. Confirmatory factor analysis is a complex statistical methodology designed to validate the construct emerging from exploratory factor analysis by ensuring that the theoretical constructs show a high level of agreement with empirical data (Karagöz, 2017). The comprehensive results of confirmatory factor analysis are shown in Figure 3.

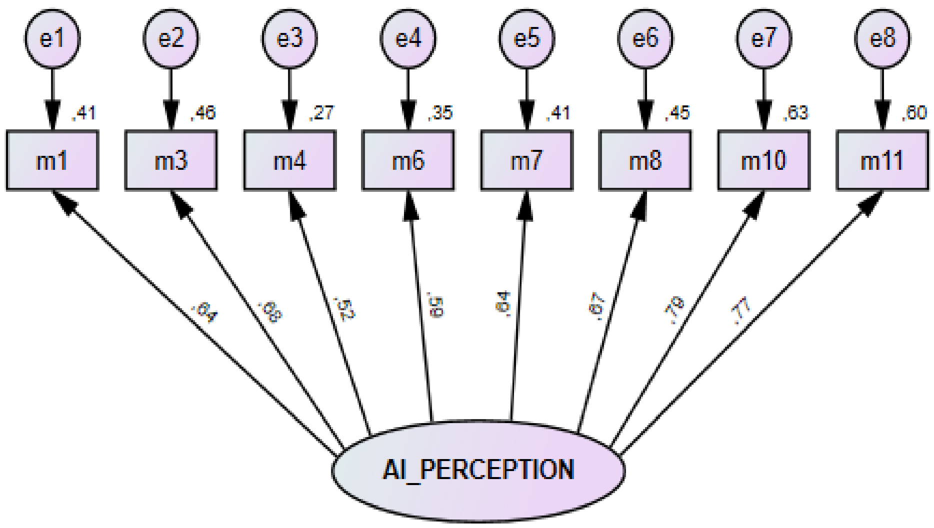


**Figure 3.** *Confirmatory Factor Analysis of Scale*

In Figure 3, it was found that all paths related to the 8 items forming the scale were highly significant at .001 level. The goodness of fit index values obtained from the first order confirmatory factor analysis are presented in Table 4. In this context, the interpretation of the goodness of fit indices is based on the reference values suggested by Hooper et al. (2008).

**Table 4.** Scale fit index values in CFA

| | $X^2$ /sd | GFI | IFI | TLI | CFI | RMSEA | RMR |
|---|---|---|---|---|---|---|---|
| *Good fit values* | <5 | >0.85 | >0.90 | >0.90 | >0.90 | <0.08 | <0.08 |
| *Perfect fit values* | <3 | >0.90 | >0.95 | >0.95 | >0.95 | <0.05 | <0.05 |
| ***Scale values*** | **1.87** | **0.94** | **0.96** | **0.95** | **0.96** | **0.07** | **0.03** |
| *Fit level* | P. fit* | P. fit | P. fit | P. fit | P. fit | G. fit** | P. fit |

*Perfect fit **Good fet

Table 4 presents the fit indices obtained from the first level confirmatory factor analysis and indicates that the model has an acceptable fit level. In particular, ($X^2/df$ = 1.87, GFI = .945, IFI = .964, TLI = .950, CFI = .960, RMSEA = .007, RMR = 0.03) values reveal that the model is adequate and shows a good fit in confirmatory factor analysis. It is observed that these indices used to evaluate the fit of the model meet the standard criteria for confirmatory factor analysis.

### Concurrent Validity

The concurrent validity (criterion validity) of the scale developed to measure school administrators' and teachers' perceptions of artificial intelligence was evaluated with reference to the SHAIP Scale (Shinners et al., 2022), which measures health professionals' perceptions of artificial intelligence. Criterion validity involves comparing the performance of a measurement with a specified criterion or its performance at the same time (Tavşancıl, 2019). Item means were calculated for both scales and Pearson correlation coefficients were derived from these means. The analysis produced a Pearson correlation coefficient of r = 0.74, indicating a significant and positive relationship between the two scales. This finding suggests that the developed scale has strong criterion validity and effectively measures perceptions of AI, consistent with the SHAIP Scale designed for healthcare professionals.

### Conclusion

Education is far beyond a process of information transmission; it is a dynamic phenomenon that shapes individuals' cognitive, emotional, and social development. This process continuously evolves in parallel with societal needs, individual differences, and global changes. Technological advancements, particularly artificial intelligence (AI) applications, have become one of the most significant driving forces behind this transformation in education. The integration of AI into education has the potential to not only change methods of knowledge delivery but also profoundly transform teaching processes. However, the effective use of AI in education is directly linked to the perceptions and attitudes of educational stakeholders toward these technologies. In this context, how school administrators and teachers perceive AI offers valuable insights into how these technologies will be incorporated into education. This study aims to develop a valid and reliable scale to measure school administrators' and teachers' perceptions of AI applications. To this end, a comprehensive pool of items was initially created, and the content validity of the items was evaluated through expert opinions. Subsequently, Exploratory Factor Analysis (EFA) was conducted to determine the factor structure of the scale and select the items. Confirmatory Factor Analysis (CFA) was applied to verify the accuracy of the obtained structure. The analysis results revealed that the scale has a unidimensional structure and consists of eight items, demonstrating satisfactory psychometric properties in terms of validity and reliability. This structure suggests that participants' perceptions of AI can be assessed within a holistic framework. The emergence of a unidimensional structure makes it possible to consider that perceptions of AI in the school environment are shaped by a common perspective. Therefore, the findings indicate that this scale provides both theoretical and practical significance as an important tool for assessing the perceptions of educational administrators and teachers toward AI.

## Discussion

The findings of this study highlight the necessity of conducting an in-depth examination of school administrators' and teachers' perceptions of artificial intelligence (AI) technologies to assess their impact on education more comprehensively. The role of AI in education is increasingly growing, contributing significantly to educational processes through functions such as providing personalized learning experiences for students (Tapalova & Zhiyenbayeva, 2022; Zavalevskyi et al., 2024), offering feedback by tracking academic performance (Taktak et al., 2024; Wongvorachan et al., 2022), and alleviating teachers' workloads (Li & Jiang, 2024; Roble, 2024; Yang, 2024). However, current measurement tools are largely limited to technology acceptance (Nazaretsky et al., 2022; Wang et al., 2023) and general attitudes toward information technology, hindering the in-depth exploration of AI-specific elements within the educational context. This clearly indicates the need for a more unique and functional scale to understand the critical role of school administrators' and teachers' perceptions of AI in educational processes. The scale developed in this study, particularly with its unidimensional structure and limited number of items (eight items), provides an opportunity to measure educators' perceptions of AI in a brief, effective, and practical manner, offering significant advantages in terms of usability. This is especially important because some existing scales, with their high number of items, create difficulties in application, complicating the data collection processes for educators (Ferikoglu & Akgun, 2022; Wang & Chuang, 2023). In this context, the developed scale facilitates a more detailed analysis of the pedagogical and managerial effects of AI in educational settings while also contributing to data-driven decision-making by policymakers. Additionally, identifying educators' awareness, expectations, and preparedness regarding AI is crucial for the effective and sustainable implementation of AI in education. In this regard, the results of the study demonstrate that scientifically measuring school administrators' and teachers' perceptions of AI can support professional development processes and ease their adaptation to AI-supported educational environments. This represents a significant step in terms of educational policies and practices, providing the foundation necessary for the successful realization of digital transformation in education.

**Limitation and Future Research**

There are several limitations that should be taken into consideration by practitioners and researchers who intend to use the developed scale.

Firstly, the sample used in this study is not representative of the general population. The participants consisted of school administrators and teachers working in Istanbul, Turkey. Since convenience sampling was used in the study, the findings may not generalise to other populations with different demographic characteristics or cultural backgrounds.

Secondly, data collection was conducted through printed forms during school visits after obtaining general legal permissions. Although high data quality was ensured, researchers using platforms such as Prolific in different countries could improve data quality by adding control questions to exclude participants who responded randomly or did not read the items fully.

Third, the developed scale was designed to measure the perception of AI by educators in a specific geography with similar cultural characteristics. Future research could adopt a cross-sectional research design to examine the perception of AI by educators in countries with different resources and infrastructure and the impact of AI on various educational variables.

Finally, the study focussed only on educators' perceptions of AI and did not consider other stakeholders such as students, parents or policy makers. Future studies should take a more comprehensive approach to include different perspectives and address the effects of AI on education from a broader perspective.

**Conflict of Interest Statement**

The author(s) report no potential conflicts of interest in relation to this study.

**Data availability**

The data that support the fndings of this study are available from the corresponding author upon reasonable request.

**Ethical Statement**

This study was conducted in accordance with the ethical guidelines established in the Helsinki Declaration. Approval was obtained from the xxxxx University Ethics Committee (Decision No: 2024-16). No personally identifiable information was collected from the participants.

**Reference**

Anderson, L. M. (1988). *Likert scales*. In Educational Research Methodology and Measurement: An International Handbook. Pergamon Press.

Atteh, E. (2023). The recommended instructional approach in Ghanaian basic schools: A review of constructivist approach of teaching and learning in the mathematics classroom. *Asian Journal of Education and Social Studies, 47*(1), 15–25. https://doi.org/10.9734/ajess/2023/v47i11013

Büyüköztürk, Ş. (2012). *Sosyal bilimler için veri analizi el kitabı* (16. baskı). Pegem Akademi.

Cam, M. B., Celik, N. C., Turan Guntepe, E., & Durukan, Ü. G. (2021). Öğretmen adaylarının yapay zekâ teknolojileri ile ilgili farkındalıklarının belirlenmesi. *Mustafa Kemal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 18*(48), 263–285. https://dergipark.org.tr/tr/download/article-file/1764677

Cohen, L., Manion, L., & Morrison, K. (2021). *Eğitimde araştırma yöntemleri* (E. Dinç, K. Kıroğlu, Çev.). Pegem Akademi.

Collins, A. W. (1967). The epistemological status of the concept of perception. *The Philosophical Review*, *76*(4), 436–459. https://doi.org/10.2307/2183282

Creswell, J. W. (2020). *Eğitim araştırmaları; nicel ve nitel araştırmanın planlanması, yürütülmesi ve değerlendirilmesi* (H. Ekşi, Çev. Ed.). EDAM.

Çokluk, Ö., Şekercioğlu, G., ve Büyüköztürk, Ş. (2012). Sosyal bilimler için çok değişkenli istatistik: SPSS ve LISREL uygulamaları. Pegem Akademi.

DeVellis, R. F. (2017). Ölçek Geliştirme: Kuram ve Uygulamalar. Ankara: Nobel.

Ferikoglu, D., & Akgun, € E. (2022). An investigation of teachers' artificial intelligence awareness: A scale development study. *Malaysian Online Journal of Educational Technology, 10*(3), 215–231. https://doi.org/10.52380/mojet.2022.10.3.407

Field, A. (2018). Discovering Statistics Using Ibm Spss Statistics.London: SAGE.

Guan, C., Mou, J., & Jiang, Z. (2020). Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. *International Journal of Innovation Studies*, *4*(4), 134–147. https://doi.org/10.1016/j.ijis.2020.09.001

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2014). Multivariate data analysis. Pearson.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. The Electronic Journal of Business Research Methods, 6(1), 53–60. https://doi.org/10.21427/D7CF7R

Jang, Y., Choi, S., & Kim, H. (2022). Development and validation of an instrument to measure undergraduate students' attitudes toward the ethics of artificial intelligence (AT-EAI) and analysis of its difference by gender and experience of AI education. *Education and Information Technologies, 27*(8), 11635–11667. https://doi.org/10.1007/s10639-022-11086-5

Kalafat, O. (2022). Eğitim ve yapay zeka. In Bilen M. (Ed.), *Yapay zekanın değiştirdiği dinamikler* (1. Baskı). Eğitim Yayınevi.

Karagoz, Y. (2017). SPSS ve AMOS Uygulamalı Nitel-Nicel Karma Bilimsel Aras¸tırma Yontemleri [Qualitative–quantitative mixed scientific research methods with SPSS and AMOS applied] (1st ed.). Nobel Publishing.

Karaoglan Yilmaz, F. G., Yilmaz, R., & Ceylan, M. (2023). Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study. *International Journal of Human–Computer Interaction*, 1–13. Advance online publication. https://doi.org/10.1080/10447318.2023.2288730

Kline, R. B. (2016). Yapısal Eşitlik Modellemesi ve Uygulaması, (Ed. S. Şen). Ankara: Nobel.

Kieslich, K., Lünich, M., & Marcinkowski, F. (2021). The threats of artificial intelligence scale (TAI) development, measurement, and test over three application domains. *International Journal of Social Robotics*, *13*(7), 1563–1577. https://doi.org/10.1007/s12369-020-00734-w

Kose, B., Radıf, H., Uyar, B., Baysal, İ., & Demirci, N. (2023). Öğretmen görüşlerine göre eğitimde yapay zekânın önemi. *Journal of Social, Humanities and Administrative Sciences, 9*(71), 4203–4209. https://doi.org/10.29228/JOSHAS.74125

Li, X., & Jiang, Y. (2024). Artificial intelligence in education: Opportunities, current status, and prospects. *Geographical Research Bulletin, 3*, 146-174. https://doi.org/10.50908/grb.3.0_146

Meco, G., & Costu, F. (2022). Eğitimde yapay zekanın kullanılması: Betimsel içerik analizi çalışması. *Karadeniz Teknik Üniversitesi Sosyal Bilimler Enstitüsü Sosyal Bilimler Dergisi, 12*(23), 171–193. https://dergipark.org.tr/tr/download/article-file/2329969

Nazaretsky, T., Cukurova, M., & Alexandron, G. (2022, March). An instrument for measuring teachers' trust in AI-based educational technology. In LAK22: 12th International Learning Analytics and Knowledge Conference (pp. 56-66). https://doi.org/10.1145/3506860.3506866

Ozer, S., Yazıcı, A. S., Akgul, S., & Yıldırım, A. (2023). Okullarda yapay zeka kullanımına ilişkin öğretmen görüşleri. *Ulusal Eğitim Dergisi, 3*(10), 1776–1794. https://doi.org/10.5281/zenodo.10085759

Ramazanoglu, M., & Akın, T. (2024). AI readiness scale for teachers: Development and validation.

*Education and Information Technologies*, 1–29. https://doi.org/10.1007/s10639-024-13087-y

Roble, J. (2024). Rethinking Teacher Workload: A Phenomenological Study of Generative Artificial Intelligence and Educator Well-Being (Doctoral dissertation, Lamar University-Beaumont).

Sanlı, A., Ateş, E., Bayburtlu, N., Bektaş, M., & Ozdemir, K. (2023). Yapay Zeka kullanımında öğretmen eğilimleri. *International Journal of Social Science*, *7*(28), 206–222. https://doi.org/10.52096/usbd.7.28.15

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. *Computers in Human Behavior Reports*, *1*, 100014. https://doi.org/10.1016/j.chbr.2020.100014

Shinners, L., Grace, S., Smith, S., Stephens, A., & Aggar, C. (2022). Exploring healthcare professionals' perceptions of artificial intelligence: Piloting the Shinners Artificial Intelligence Perception tool. *Digital Health*, *8*. https://doi.org/10.1177/20552076221078110

Tabachnick, B.G. & Fidell, L.S. (2015). Use of multivariate statistics . Nobel.

Tang, K. Y., Chang, C. Y., & Hwang, G. J. (2021). Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019). *Interactive Learning Environments*, *31*(4), 2134–2152. https://doi.org/10.1080/10494820.2021.1875001

Taktak, M., Bellibas, M. S., & Özgenel, M. (2024). Use of ChatGPT in Education: Future Strategic Road Map with SWOT Analysis. *Educational Process: International Journal*, 13(3), 7-21. https://doi.org/10.22521/edupij.2024.133.1

Tavşancıl, E. (2019). *Tutumların ölçülmesi ve SPSS ile veri analizi* (6. Baskı). Nobel Yayınları.

Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial intelligence in education: AIEd for personalised learning pathways. *Electronic Journal of e-Learning*, 20(5), 639-653. https://files.eric.ed.gov/fulltext/EJ1373006.pdf

Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 42(9), 1324-1337. https://doi.org/10.1080/0144929X.2022.2072768

Wang, Y. Y., & Chuang, Y. W. (2023). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, 29(4), 4785–4808. https://doi.org/10.1007/s10639-023-12015-w

Wongvorachan, T., Lai, K. W., Bulut, O., Tsai, Y. S., & Chen, G. (2022). Artificial intelligence: Transforming the future of feedback in education. *Journal of Applied Testing Technology*, 95-116. https://jattjournal.net/index.php/atp/article/view/170387

Yang, Z. (2024). Empowering teaching and learning with artificial intelligence. *Frontiers of Digital Education*, 1(1), 1-3. https://doi.org/10.1007/s44366-024-0017-8

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2020). Systematic review of research on artificial intelligence applications in higher education: A meta-analysis of published literature. *Computers & Education*, 147, 103773. https://doi.org/10.1016/j.compedu.2019.103773

Zhang, L., Xu, Y., & Zhang, L. (2024). Application of artificial intelligence in education: A systematic review. *Frontiers in Psychology*, 11, 2416. https://doi.org/10.3389/fpsyg.2020.558098

Zavalevskyi, Y., Kyrilenko, S., Kijan, O., Bessarab, N., & Mosyakova, I. (2024). The role of AI in individualizing learning and creating personalized programs. *Amazonia Investiga*, 13(73), 200-208. https://doi.org/10.34069/AI/2024.73.01.16

| Teachers' perception of AI | I totally disagree | I disagree | Partially Agree | I agree | Totally Agree |
|---|---|---|---|---|---|
| I believe that artificial intelligence saves time. | | | | | |
| Artificial intelligence increases teacher efficiency. | | | | | |
| Artificial intelligence applications increase teacher-student communication. | | | | | |
| Artificial intelligence is an effective tool in increasing academic success. | | | | | |
| Artificial intelligence supports classroom management . | | | | | |
| Artificial intelligence will strengthen my communication with younger generations. | | | | | |
| Artificial intelligence skills is important for my professional development. | | | | | |
| Artificial intelligence increases students' interest in lessons. | | | | | |