An Investigation of Teachers' Artificial Intelligence Awareness: A Scale Development Study

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To Cite: Ferikoğlu, D. & Akgün, E. (2022). An investigation of teachers' artificial intelligence awareness: A scale development study. *Malaysian Online Journal of Educational Technology, 10*(3), 215-231. http://dx.doi.org/10.52380/mojet.2022.10.3.407

ABSTRACT

In this study, a scale was designed and developed by the researchers in order to resolve the awareness of teachers about the integration of artificial intelligence into education, as well as their predisposition to developing the concept of artificial intelligence and its sub-branches. Awareness of teachers on artificial intelligence were converted into score ranges and maximum competencies that could be reached for each level were established. In the research, it was aimed to develop a scale that reveals the awareness of artificial intelligence of teachers with a reliable, current and valid scale and to contribute to the literature by providing a measurement tool. "Teachers' Artificial Intelligence Awareness Scale", developed by the researchers as a data collection tool, was first tested on 30 teachers as a pilot application and then on 561. The research population is an appropriate sample. Data collection was done through a questionnaire on Google Form. The population sample of the study consists of 561 private school and public school teachers. Likert-type scale items were created to examine the awareness of teachers. The research method was designed quantitatively. In the validity and reliability tests of the scale items, frequency and percentage calculations were made using the SPSS program and the data obtained were then shuffled into the research.

Keywords: *Artificial intelligence, scale, awareness.*

Article History:
Received: 7 February 2022
Received in revised form: 5 April 2022
Accepted: 1 July 2022
Article type: Research Article

INTRODUCTION

It can be stated that if one of the aims of science is to solve the problems encountered by human beings, the other is to offer a long and healthy life by raising the living standards. Depending on the aim, many technologies have become a natural part of daily life, and problems that were considered very important and complex half a century ago can currently be solved with one click of a mouse or two. Radical changes emerged not only in daily life but also in professional life. For example, in The Future of Jobs Report (WEF, 2018), it is predicted that while there will be a great decrease in the number of employees in the next 5 years, automated establishments will replace the existing employees (Kılınç & Özdemir 2019). Therefore, it is necessary to be aware of the requirements of technological developments in the future journey (Ermut, 2020). Because while the transformation takes place, it is a matter of debate to what extent the individuals will endorse this change or how much resistance they will show. In other words, in the process of change, people develop an attitude by assessing the impacts of changes, and noticing their advantages and disadvantages (Kılınç & Özdemir 2019).

It is possible to say that one of the biggest contributions of digital transformation to education is artificial intelligence. Since the early 21st century, new and different tools have been developed in the field of artificial intelligence. For example, artificial intelligence algorithms have been the basis of the ability to offer song suggestions to users on online music platforms. In addition, smart assistants, which are frequently encountered in banking applications, constitute examples of artificial intelligence algorithms. Similarly, Kutlusoy (2019) states that artificial intelligence algorithms have been an important application area for sectors such as the health, tourism and defence industry where information technologies are used actively.

As in many different business and service sectors, artificial intelligence integrations in many educational technologies, especially learning management systems, have recently attracted attention (Roll & Wylie, 2016). When artificial intelligence and its contribution to classroom activities are evaluated, it is discerned that artificial intelligence education materials that increase visualization entice the interest of students in the lesson (Kreps & Neuhauser, 2013). Not only for the student, artificial intelligence algorithms concretize all the data about the learning process of the students, making it easier for the teachers to monitor the development process of the students more closely (Tao, Díaz, & Guerra, 2019). In addition, the Digital Education Action Plan published by the European Commission, which sets out the roadmap for 2021-2027, emphasizes the importance of using artificial intelligence and data in learning and teaching activities. In this roadmap, the importance of artificial intelligence in education is emphasized in Action 6, by stating that individuals' digital literacy and emerging technologies, including artificial intelligence, are required in the digital transformation process (European Commission, 2018). Therefore, it is predicted that artificial intelligence will provide the means for many different headings to develop in the field of education in the not-too-distant future (Erümit, Calap, Çolak, Yavuz, & Aydın, 2020). However, although the interest and need for artificial intelligence have reached remarkable levels, the content that will provide students with knowledge, skills and competence in this regard has not yet evolved in education systems (Westerheide, 2019). Arslan (2020) emphasizes that if better education models emerge with the developing technologies, more qualified people will be raised for the future. Because with the transformation and change, the perspective of educators will also change. Thus, educators will have more interest and time to assimilate new information. When the scale studies on teacher awareness in artificial intelligence are examined, it is seen that there is an important gap in the field. The general problem of the research is to develop a scale that determines teacher awareness and assists the steps that can be taken to improve this awareness in order to adapt to the education world of the future quickly. In addition, in this process, educators must have a high level of professional awareness in order to catch up with the digitalized society and students.

The Concept of Artificial Intelligence and its Development

The first steps of artificial intelligence were taken by the scientist Alan Turing. In 1950 Turing published an article titled "Computing Machinery and Intelligence". In this article, he posed the question “Can machines think?” and rejected the objections in the form of “No, they cannot think” (Pirim, 2006). Turing made studies in this field because he thought machines could handle the abilities such as decision-making and problem-solving which are traits peculiar to humans. As a result of these studies, the Turing test was introduced (Arslan, 2020). After Turing, who is accepted as the ancestor of artificial intelligence, research and applications in this field continued without losing any momentum. In the light of these research and applications, it has become possible to assert that beyond establishing intelligent systems, artificial intelligence constitutes the basis of systems that think like humans and develop solutions (Joshi, 2020).

Artificial intelligence, which has been the subject of many studies in the artificial intelligence literature for more than half a century, is defined as the computer's capacity of performing tasks related to processes that require logic such as perceiving, interpreting, generalizing, learning through past experiences and finding solutions like humans in the face of a problem (Nabiyev, 2012). In the field of education, artificial intelligence is defined as a means to improve education in an individualized, flexible, inclusive and interesting way by processing real-time data (UNESCO, 2017). The purpose of artificial intelligence in education is to ameliorate classroom education and enhance the capacity of teachers to augment such a process (Kış, 2019). While artificial intelligence can provide early warning about students; it can also deal with routine work (homework, exam checks, missing topics, etc.). Therefore, it can be said that artificial intelligence contributes to many stages of the teaching process. For this reason, since it is possible to predict that it may be used very effectively in the education process in the near future, it is essential that education policymakers and education administrators recognize the validity of utilizing such technology.

The steps to be taken toward the effective use of artificial intelligence in the education system will initiate a process of change and innovation. Especially considering the National Artificial Intelligence Strategy 2021-2025 (Presidency of the Republic of Turkey Digital Transformation Office, 2021) document, it is possible to assert that there will be a change in the education system by taking appropriate steps in the field of artificial intelligence according to the Turkish context. However, the rate of adoption of innovations varies according to the individual and the social environment in which the innovations are cultivated, and it is possible for some to resist this innovation (Rogers, 2003). Therefore, while planning the steps that will trigger a change process, it is necessary to consider the competence, awareness and attitudes of the people who will implement this change (Seçkin, Demirel & Özçınar, 2016). Therefore, there is a need not only for the contributions of artificial intelligence to the education system but also for ascertaining the artificial intelligence awareness of teachers who play one of the leading roles in the teaching process and drawing a roadmap for the steps that can be taken to fulfill such an end.

The aim of this study is to examine the competence and interest of teachers in this subject with the "Artificial Intelligence Awareness of Teachers Scale".

RESEARCH METHOD

Research Design

A scale development study was carried out in the light of the collected data in this research, in which teachers' views on the integration of artificial intelligence into education and their awareness of artificial intelligence were examined. In addition, the cross-sectional survey model, one of the survey research types, was preferred for surveying phase.

Participants

The convenience sampling method, which is one of the non-random sampling types, was used in the formation of the participants of the research. The convenience sampling method includes the process of continuing the sampling until an appropriate population is created and the most accessible and nearby people are chosen as participants (Cohen, Morrison & Manison, 2007). The sample population of the study consisted of 561 public and private school teachers working in metropolitan cities in the 2019 – 2020 academic year. The scale was applied to a focus group of 30 teachers as a pilot study. The ages of the participants ranged from 22 to 64 years, and the average age of the participants was 37.65. When the years of professional experience of the participants were examined, it was seen that the years of professional experience varied between 1 and 44 years. While the majority of the participants worked in public schools, few of them were employed by private schools. When the branches of the teachers included in the study are examined, 26 teaching branches emerge. It was observed that teachers were mostly involved in classroom teaching (23.9%), mathematics (11.1%) and Turkish (9.6%) branches, while teachers were least involved in creative drama (0.2%). In addition to this, it was observed that 76.3% of the teachers had a bachelor's degree and 18.7% a master's degree. 3.2% of the teachers have an associate degree and 1.8% have a doctorate degree.

Data Collection Tool

In the research, a form consisting of two parts was used as a data collection tool. In the first part of the form, information about the demographic variables of the participants (age, years of experience, branch, education level, school where they work) could be found. The second part subsumed the "Teachers' Artificial Intelligence Awareness Scale", which was prepared by the researchers in a five-point Likert type.

In order to measure the teachers' views on the integration of artificial intelligence into education and their awareness on this subject, a scale titled “Artificial Intelligence Awareness Scale" was created by the researchers and experts were consulted for their comments in line with the purposes of the study.

Collection of Data

First Phase

During the scale creation and development process, an extensive literature review was conducted and a scale consisting of three parts was prepared. The first part of the scale consisted of items that reflected the personal and demographic data of the participants, and the second part comprised 78 questions prepared in Likert type, referring to the knowledge and opinions of the participants about artificial intelligence. The third part of the scale-covered four questions that include teachers' personal use and opinions of artificial intelligence. In total, the scale consisted of four two-choice, five short-answer, and 78 Likert-type items. In this process, for establishing the reliability and the validity of the items to be measured and for establishing the suitability of the items for the purpose of the research, the opinions of two different experts in the field were sought after. The questionnaire was arranged according to the opinions of the experts in the field. Then, a Turkish teacher, who has seven years of professional experience in the field of Turkish Language and Literature, was summoned and his opinion was acquired on the clarity and language intelligibility of the scale items.

The Second Phase

After the scale was finalized, a pilot study was conducted by sending it to 30 participants via e-mail. As a result of this preliminary application, it was determined that the questions in the questionnaire were understandable and required only a few final adjustments. After the questionnaire was delivered to the participants, no time limit was applied to them regarding their responses.

The Third Phase

After the scale was presented to the study group, factor analysis and reliability analysis were performed. At this stage, factor analysis preconditions such as sample size and the number of items should be examined, outliers should be excluded and appropriateness tests should be performed for factor analysis (Kalaycı, 2006). The measurement tool, which was prepared during the scale development process, was distributed to the sample group selected randomly from the research population, and factor analysis was performed by scoring the answers given. According to the results of the analysis, the analysis was repeated after removing or adding some items from the tool. The process of repeating the analysis was continued until an appropriate solution containing a maximum number of items to cover the area to be evaluated was reached (Karakoç & Dönmez, 2014, p. 44).

Kaiser Meyer Olkin (KMO) and Bartlett tests, which are reliability tests, were undertaken to check whether the size of the study sample would be suitable for factor analysis. KMO values above 0.9 indicate a near-perfect fit for factor analysis (Field, 2009, p. 647). In the study, the result of the KMO test was 0.983, which signifies suitability for factor analysis. The Bartlett sphericity test, on the other hand, tests the homogeneity and consistency of the factors (Yurdugül, 2005). In the study, the Bartlet test result showed reliability at $p<0.01$ level of significance. After establishing suitability for factor analysis, the factor extraction method was to be applied and the principal component analysis technique was used to reveal the scale construct validity. This method was preferred because the total variance of the variables, their specific variances and the relations between the items were taken into account in the principal component analysis (Büyüköztürk, 2002).

Data Analysis

During the development of the Artificial Intelligence Awareness of Teachers scale, validity and reliability analyzes were made. Within the scope of the study, the sample adequacy required for performing the relevant factor analysis was examined and the study group was deemed sufficient (Tabachnick & Fidell, 2001). Some items in the scale were excluded from the study after examining the within-group and between-groups correlation values according to exploratory factor analysis, and the number of items was reduced from 78 to 51. Scale items were grouped under four factors. Afterwards, confirmatory factor analyzes were performed. SPSS and SPSS Amos statistical programs were used for these analyses.

In order to determine the construct validity of the Artificial Intelligence Awareness scale, Exploratory Factor Analysis (EFA) was performed using principal component analysis with varimax rotation. In addition, Confirmatory Factor Analysis (CFA) was employed to test the accuracy of the structure revealed by EFA. In the analysis, factor loads were determined as at least 0.30 (Çokluk, Şekercioğlu, & Büyüköztürk, 2016). The Cronbach Alpha coefficient was calculated for the sub-dimensions and overall reliability of the scale.

FINDINGS

In the findings section of the study, the outputs and comments obtained through the analyzes from the SPSS statistical program are given.

Teachers' Artificial Intelligence Awareness Scale Validity Reliability Analysis

In this part of the study, item extraction scale averages and corrected item total correlations were given in order to study the validity and reliability analyzes of the scale. Reliability analysis results are given in Table 1.

Table 1. *Reliability Analysis Results of Artificial Intelligence Awareness Scale*

Item	Item Extraction Scale Averages	Item Extraction Scale Variance	Corrected Item -Total Correlation	Item Extraction Scale Reliability
Item 1	270,420	2709,727	0,537	0,981
Item 2	270,410	2706,846	0,556	0,981
Item 3	270,690	2706,563	0,506	0,981
Item 4	270,540	2706,334	0,528	0,981
Item 5	270,560	2700,990	0,582	0,981
Item 6	270,510	2699,954	0,572	0,981
Item 7	270,290	2701,427	0,631	0,981
Item 8	270,930	2697,535	0,530	0,981
Item 9	270,810	2708,046	0,535	0,981
Item 10	270,870	2702,175	0,553	0,981
Item 11	270,270	2697,723	0,666	0,981
Item 12	270,820	2719,760	0,386	0,981
Item 13	270,590	2713,881	0,433	0,981
Item 14	270,540	2702,305	0,528	0,981
Item 15	270,710	2706,441	0,508	0,981
Item 16	271,530	2733,714	0,221	0,981
Item 17	270,550	2698,277	0,654	0,981
Item 18	270,750	2693,154	0,636	0,981
Item 19	270,530	2692,758	0,707	0,981
Item 20	271,250	2721,559	0,332	0,981
Item 21	271,050	2707,944	0,463	0,981
Item 22	271,300	2705,575	0,466	0,981
Item 23	270,460	2701,512	0,515	0,981
Item 24	270,690	2699,622	0,609	0,981
Item 25	270,550	2694,860	0,699	0,981
Item 26	270,870	2701,167	0,618	0,981
Item 27	270,440	2694,661	0,599	0,981
Item 28	270,270	2700,228	0,585	0,981
Item 29	270,540	2699,266	0,492	0,981
Item 30	270,650	2687,900	0,711	0,980
Item 31	270,270	2686,602	0,694	0,981
Item 32	270,320	2684,224	0,746	0,980
Item 33	270,370	2685,624	0,717	0,980
Item 34	270,370	2686,825	0,715	0,980

Item 35	270,510	2690,493	0,724	0,980
Item 36	270,910	2688,540	0,640	0,981
Item 37	270,560	2686,353	0,768	0,980
Item 38	270,530	2686,116	0,754	0,980
Item 39	270,550	2687,322	0,775	0,980
Item 40	270,550	2686,727	0,766	0,980
Item 41	270,560	2683,903	0,793	0,980
Item 42	270,410	2680,900	0,768	0,980
Item 43	270,840	2682,631	0,684	0,981
Item 44	270,630	2681,061	0,758	0,980
Item 45	270,490	2683,872	0,718	0,980
Item 46	270,680	2683,868	0,667	0,981
Item 47	270,760	2682,501	0,663	0,981
Item 48	271,410	2690,706	0,536	0,981
Item 49	270,990	2682,031	0,657	0,981
Item 50	271,230	2689,709	0,600	0,981
Item 51	271,170	2690,131	0,552	0,981
Item 52	270,950	2681,024	0,684	0,981
Item 53	270,770	2680,315	0,732	0,980
Item 54	270,620	2678,570	0,765	0,980
Item 55	270,620	2679,588	0,730	0,980
Item 56	270,990	2680,558	0,682	0,981
Item 57	270,970	2679,113	0,701	0,980
Item 58	270,660	2678,872	0,760	0,980
Item 59	270,480	2680,389	0,766	0,980
Item 60	270,430	2684,317	0,736	0,980
Item 61	271,210	2705,256	0,440	0,981
Item 62	271,250	2694,529	0,524	0,981
Item 63	270,640	2681,675	0,716	0,980
Item 64	270,710	2682,595	0,744	0,980
Item 65	271,340	2699,000	0,490	0,981
Item 66	270,780	2685,905	0,730	0,980
Item 67	271,080	2694,454	0,580	0,981
Item 68	271,170	2698,475	0,543	0,981
Item 69	270,720	2684,913	0,723	0,980
Item 70	270,890	2685,276	0,698	0,981
Item 71	270,730	2686,397	0,731	0,980
Item 72	270,940	2687,251	0,689	0,981
Item 73	270,920	2695,838	0,577	0,981
Item 74	271,110	2685,342	0,653	0,981
Item 75	270,750	2680,207	0,756	0,980
Item 76	270,810	2683,249	0,715	0,980
Item 77	271,040	2697,238	0,542	0,981
Item 78	270,720	2685,298	0,676	0,981

When the item analysis of the artificial intelligence awareness of the teachers in Table 2 are examined, since the relationship of an item with other items should not be less than 0.4, the extraction process was performed one by one, starting with the item with the lowest relationship (Wolfinbarger & Gilly, 2003). The final version of the scale as a result of the item analysis in the scale is given in Table 2.

Table 2. *Reliability Analysis Results of Artificial Intelligence Awareness Scale*

Item	Item Extraction Scale Average	Item Extraction Scale Variance	Corrected Item-Total Correlation	Item Extraction Scale Reliability
Item 1	181,209	1410,122	0,591	0,986
Item 2	181,141	1408,485	0,639	0,986
Item 4	181,307	1409,763	0,582	0,986
Item 5	181,283	1403,928	0,668	0,986
Item 6	181,253	1403,725	0,637	0,986
Item 9	181,544	1409,802	0,592	0,986
Item 11	181,059	1400,863	0,764	0,986
Item 14	181,317	1407,810	0,556	0,986
Item 17	181,323	1401,605	0,735	0,986
Item 18	181,494	1402,375	0,691	0,986
Item 19	181,326	1398,338	0,785	0,986
Item 23	181,226	1406,840	0,564	0,986
Item 24	181,451	1405,484	0,660	0,986
Item 30	181,398	1395,676	0,786	0,986
Item 31	181,050	1391,969	0,791	0,986
Item 32	181,105	1391,401	0,835	0,986
Item 33	181,169	1390,766	0,816	0,986
Item 34	181,139	1392,398	0,810	0,986
Item 35	181,275	1395,910	0,800	0,986
Item 37	181,333	1393,519	0,848	0,986
Item 38	181,266	1393,674	0,843	0,986
Item 39	181,305	1393,866	0,852	0,986
Item 40	181,337	1393,613	0,857	0,986
Item 41	181,335	1391,562	0,867	0,986
Item 42	181,169	1390,098	0,853	0,986
Item 43	181,520	1394,114	0,753	0,986
Item 44	181,346	1391,012	0,845	0,986
Item 45	181,226	1392,525	0,814	0,986
Item 46	181,387	1390,895	0,769	0,986
Item 47	181,460	1391,820	0,740	0,986
Item 52	181,642	1391,662	0,742	0,986
Item 53	181,462	1390,156	0,818	0,986
Item 54	181,346	1389,605	0,845	0,986
Item 55	181,355	1389,433	0,806	0,986
Item 56	181,658	1394,379	0,709	0,986
Item 57	181,649	1393,150	0,738	0,986
Item 58	181,383	1389,965	0,841	0,986
Item 59	181,237	1389,431	0,857	0,986
Item 60	181,193	1389,706	0,847	0,986
Item 63	181,353	1389,607	0,820	0,986
Item 64	181,389	1392,417	0,823	0,986
Item 66	181,501	1393,772	0,814	0,986
Item 67	181,772	1401,751	0,610	0,986
Item 69	181,474	1393,571	0,791	0,986
Item 70	181,610	1394,013	0,773	0,986
Item 71	181,480	1394,429	0,815	0,986
Item 72	181,633	1395,772	0,763	0,986
Item 74	181,754	1398,439	0,691	0,986
Item 75	181,472	1392,482	0,828	0,986
Item 76	181,517	1393,172	0,770	0,986
Item 78	181,460	1393,960	0,746	0,986

Cronbach's Alpha = 0,986

When the relationships between the items was examined in the artificial intelligence awareness scale, and when the extraction process of the items were carried out one by one, starting from the item with the lowest relationship with others, a total of 27 items, namely 3, 7, 8, 10, 12, 13, 15, 16, 20, 21, 22, 25, 26, 27, 28, 29, 36, 48, 49, 50, 51, 61, 62, 65, 68, 73, 77 were found to be at a correlation level below 0.40. These items were removed from the study in order to increase the reliability of the scale. In the last case, Cronbach's Alpha was used to determine the general reliability level of the scale. (Cronbach's Alpha = 0.986) The remaining items in the scale were renumbered and sorted. When the item-total correlation values of the scale were examined, it was found that the item-total score correlations of the remaining 51 items on the scale ranged from 0.556 to 0.867. These findings prove that the items have a high correlation with the total score and reveal a high level of consistency.

The prerequisite for factor analysis of the 51-item scale of the teachers' artificial intelligence awareness scale was that there should be a high level of correlation between the variables and the KMO value should be above 0.60 (Pallant, 2001). KMO is related to the suitability of the sample and the correlation between the scale items (Ntoumanis, 2001).

Table 3. *KMO and Bartlett Test Results of Teachers' Artificial Intelligence Awareness Scale*

Results of KMO ve Bartlett Test		
Kaiser-Meyer-Olkin (KMO) measure of suitability of sample	0,983	
Bartlett Spherical Test	Approx. Chi-Square Val.	31.432,106
	SD	1.275
	p.	0,000

When the KMO test was examined, it was observed that the coefficient was 0.983 and this value was perfect for sample adequacy. The result of the Bartlett test was found to be significant at the $p<0.01$ significance level. The Bartlett test becomes statistically significant when the KMO is high. The fact that the two tests have such values together confirms the applicability of factor analysis and the large correlations between the items (Ntoumanis, 2001, p. 142). When the test results were studied, it was resolved that the factor analysis conditions were met. Factor analysis of the 51-item artificial intelligence awareness scale was applied. Principal component methods of varimax rotation were used as exploratory factor analysis.

Table 4. *Teachers' Core Values and Factor Distribution Results Regarding Artificial Intelligence Awareness Scale*

	Initial Core Values			**Sum of the Loads Squared**		
Components	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %
1	30,693	60,182	60,182	10,634	20,851	20,851
2	2,568	5,036	65,218	8,735	17,127	37,977
3	1,404	2,754	67,972	8,433	16,534	54,512
4	1,174	2,302	70,274	8,039	15,762	70,274

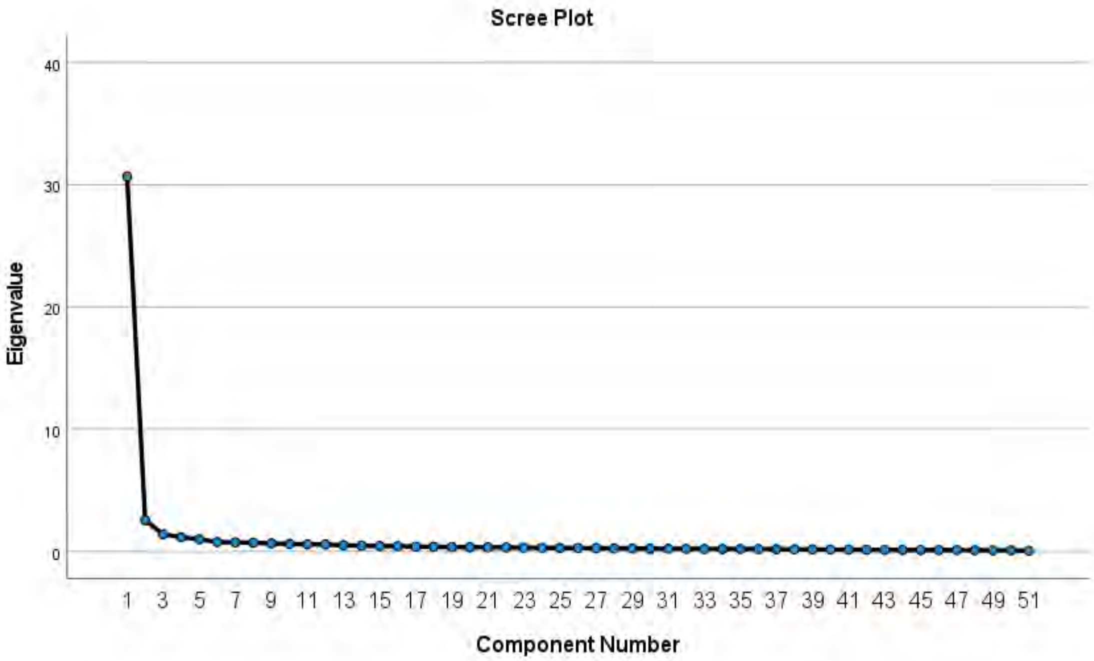

Figure 1. *Scree Plot Test Result of Teachers' Artificial Intelligence Awareness Scale (Slope – Scum Graph)*

When exploratory factor analysis results displayed in Table 5 were studied, the eigenvalue of the 51-item scale was found to be over 1, and the common variance of the factors varied between 0.878 and -0.392. According to the data in the table, 51 items were collected in four factors. The four-factor test explains 70.27 percent of the total variance. It is thought that the ratio of variance explained in studies conducted in social sciences in the literature is between 40-60% (Karagöz, 2016). At this point, it can be said that it is sufficient for the scale to explain 70.27 percent of the total variance. When Figure 3 is scrutinized, it is observed that the graph tends to a horizontal position after the fourth factor, so it would be sufficient to limit the number of factors to four.

Table 5. *Distribution of Teachers' Artificial Intelligence Awareness Scale by Factor Structure: Component Matrix*

Item	Component			
	1	2	3	4
Item 39	0,863	0,135	-0,088	-0,122
Item 40	0,867	0,135	-0,056	-0,113
Item 41	0,878	0,138	-0,116	-0,119
Item 32	0,845	0,231	-0,164	-0,083
Item 35	0,812	0,185	-0,015	-0,165
Item 34	0,823	0,166	-0,121	-0,134
Item 31	0,804	0,286	-0,198	-0,129
Item 38	0,853	0,172	-0,023	-0,123
Item 33	0,829	0,174	-0,160	-0,151
Item 37	0,858	0,146	-0,024	-0,145
Item 30	0,796	0,118	-0,016	-0,013
Item 44	0,855	-0,026	-0,235	0,059
Item 60	0,858	-0,041	-0,158	-0,129
Item 24	0,670	0,193	0,049	0,023
Item 23	0,577	0,367	0,115	-0,124
Item 59	0,867	-0,081	-0,132	-0,088
Item 47	0,752	-0,213	-0,247	0,221
Item 46	0,780	-0,154	-0,253	0,208
Item 57	0,748	-0,392	0,007	0,245
Item 43	0,764	-0,138	-0,224	0,239

Item 56	0,718	-0,341	0,029	0,281
Item 52	0,752	-0,336	-0,071	0,253
Item 53	0,827	-0,253	-0,084	0,107
Item 54	0,854	-0,177	-0,125	0,020
Item 45	0,825	0,025	-0,275	0,079
Item 55	0,816	-0,109	-0,143	0,074
Item 74	0,699	-0,354	0,240	0,110
Item 58	0,851	-0,139	-0,037	-0,063
Item 42	0,865	0,065	-0,240	-0,058
Item 75	0,837	-0,204	0,042	-0,093
Item 67	0,622	-0,301	0,412	-0,156
Item 72	0,771	-0,310	0,211	-0,034
Item 69	0,799	-0,175	0,245	-0,167
Item 70	0,781	-0,257	0,178	-0,043
Item 66	0,822	-0,269	0,113	-0,055
Item 71	0,823	-0,158	0,165	-0,143
Item 76	0,781	-0,186	0,186	-0,251
Item 64	0,832	-0,166	0,076	-0,132
Item 63	0,832	-0,104	0,007	-0,188
Item 78	0,758	-0,138	0,136	-0,187
Item 2	0,649	0,359	0,174	0,235
Item 5	0,677	0,252	0,183	0,253
Item 1	0,601	0,307	0,278	0,110
Item 4	0,591	0,325	0,277	0,184
Item 11	0,773	0,334	0,000	0,049
Item 6	0,648	0,257	0,077	0,221
Item 9	0,602	0,188	0,262	0,197
Item 14	0,567	0,276	0,160	0,191
Item 17	0,744	0,256	0,117	0,029
Item 19	0,794	0,212	0,015	0,123
Item 18	0,702	0,078	0,063	0,143

It is a good choice if the factor loads of the items in a factor are 0.45 and above, and in practice, this limit value can be reduced to 0.30 for a small number of items (Büyüköztürk et al., 2018). The component matrix of the 51-item scale was arranged from largest to smallest according to the four-factor loads. It was understood that the highest factor loadings for each item take values between 0.878 and 0.567. According to the component matrix factor analysis, the scale items were grouped under four components: Theoretical Knowledge, Practical Knowledge, Ability to Associate and Belief-Attitude.

Table 6. *Distribution by Factor Structure of Teachers' Artificial Intelligence Awareness Scale: Rotating Component Matrix*

Item	**Component**			
	Practical Knowledge	**Belief-Attitude**	**Ability to Associate**	**Theoretical Knowledge**
Item 39	0,720			
Item 40	0,720			
Item 41	0,718			
Item 32	0,698			
Item 35	0,696			

Item 34	0,688	
Item 31	0,686	
Item 38	0,669	
Item 33	0,667	
Item 37	0,660	
Item 30	0,530	
Item 44	0,527	
Item 60	0,516	
Item 24	0,501	
Item 23	0,490	
Item 59	0,458	
Variance % explained by pract. knowl.	**20,85**	
Item 47		0,731
Item 46		0,717
Item 57		0,707
Item 43		0,706
Item 56		0,686
Item 52		0,679
Item 53		0,666
Item 54		0,610
Item 45		0,581
Item 55		0,568
Item 74		0,496

Item 58	0,486		
Item 42	0,484		
Item 75	0,464		
Variance % explained by belief-attitute	**17,13**		
Item 67		0,745	
Item 72		0,685	
Item 69		0,676	
Item 70		0,655	
Item 66		0,641	
Item 71		0,638	
Item 76		0,632	
Item 64		0,576	
Item 63		0,526	
Item 78		0,520	
Variance % explained by ability to associate		**16,53**	
Item 2			0,708
Item 5			0,689
Item 1			0,644
Item 4			0,640
Item 11			0,625
Item 6			0,605
Item 9			0,519
Item 14			0,513
Item 17			0,488
Item 19			0,459
Item 18			0,401

Variance % explained by Theoret. Knowl.		**15,76**
Total variance % explained	**70,27**	

There are two common methods for transforming factors - orthogonal (Varimax) and oblique. Orthogonal transformation is used to distinguish between unrelated or independent items (Bryman and Cramer, 2001). The Oblique transform shows which factors are correlated. When the component matrix was examined, it was recognized that the 51-item scale consisted of four factors. Rotational matrix results, which allowed the items to be classified more easily, were used in the research. According to the findings in the rotational component matrix, items 23, 24, 30, 31, 32, 33, 34, 35, 37, 38, 39, 40, 41, 44, 59, 60 were grouped under the Practical Knowledge factor; Items 42, 43, 45, 46, 47, 52, 53, 54, 55, 56, 57, 58, 74, 75 under the Belief-Attitude factor; Items numbered 63, 64, 66, 67, 69, 70, 71, 72, 76, 78 under the Ability to Associate factor; Items 1, 2, 4, 5, 6, 9, 11, 14, 17, 18, 19 were clustered in the Theoretical Information factor.

Teachers' Artificial Intelligence Awareness Confirmatory Factor Analysis

The confirmatory factor analysis results of the Teachers' Artificial Intelligence Awareness Scale can be found in Figure 2.

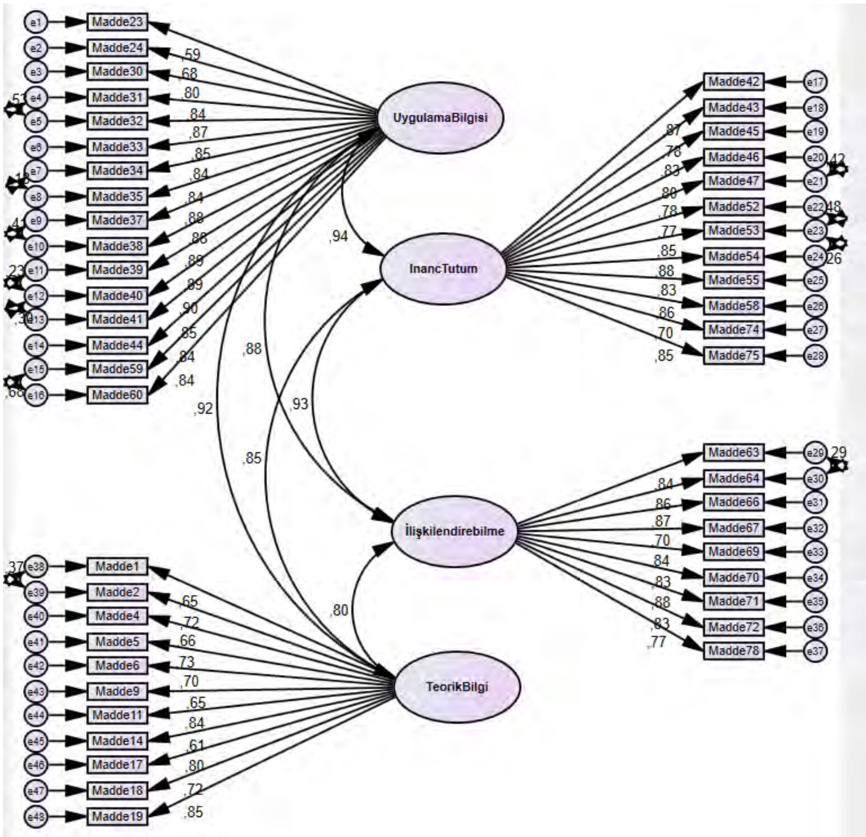

Figure 2. *Confirmatory Factor Analysis Model*

UygulamaBilgisi = Practica lKnowledge, InancTutum=Belief-Attitude, İlişkilendirebilme=Ability to Associate, TeorikBilgi=Theoretical Knowledge, Madde=Item

When the confirmatory factor analysis results in Figure 1 are examined, it is noted that all goodness-of-fit indices have acceptable values, and thus, it can be concluded that the models of the scale items with the relevant structure are appropriate (Schermelleh-Engel, Moosbrugger & Müller, 2003). The results show that this four-dimensional structure is a structure that reflects the artificial intelligence awareness of teachers. Goodness-of-fit indices and related thresholds of fit of the model are given in Table 7.

Table 7. *CFA and Confirmatory Factor Analysis Results of the Established Four-Dimensional Implicit Structure*

Model	χ2/df	NNFI	NFI	CFI	RMSEA
Four Factor Struc.	3,67	0,957	0,951	0,903	0,069
Metrics	2,5	≥0,95	≥0,95	≥0,90	≤0,08

NNFI= Non-normed fit index, NFI= Normed-fit index, CFI= Comparative Fit Index, RMSEA= Root Mean Square Error of Approximation

Evaluation of the extent of the fit of the model may vary according to the statistical program used, but the most commonly used one is the statistical Chi-Square (χ2) test, which can be considered as the initial fit value. In the simplest sense, this test is obtained by multiplying the fit value between the two covariances by the number of subjects in the sample used minus 1. The result obtained is delineated as Chi-Square distribution. If the fit between the data and the model is perfect, the obtained value should be close to zero and the significance value should not be consequential. In large samples, insignificant differences between the expected covariance matrix and the observed covariance matrix often cause the Chi-Square to be significant. In this case, the degree of freedom (df) is an important criterion in the Chi-Square test. In large samples, the ratio of degrees of freedom to Chi-square can be used as a criterion for adequacy. For this, ratios of three or less are considered good, and ratios up to five are considered adequate (Büyüköztürk et al., 2018). When the fit of the model was evaluated according to the Chi-Square test, the value was found to be 3.67 which lay within the limits of fit.

In the normalized fit index (NFI), model fit estimation is made by comparing the Chi-Square value of the independence model with the model's Chi-Square value. Since the NFI can fit less than it does in small samples, at such times the NFI is recalculated by taking into account the degree of freedom, and this value is called the non-normalized fit index (NNFI) (Büyüköztürk et al., 2016). These values range from zero to one. A value approaching one corresponds to a perfect fit, and a value approaching zero corresponds to a model mismatch (Tabachnick & Fidell, 2001). When the model fit of the research was examined, it was discovered that the level of fit was high because both values were above 0.95 and close to one.

Comparative fit index (CFI) indicates whether the model is fit and adequate or not by comparing it with a basic model called the independence model or the absence model, which assumes that no relationship exists between the variables (Büyüköztürk et al., 2016, p. 270). CFI works well in small sample studies because it takes sample size into account. CFI returns a value between zero and one. If the value approaches one, it implies a perfect fit, and if it approaches zero, it denotes a mismatch of the model (Tabachnick & Fidell, 2001). When the comparative fit index of this research was assessed, the value was resolved to be 0.903 which is close to one, and it is close to a perfect fit.

RMSEA (Root Mean Square Error of Approximation) is an index used to estimate population covariances in a decentralized Chi-Square distribution and takes values between zero and one. A RMSEA of zero indicates a perfect fit. It shows that there is no difference between population and sample covariances (Brown, 2006). The Root Mean Square Error of Approximation (RMSEA) value of this research was 0.069, which is very close to zero which means that it is very close to a perfect fit.

DISCUSSION AND CONCLUSION

Measurement tools such as scales contribute to the determination of validity and reliability of a situation scientifically. However, measurement tool development is a process that requires extensive and intensive work. In the process of developing a measurement tool, researchers should consider (1) whether they will obtain evidence for the structure of the feature they are measuring, (2) whether the items can be defined under a certain structure, and (3) what kind of a pattern the correlations between the structures will reveal (Karakoç & Dönmez, 2014). The working process should be planned within the framework of these three important points. In the process of this research, the researchers, considering these requirements, first made a comprehensive literature review, prepared the scale items in line with the opinions of the field experts and completed the pilot application.

Cronbach's Alpha value was calculated as 0.986 in line with the findings obtained from the pilot application carried out within the scope of this research. It was determined that the Kaiser Meyer Olkin (KMO) coefficient was 0.983 and the result of the Bartlett test was meaningful at the $p<0.01$ significance level. In addition, it was determined that the item-cumulative score correlations of the scale ranged from 0.556 to 0.867. Item score ranges in the five-point Likert form in the scale were determined as one to five. As a result, the final version of the 51-item scale was obtained by eliminating 27 items. The final version of the scale, which aimed to measure the artificial intelligence awareness of teachers, is presented in Appendix1

According to the research findings, depending on the type of school, private school teachers were found to have 0.44 more points than the average public school teachers. It was discerned that as the level of education increases, the awareness of artificial intelligence also increases. This indicates that teachers should be directed to various certificate programs, especially postgraduate education, in order to continue their professional development after completing their undergraduate education (Avalos, 2011).

An investigation of the age range of the participants revealed that while the participants in the 20-49 age range had similar scores; participants in the 50-59 age range had lower average scores. For this situation, plans should be made in line with the suggestion of Cangöz (2009) which was that because the rate of processing of information slows down with aging, older individuals should be given more access to learning opportunities to utilize developing technologies. Similarly, when the years of professional experience were considered, it was observed that the participants between 1-39 years of experience had similar score averages. In this context, it was verified that the participants with less than 20 years of experience had higher average scores than the participants between 20-39 years of experience. In addition, since the number of participants with 40 or more years of experience was very low, it was not possible to interpret the average scores of 4 and above in a meaningful manner. However, considering some OECD (2019) countries such as Turkey, the situation of having young teachers with relatively less experience seems to stand out as an advantage. Therefore, considering the demographic structure of teachers in Turkey, it can be surmised that progress can be made in a much shorter time in supporting the awareness of teachers on artificial intelligence. When the artificial intelligence awareness of the teachers according to their branches were investigated, it was established that the highest average belongs to the Education Technologies branch. Considering their undergraduate education and field expertise, it is possible to express this as a finding that is not surprising. It was determined that among the participants, those whose branches are Philosophy, Chemistry, Physics and Information Technologies followed those in Educational Technologies with close averages. The branches with the lowest score were Special Education, Visual Arts and Health Sciences. These findings obtained within the scope of the research are compatible with the literature. In their study, Lee, Ali, Zhang, DiPaola, and Breazeal (2021) revealed that today's individuals had deficiencies in their professional life in terms of carrying out research on artificial intelligence, gaining awareness about innovations and using artificial intelligence effectively in business processes. In the light of these findings, it may be construed that in order for teachers to be competent in digital transformation and digital technologies, inculcation of both theoretical and practical learning on digitalization should start as early as the undergraduate level of the field they are specializing in and continue through the professional stages they may be climbing (Lindsey, 2015). In this context, the number of content and training opportunities for both teacher candidates and teachers should be increased and thus their awareness of new technologies should be raised by closely tracking the developing technologies.

Suggestions

Based on these findings the following suggestions are made:

- When the literature was examined, no scale was found on the level of artificial intelligence awareness of teachers. Since this indicates an important deficiency, a scale has been developed to determine the artificial intelligence awareness status of teachers within the scope of this study.

However, since there is a need for different scales for teachers in the field of artificial intelligence, it is recommended that researchers focus on this area. It was decided to be a scale development study.

- Educational institutions use information technologies effectively to meet innovations that will increase their competitiveness, teachers need to find time to focus on their development in order to update the education they actively give to the developing generation, and they need to focus on teaching activities for the different abilities and competencies of their students (Şişman, Odabaşı, & Akkoyunlu, 2019, p. 257). There are applications that enable teachers working in private schools to benefit from artificial intelligence-supported platforms in the relevant curriculum, and related teacher training can be given in many private schools. These and similar practices can also be expanded in public schools. In addition, artificial intelligence in-service training should be given to educators from all age groups and from all branches, which will enable them to be mentally and emotionally ready for digital change in education.

REFERENCES

Arslan, K. (2020). Eğitimde yapay zeka ve uygulamaları. *Batı Anadolu Eğitim Bilimleri Dergisi*, *11*(1), 71-88.

Avalos, B. (2011). Teacher professional development in teaching and teacher education over ten years. *Teaching and Teacher Education, 27*(1), 10-20. https://doi.org/10.1016/j.tate.2010.08.007

Büyüköztürk, Ş. (2002). *Testlerin geçerlik ve güvenirlik analizlerinde kullanılan bazı istatistikler, sosyal bilimler için veri analizi el kitabı*. Pegem.

Büyüköztürk, Ş., Çakmak, E., Akgün, E., Karadeniz, Ş., & Demirel, F. (2018). *Bilimsel araştırma yöntemleri*. Pegem.

Cangöz, B. (2009). Yaşlılıkta bilişsel ve psikolojik değişim. *Geriatri: Multidisipliner yaklaşım.* Ankara: Türk Eczacılar Birliği. 99-104.

Cohen, L., Morrison, K. & Manion, L. (2007). Research methods in education. Routledge.

Çokluk, Ö., Şekercioğlu, G., & Büyüköztürk, Ş. (2016). *Sosyal bilimler için çok değişkenli istatistik.* Pegem

Ermut, N. K. (2020). Geleceğin iş yaşamında insan ve teknolojinin akıllı dengesi. *Harvard Business Review*. Retrivied from https://hbrturkiye.com/

European Commission (2018). On the digital education action plan. The European Commission. Retrieved from https://eurlex.europa.eu/legal-content/EN/TXT/?uri=COM:2018:22:FIN

Erümit, A.K., Calap, T., Çolak, A.F., Yavuz, S. & Aydın, E. (2020). Okullarda yapay zeka öğretimi. Vasif Nabiyev and Ali Kürşat Erümit (Ed.) *Eğitimde yapay zeka kuramdan uygulamaya*. Pegem.

Field, A. (2009). *Discovering statistics using SPSS.* Sage.

Joshi, A. V. (2020). *Machine learning and artificial ıntelligence* (pp. 53-61). Springer.

Karagöz, Y. (2016). *SPSS 23 ve AMOS 23 uygulamalı istatistiksel analizler*. Nobel.

Karakoç,. F. Y., & Dönmez, L. (2014). Ölçek geliştirme çalışmalarında temel ilkeler. *Tıp Eğitimi Dünyası*, *13(*40), 39-49. https://doi.org/10.25282/ted.228738

Kılınç, D. & Özdemir, Ş. (2019). *Geleceğin meslekleri, dijital dönüşüm, veri bilimi, yapay zeka*. Abaküs.

Kış, A. (2019). *Eğitimde yapay zeka* [Conference presentation abstract]. *14th International Education Management Congress,* 197-201, İzmir, Türkiye.

Kreps, G. L., & Neuhauser, L. (2013). Artificial intelligence and immediacy: designing health communication to personally engage consumers and providers. *Patient Education and Ccounseling*, *92*(2), 205-210. https://doi.org/10.1016/j.pec.2013.04.014

Kutlusoy, Z. (2019). Felsefe açısından yapay zeka. Gonca Telli(Ed.), *Yapay zeka ve gelecek* (p.25-43). Doğu.

Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021, March). Developing middle school students' ai literacy [Conference presentation abstract].. Proceedings of the *52nd ACM Technical Symposium on Computer Science Education* (pp. 191-197). https://doi.org/10.1145/3408877.3432513

Nabiyev, V. V. (2012). *Yapay zekâ: İnsan-bilgisayar etkileşimi*. Seçkin.

Ntoumanis, N. (2001). *Step-by-step guide to SPSS for support*. Routledge.

OECD (2019), *TALIS 2018 Results (Volume I): Teachers and school leaders as lifelong learners*, TALIS, OECD Publishing, Paris, Retrivied from https://doi.org/10.1787/1d0bc92a-en

Pallant, J. (2001). *The SPSS survival manual: A step-by-step guide to data analysis using SPSS*, St. Leonards Publications. https://doi.org/10.4324/9781003117452

Pirim, A. (2006). Yapay zeka. *Journal of Yaşar University*, *1*(1), 81-93.

Presidency of the Republic of Turkey Digital Transformation Office. (2021). *National artificial intelligence strategy 2021-2025* Retrivied from https://cbddo.gov.tr/uyzs

Rogers, E. M. (2003). *Diffusion of innovation*. Free Press.

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*(2), 582-599. https://doi.org/10.1007/s40593-016-0110-3

Schermelleh-Engel, K., Moosbrugger, H., ve Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online, 8*(2), 23-74

Seçkin, Z., Demirel, Y., & Özçınar, M. F. (2016). Örgütsel değişim sürecinin algılanmasına yönelik betimsel bir araştırma. *Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *8*(1), 125-134.

Tabachnick, B., ve Fidell, L. (2001). *Using multivariate statistics*. Pearson.

Tao, B., Díaz, V., & Guerra, Y. (2019). Artificial Intelligence and Education, Challenges and Disadvantages for the Teacher. *Arctic Journal*, *72*(12), 30-50.

UNESCO (2017). *Data Revolution to measure equity in education for SDGs #CIES2017*. Retrieved from http://www.iiep.unesco.org/en/data-revolution-measure-equity-educationsdgs-cies2017-3886

WEF (World Economic Forum). 2018. The future of jobs report. Retrivied from https://www.weforum.org/reports/the-future-of-jobs-report-2018

Westerheide, F. (2019). The artificial ındustry and global changes. Retrivied from https://www.forbes.com/sites/cognitiveworld/2019/11/27/the-artificial-intelligence-industry-and-global-challenges/?sh=68c2f0a53deb

Wolfinbarger, M., ve Gilly, M. (2003). eTailQ: Dimensionalizing, measuring and predicting etail quality. *Journal of Retailing, 79*(3), 183-198. https://doi.org/10.1016/S0022-4359(03)00034-4

Yurdugül, H. (2005). Ölçek geliştirme çalışmalarında kapsam geçerliği için kapsam geçerlik indekslerinin kullanılması [Conference presentation abstract]. *XIV. Ulusal Eğitim Bilimleri Kongresi. Pamukkale Üniversitesi Eğitim Fakültesi.* p.1-6. Denizli, Türkiye, Retrivied from http://yunus.hacettepe.edu.tr/~yurdugul/3/indir/PamukkaleBildiri.pdf