Instructional Technology and Lifelong Learning Vol. 4, Issue 2, 291-306 (2023)

https://dergipark.org.tr/en/pub/itall

ITALL

ISSN: 2717-8307

Research Article

Artificial Intelligence Literacy: An Adaptation Study

Celalettin ÇELEBİ*[1], Fatih YILMAZ[2], Uğur DEMİR[3], Ferhat KARAKUŞ[4]

** Corresponding Author, celalcelebi75@gmail.com*

[1]*Necmettin Erbakan University, Türkiye*

[2]*Ministry of National Education, Türkiye*

[3] *Necmettin Erbakan University, Türkiye*

[3]*Ministry of National Education, Türkiye*

Abstract

The purpose of this research is to adapt the Artificial Intelligence Literacy Scale (AILS) developed by Wang et al. (2022) into Turkish and study its validity and reliability. The scale aims to measure the artificial intelligence literacy levels of non-expert adults. The research data were gathered from 402 participants, and the researchers did Confirmatory Factor Analysis (CFA) to test the validity of the adapted scale, and to test the reliability, they adopted Cronbach's alpha technique. The adapted scale consists of 12 items and 4 factors, as is the case in the original version. CFA results indicate that X^2/df=1.82, RMSEA = 0.04, RMR = 0.03, NFI = 0.95, CFI = 0.98, GFI = 0.96 and AGFI = 0.94. Considering CFA results, it is concluded that the adapted scale is a good fit. As for reliability, as far as the factors are concerned, the internal consistency results are 0.72, 0.74, 0.76, and 0.72 respectively. Additionally, α=0.85 for the whole scale. Consideringly, the scale and its factors are adequately reliable, and the adapted scale can be used in Turkish culture.

Keywords: Artificial Intelligence, AI literacy, Digital literacy, AI literacy scale

Citation: Çelebi, C., Yılmaz, F., Demir, U., & Karakuş, F. (2023). Artificial intelligence literacy: An adaptation study. *Instructional Technology and Lifelong Learning,* 4/2, 291-306. https://doi.org/10.52911/itall.1401740

Yapay Zekâ Okuryazarlığı: Bir Ölçek Uyarlama Çalışması

Özet

Bu çalışmada Wang ve diğerleri (2022) tarafından geliştirilmiş Yapay Zekâ Okuryazarlık Ölçeği'ni Türkçe diline uyarlayarak güvenirlik ve geçerliliğinin incelenmesi amaçlanmıştır. Ölçek yapay zekâ konusunda uzman olmayan yetişkin bireylerin yapay zekâ okuryazarlık düzeylerini ölçmeyi amaçlamaktadır. Çalışma kapsamında 402 katılımcının oluşturduğu yetişkin bireylerden veri toplanmıştır. Ölçeğin geçerliliğini test etmek amacıyla doğrulayıcı faktör analizi yapılmıştır. Güvenirliği için ise Cronbach Alpha iç tutarlılık katsayısı hesaplanmıştır. Dört boyut ve 12 maddeden oluşan Yapay Zekâ Okuryazarlığı Ölçeği için yapılan doğrulayıcı faktör analizinde; $x2/df$ için 1.82, RMSEA için 0.04, RMR için 0.03, NFI için 0.95, CFI için 0.98, GFI için 0.96 ve AGFI için 0.94 değerlerine ulaşılmıştır. Elde edilen uyum indeksleri değeri sonucunda modelin iyi bir uyuma sahip olduğu ortaya konulmuştur. Güvenirlik analizi için yapılan Cronbach's Alpha iç tutarlılık katsayısının hesaplanmasında ölçeğin alt boyutları için sırasıyla 0.72, 0.74, 0.76, 0.72 değerlerine ulaşılmıştır. Ölçeğin tümü için 0.85 iç tutarlılık katsayısı hesaplanmıştır. Buna göre ölçeğin hem boyutları hem de tamamı için elde edilen değerler ölçeğin güvenirliğine yönelik yeterli kanıtlar sunmaktadır. Türkçe diline uyarlanan yapay zekâ okuryazarlık ölçeği'nin, yapay zekâ konusunda uzman olmayan yetişkin bireylerin yapay zekâ okuryazarlık düzeylerini ölçmek için geçerli ve güvenilir bir ölçme aracı olduğu sonucuna ulaşılmıştır.

Anahtar Kelimeler: Yapay Zekâ, Yapay Zekâ Okuryazarlığı, Dijital okuryazarlık, Yapay Zekâ Okuryazarlığı Ölçeği

Date of Submission	07.12.2023
Date of Acceptance	31.12.2023
Date of Publication	31.12.2023
Peer-Review	Double anonymized - Two External
Ethical Statement	It is declared that scientific and ethical principles have been followed while carrying out and writing this study and that all the sources used have been properly cited.
Acknowledgements	---
Author(s) Contribution	**Çelebi:** %25 Conceptualization, Data collection, Writing- Original draft preparation. **Yılmaz:** %25 Writing- Methodology, Original draft preparation, and Editing. **Demir**: Supervision, Methodology, Validation. **Karakuş:** %25 Data collection, Writing, Original draft preparation
Plagiarism Checks	Yes - Turnitin
Conflicts of Interest	The author(s) has no conflict of interest to declare.
Complaints	ithalljournal@gmail.com
Grant Support	The author(s) acknowledge that they received no external funding in support of this research.
Copyright & License	Authors publishing with the journal retain the copyright to their work licensed under the **CC BY 4.0**.

1. Introduction

The article "Computing Machinery and Intelligence" by Turing is considered a milestone for artificial intelligence (AI) studies (Topal, 2017). Turing (1950) states that machines would eventually compete with humans. Only six years after the abovementioned article, a group of scientists coined the term "Artificial Intelligence" for the first time at a conference held at Dartmouth College, US, in 1956 (Öztürk & Şahin, 2018). Later on, studies on AI followed an up-and-down path for a considerably long period. Although AI studies were well funded until the 1970s, in 1973, first the USA and then the UK made a major cut in funds due to lack of success. This period was named the AI winter. However, in the 1980s, thanks to Japanese funds, there was a great increase in the number of AI studies again (Haenlein & Kaplan, 2019). Moreover, expert AI systems, aiming to help people to make decisions, were introduced in the 1970s and became popular in the 1980s. Nevertheless, they were not very successful in the end, despite the great interest. However, the most striking leap in AI studies happened in the 1980s with the increasing interest in artificial neural network (ANN) models. Unlike expert AI systems, ANN was able to learn from data and was more successful (Alpaydın, 2004). On account of new approaches in ANN models and learning algorithms and advances in computer technology, today AI is used in computers, mobile phones, smartwatches, and even in refrigerators. The revolutionary development of AI is clear in many areas such as Industry 4.0, cancer diagnostics, Instagram effects, the defense and space industry, autonomous vehicles, and energy management networks (Gür et al., 2019).

AI is getting a place in daily life at a speed that no technological tool has ever reached before. For example, ChatGPT, developed by OpenAI, reached 100 million users in January 2023, just two months after its launch in November 2022 (Lo, 2023). Developments in AI technologies have reached a size that can affect the global economy, too. It is estimated that AI, which had a market size of 454 billion dollars in 2022, is expected to reach a market size of 2.5 trillion dollars in 2032, and that the active use of AI can contribute 16 trillion dollars to the global economy in 2030 (Karpunina et al., 2020; Precedence Research, 2023). It is anticipated that AI will continue to be more and more influential in daily life each day. That's why, the AI-human relationship or the human approach towards AI technologies is considered an important issue.

Yavuz Aksakal and Ülgen (2021), state that with the emergence of AI, some of the professions existing today will change, and some new professions will emerge in the future. For that reason, equipping human resources with the skills that will be needed in future professions is among the issues that should be paid attention to. One of these skills is "AI literacy". Literacy is about meaning construction, which is a higher-level mental process different from reading-writing skills which includes interpretation, evaluation, and construction (Kurudayıcıoğlu & Tüzel, 2010). Therefore, AI literacy, unlike literacy, usually refers to making sense of AI. Çelebi et al. (2023) define AI literacy as a set of skills that enable individuals to critically evaluate AI technologies, understand AI concepts, and have the ability to use them in practical applications, as well as ethically and effectively use AI in their daily lives. Similarly, Long and Magerko (2020) state that some skills such as digital literacy and data literacy overlap with some competencies of AI literacy. Therefore, these skills are highly related.

Artificial intelligence can have various factors like technical (McDermid, 2021), social, ethical, legal, and responsibility (Rosemann & Zhang, 2022). These factors are indicators of various impact areas of artificial intelligence. The Artificial Intelligence Literacy scale developed by Wang et al. (2022), which was adapted into Turkish, consists of four factors, of which awareness is about the ability to understand AI technology, and measures one's ability to recognize AI technology; usage is about the ability to use AI technology efficiently and to successfully integrate AI tools into one's life; evaluation is about the ability of users to choose the right AI applications, reflect on the results and critically evaluate them; ethics is about one's ability to recognize the responsibilities associated with the use of AI technologies and to understand ethical issues accurately.

The literature review indicates that there are various adaptations (Akkaya et al.,2021; Kaya et al. 2022; Schepman & Rodway, 2020; Terzi, 2020) and development studies (Ferikoğlu & Akgün, 2022; Grassini, 2023; Kaya et al., 2022; Kieslich et al., 2021; Kim & Lee, 2023; Schepman & Rodway, 2020; Suh & Ahn, 2022; Wang et al., 2022) as far as artificial intelligence is concerned. Each of those scales measures a different aspect of AI. The fact that the majority of the scale development studies found in the literature review have recently been done is due to the increasing popularity of artificial intelligence, which is rapidly developing in the field of science and technology, and new knowledge is emerging about its future applications and possible effects.

Apart from the AILS developed by Wang et. al (2022); there are three other scales developed to measure the AI literacy levels of participants who are not experts in AI. General AI Literacy (GAIL) developed by Pinski and Benlian (2023) is a seven-point Likert-type scale consisting of 13 items, and five factors called "AI technology knowledge, human actors in AI knowledge, AI steps knowledge, AI usage experience, and AI design experience". The scale was applied to a small group of 50 people. However, the fact that people with a certain level of programming knowledge were asked to participate may indicate that this scale is not a general scale aiming to measure the AI literacy levels of individuals who are not experts in AI. The Meta AI Literacy Scale (MAILS) developed by Carolus et al. (2023) is a 34-item scale developed in five-point Likert type, and consists of four factors called "AI literacy, create AI, AI self-efficacy, and AI self-competency". However, this scale not only aims to measure the AI literacy of individuals but also aims to measure the psychological competencies of participants regarding AI. Lastly, a Delphi study was done by Laupichler et al. (2023a) to develop an item set for the assessment of non-experts' AI literacy. The 37 items identified in this study were later used by Laupichler et al. (2023b) to develop the Scale for the assessment of non-experts' AI literacy" (SNAIL). After exploratory factor analysis, they reached a structure consisting of three factors called "Technical Understanding, Critical Appraisal, Practical Application" and 31 items.

A thorough literature review indicated that although there are various scales for artificial intelligence, there is no scale measuring the artificial intelligence literacy levels of participants. That's why, the researchers thought that adapting the Artificial Intelligence Literacy scale into Turkish to determine the artificial intelligence literacy levels of participants would contribute to the literature. With this in mind, the purpose of this research is to adapt the Artificial Intelligence Literacy Scale into Turkish and to conduct validity and reliability studies.

2. Method

Methodology can be defined as the guideline for the research approach. It allows the researcher to organize, design, and conduct an effective study (Mohajan, 2017). In this research, a psychometric scale is adapted into another language, which is expected to contribute to the literature. For the adaptation process, the Artificial Intelligence Literacy Scale (AILS) was translated into the target language. To test the validity of the scale, the researchers adopted confirmatory factor analysis; and to check the reliability, they made use of Cronbach's alpha coefficient technique.

2.1. The Artificial Intelligence Literacy Scale

The Artificial Intelligence Literacy Scale developed by Wang et al. (2022) is a seven-point Likert scale consisting of four factors and 12 items. To adapt the original scale to the target language, the researchers contacted the corresponding author through e-mail and got his permission for the adaptation. The AILS asks participants whether they agree or disagree with the research questions, and has "Strongly Agree, Agree, More or Less Agree, Undecided, More or Less Disagree, Disagree, Strongly Disagree" response options. Therefore, the lowest score to from the scale is 12, and the highest score is 84. The scale has also reverse coded items in "Awareness, Usage, Ethics" factors; one in each.

The factors of the scale are called "Awareness, Usage, Evaluation, Ethics" respectively; and each factor has 3 items. The reliability of the original scale was tested using Cronbach's alpha, composite reliability (CR), Average variance extracted (AVE), and heterotrait-monotrait ratio (HTMT). The alpha coefficients of the scale range between 0,83-0,73. The CR values range between 0,88-0,73. The AVE values range between 0,48-0,55. HTMT values range between 0,30-0,78. All reliability coefficients indicate that the AILS is reliable. The researchers report that fit results are CFI=0.99; TLI= 0.99; RMSEA= 0.01; and SRMR= 0.03.

2.2. The Adaptation

The translation process is important in adapting scales from one language to another. For correct translation, the translators should master the subtleties of both languages, in this case, both English and Turkish. With this in mind, the researchers asked two different translators to translate the original scale into Turkish. They asked another translator to translate the Turkish version into English and compared the translations. 65 participants participated in the pilot study. Eventually, the final form of the translation was prepared, and the analyses were done using SPSS 23.0 and LISREL 8.51.

2.3. The Participants

402 participants participated in the validity and reliability studies of the adapted scale. The research data was collected through Google Forms. The online form allowed no missing values, therefore, all the answers were valid. The research data were collected from a wide range of participants so that the adapted form could be used by many researchers in various samples.

Table 1:
The Demographic Data

Demographic Categories	Variables	*f*	%
Gender	Female	274	68.2
	Male	128	31.8
Educational Background	Primary School	6	1.5
	Secondary School	4	1
	High School	15	3.7
	Bachelor	311	77.4
	Postgraduate	66	16.4
Age	Below 20 Years old	33	8.2
	20-30 Years old	193	48
	30-40 Years old	74	18.4
	40 years or more	102	25.4
Total		402	100

3. Findings

The idea that unobservable causes affect observable phenomena has been widely accepted since mankind. When it comes to psychometric scales those unobservable constructs are called latent variables or factors which allow us to see relationships between variables that have something in common (Bollen, 2002). To get consistent results and to be able to make inferences, the researchers need to use both valid and reliable tools when they develop or adapt scales (Harrington, 2009). With this aim in mind, to check whether the adapted scale has acceptable fit indices, the researchers did confirmatory factor analysis using LISREL 8.80.

On the other hand, Gerbing and Hamilton (1996) suggest that "most uses of confirmatory factor analyses are, in actuality, partly exploratory and partly confirmatory" (p. 71). The idea behind factor analysis is that the correlations in a set of observed variables can be modeled by a smaller set of unobserved ones called factors (Hox, 2021). Confirmatory factor analysis is useful when the model(s) has a strong underlying theory (Hurley et al., 1997), and it gives the researcher a picture of how well the model fits the data (Hox, 2021). The fit indices range between 0-1. 0 indicates a total lack of fit, however, 1 indicates perfect fit (Mulaik et al., 1989).

The gist of CFA is that the model indicating the number of factors and items in each factor is determined and tested whether the model fits the available data (Gillaspy, 1996). In other words, it tests whether the assumed relationship(s) is in line with the real data (Goretzko et al., 2023) Given this, the researchers anticipate that since the factorial structure of AILS was already tested in another culture, and it has an underlying theory, it would be adequate to do CFA for the adapted version.

There are lots of fit indices as far as CFA is concerned. Although there are no clear-cut boundaries for what the lowest values for an acceptable fit are, the general tendency is that the standard errors of the parameter estimates are reasonable (Schermelleh-Engel & Moosbrugger, 2003). Taking these into consideration, the results of the CFA analysis are given in Table 2 below.

Table 2:
CFA Indices

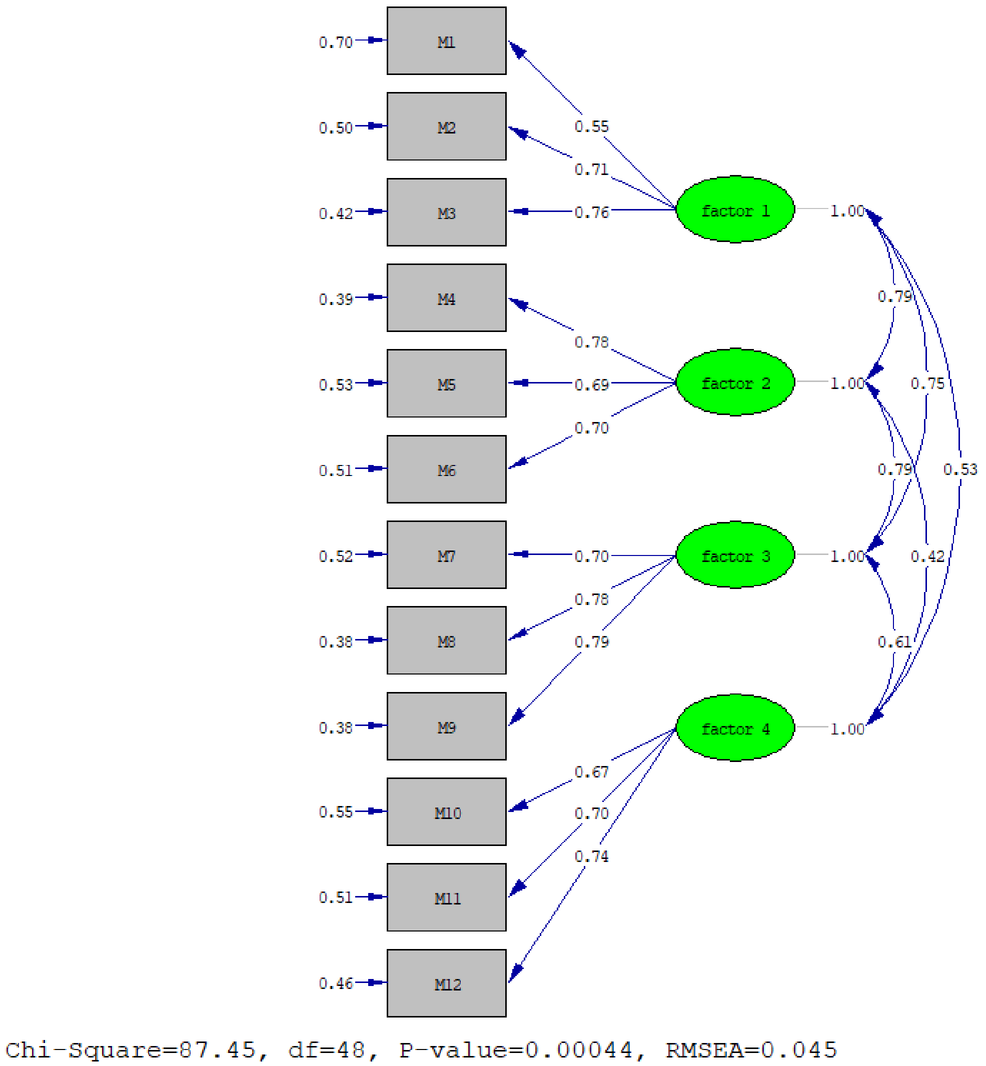
Fit Indices	Good Fit	Outputs
$x^2/sd \leq 3$	$x^2/sd \leq 3$	1.82
RMSEA ≤ 0.05	RMSEA ≤ 0.05	0.04
RMR ≤ 0.05	RMR ≤ 0.05	0.03
NFI ≥ 0.95	NFI ≥ 0.95	0.95
CFI ≥ 0.97	CFI ≥ 0.97	0.98
GFI ≥ 0.90	GFI ≥ 0.90	0.96
AGFI ≥ 0.90	AGFI ≥ 0.90	0.94

Adapted from: (Karagöz & İrge, 2023)

Some researchers state that all goodness-of-fit measures are a function of the chi-square and the degrees of freedom (Hox, 2021). Thus, the X^2/df ratio is regarded as the adequacy criterion of the model (Cihangir Çankaya, 2009; Kalafat, 2012). Browne and Cudeck (1993), and Jöreskog and Sörbom (1993) suggest that RMSEA < 0.05 indicates a close fit (Xia & Yang, 2019). The smaller values of RMSEA and RMR indicate a better fit (Büyüköztürk et al., 2004; Taasoobshirazi & Wang, 2016). NFI and CFI values closer to 1 indicate a better fit. In other words, the larger NFI and CFI values, the better model fit (Elrehail, 2018). Greater values than 0.9 for GFI is an indicator of good fit (Hu & Bentler, 1999; Muenjohn & Armstrong, 2008). AGFI is a measure of the relative amount of variance and covariance explained and values above 0.85

are acceptable. Greater AGFI values indicate a better fit (Pedroso et al., 2016). Taking Table 2 into consideration, and the abovementioned references, the adapted AILS has a good fit. The path analysis of the adapted scale is available in Figure 1 below.

Figure 1:
The Path Analysis



3.1. Reliability

In brief, the reliability is about getting consistent results from a measurement. A reliable measurement tool should be free of errors. There is more than one reliability method in the literature. Cronbach's alpha technique is one of the most frequently used (Thanasegaran, 2009; Amirrudin et al., 2020). The alpha technique is a measure of the internal consistency of a test or scale and ranges between 0-1. The internal consistency is also important for validity (Tavakol

& Dennick, 2011). In other words, a measurement tool cannot be valid if it is not reliable (Amirrudin et al., 2020). There are no clear-cut boundaries on how to interpret alpha, which makes it difficult for some researchers to interpret alpha results. Alpha coefficients between 0.70-0.80 are recommended (Nunally, 1978 as cited in Panayides, 2013).

Table 3:
The reliability results of AILS

Factors	Items	α
Awareness	1, 2, 3	0.72
Usage	4, 5, 6	0.74
Evaluation	7, 8, 9	0.76
Ethic	10, 11, 1	0.72
Total Scale		0.85

Considering Cronbach's alpha outputs for the adapted version of AILS, the results vary between 0.72-0.85, and they are similar to the original ones in the original version. Consequently, it can easily be concluded that the adapted version is also reliable.

4. Discussion and Conclusion

Recently, AI has become widespread in all walks of life, and researchers believe that it will continue to increase its impact. That's why, AI literacy enabling individuals to know, use, evaluate, and ethically utilize AI tools becomes an important matter. On the other side, the literature review revealed that there is no measurement tool aiming to measure the AI literacy levels of individuals in the Turkish language. For that reason, the adapted AILS is expected to contribute to the literature. Taking this into account, the purpose of this research is to adapt the Artificial Intelligence Literacy Scale (AILS), developed by Wang et al. (2022), into Turkish language. The scale aims to measure the AI literacy levels of non-expert adult AI users. Since the adapted version consists of four factors as in the original scale, the researchers called the factors the same as in the original version.

A high score on the scale indicates a high level of artificial intelligence literacy. After the translation, the pilot study was done with 65 participants, however, the actual research data were gathered from 402 participants via Google Forms. CFA and reliability analyses were performed with IBM SPSS Statistics (Version 23.0) and LISREL 8.80 (Jöreskog & Sörbom, 2019). The results indicate that the scale is a good fit. In the reliability analysis, Cronbach's Alpha coefficient varies between 0.72 and 0.76 for the factors, and it is 0.85 for the whole scale.

Wang et al. (2022) associated AI literacy with digital literacy (DL) and information and communication technology (ICT) literacy. In other words, they took these different literacy types into account while developing AILS. They utilized some common models, such as technological, cognitive and ethical, in various digital literacy definitions (Eshet, 2004; Gapski, 2007; Calvani et al., 2008; Calvani et al., 2009; Ferrari, 2012; Balfe et al., 2018) and the KSAVE model proposed by Wilson et al. (2015) for ICT consisting of knowledge (K), skills (S), attitudes (A), values (V), and ethics (E). Based on these models, Wang et al. (2022) define AI literacy as the ability to be aware of and comprehend AI technology in practical applications.

This research has some limitations, too, as in every research. For instance, the majority of the participants are bachelors and postgraduates, and they completed the scale over the Internet. In turn, the average AI literacy score of the participants was high. In the following research, the AI literacy levels of individuals can be studied with participants who have lower educational backgrounds, and the relationship between individuals' educational background and digital literacy skills on AI literacy can be revealed.

5. References

Akkaya, B., Özkan, A., & Özkan, H. (2021). Artificial intelligence anxiety (AIA) scale: adaptation to Turkish, validity and reliability study. *Alanya Academic Review, 5*(2), 1125 - 1146. https://doi.org/10.29023/alanyaakademik.833668

Alpaydın, E. (2004). Introduction to machine learning. The MIT Press.

Amirrudin, M., Nasution, K., & Supahar, S. (2020). Effect of variability on Cronbach alpha reliability in research practice. *Jurnal Matematika, Statistika Dan Komputasi, 17*(2), 223–230. https://doi.org/10.20956/jmsk.v17i2.11655

Balfe, N., Sharples, S., & Wilson, J. R. (2018). Understanding Is Key: An Analysis of Factors Pertaining to Trust in a Real-World Automation System. *Human Factors, 60*(4), 477-495. https://doi.org/10.1177/0018720818761256

Bollen, K. A. (2002). Latent variables in psychology and the social sciences. *Annual Review of Psychology, 53*(1), 605–634. https://doi.org/10.1146/annurev.psych.53.100901.135239

Calvani, A., Cartelli, A., Fini, A., & Ranieri, M. (2008). Models and instruments for assessing digital competence at school. *Journal of E-learning and Knowledge Society, 4*(3), 183-193.

Calvani, A., Fini, A., & Ranieri, M. (2009). Assessing digital competence in secondary education. Issues, models and instruments. In *Issues in information and media literacy: Education, practice and pedagogy* (s. 153-172). Informing Science Press.

Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). MAILS - Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies.

Computers in Human Behavior: Artificial Humans, 1(2). https://doi.org/10.1016/j.chbah.2023.100014

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen and J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Newbury Park, CA: Sage.

Büyüköztürk, Ş., Akgün, Ö. E., Özkahveci, Ö., & Demirel, F. (2004). The validity and reliability study of the Turkish version of the motivated strategies for learning questionnaire. *Educational Sciences: Theory & Practice, 4*(2), 231–237.

Cihangir Çankaya, Z. (2009). Autonomy support, basic psychological need satisfaction and subjective well-being: Self-determination theory. *Turkish Psychological Counseling and Guidance Journal, 4*(31), 23-31.

Çelebi, C., Demir, U., & Karakuş, F. (2023). Artificial intelligence literacy: A systematic review. *Journal of Necmettin Erbakan University Ereğli Faculty of Education, 5*(2), 536-560. https://doi.org/10.51119/ereegf.2023.67

Eshet, Y. (2004). Digital literacy: A conceptual framework for survival skills in the digital era. *Journal of educational multimedia and hypermedia, 13*(1), 93-106.

Ferrari, A. (2012). *Digital competence in practice: An analysis of frameworks.* Publications Office of the European Union.

Elrehail, H. (2018). The relationship among leadership, innovation and knowledge sharing: A guidance for analysis. *Data in Brief, 19*, 128–133. https://doi.org/10.1016/j.dib.2018.04.138

Ferikoğlu, D., & Akgün, E. (2022). An ınvestigation 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

Harrington, D. (2009). Confirmatory factor analysis. Oxford University Press.

Gapski, H. (2007). Some reflections on digital literacy. *Proceedings of the 3rd International Workshop on Digital Literacy* (s. 49-55). Crete, Greece: CEUR Workshop Proceedings. Retrieved from http://ftp.informatik.rwth-aachen.de/Publications/CEUR-WS/Vol-310/paper05.pdf

Gerbing, D. W., & Hamilton, J. G. (1996). Viability of exploratory factor analysis as a precursor to confirmatory factor analysis. Structural Equation Modeling: *A Multidisciplinary Journal, 3*(1), 62–72. https://doi.org/10.1080/10705519609540030

Gillaspy, J. A. Jr. (1996). *A primer on confirmatory factor analysis*. The Annual Meeting of the Southwest Educational Research Association.

Goretzko, D., Siemund, K., & Sterner, P. (2023). Evaluating model fit of measurement models in confirmatory factor analysis. *Educational and Psychological Measurement*, https://doi.org/10.1177/00131644231163813

Grassini, S. (2023). Development and validation of the AI attitude scale (AIAS-4): a brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology*, 14, 1191628. https://doi.org/10.3389/fpsyg.2023.1191628

Gür, Y. E., Ayden, C., & Yücel, A. (2019). Effects to human resources managements of developments in artificial intelligence. *International Journal of Economics and Administrative Sciences, 3*(2), 137-158.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5-14. https://doi.org/10.1177/0008125619864925

Hox, J. (2021). Confirmatory factor analysis. J. Barnes, & D. R. Forde içinde, *The Encyclopedia of Research Methods in Criminology and Criminal Justice.* John Wiley & Sons, Inc.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: *A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hurley, A. E., Scandura, T. A., Schriesheim, C. A., Brannick, M. T., Seers, A., Vandenberg, R. J., & Williams, L. J. (1997). Exploratory and confirmatory factor analysis: guidelines, issues, and alternatives. *Journal of Organizational Behavior, 18*(6), 667–683. https://doi.org/10.1002/(SICI)1099-1379(199711)18:6<667::AID-JOB874>3.0.CO;2-T

IBM Corp. (2020). IBM SPSS Statistics for Windows (Version 27.0) [Computer software]. IBM Corp.

Jöreskog, K. G., & Sörbom, D. (1993). *LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language.* Scientific Software International.

Jöreskog, K. G. & Sörbom, D. (2019). L*ISREL 8.80. Mooresville*, Ind. : Scientific Software,

Karpunina, E. K., Dedov, S. V., Kholod, M. V., Ponomarev, S. V., & Gorlova, E. A. (2020). Artificial intelligence and its impact on economic security: trends, estimates and forecasts. In E. G. Popkova, & B. S. (Eds), *Scientific and Technical Revolution: Yesterday, Today and Tomorrow* (p. 213-225). Springer. https://doi.org/10.1007/978-3-030-47945-9_23

Kalafat, S. (2012). The influence of personality traits of high school teachers on their teacher qualifications. *Journal of Higher Education and Science, 2*(3), 193. https://doi.org/10.5961/jhes.2012.050

Karagöz, B., & İrge, N. T. (2023). The effect of personnel empowerment on organizational commitment and individual work performance: A research in the health sector. Eurasian *Academy of Sciences Social Sciences Journal*, (48), 46-53.

Kaya, F., Aydın, F., Schepman, A., Rodway, P., Yetişensoy, O., & Kaya, M. D. (2022). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human–Computer Interaction.* https://doi.org/10.1080/10447318.2022.2151730

Kieslich, K., Lünich, M. & Marcinkowski, F. The Threats of Artificial Intelligence Scale (TAI). *Int J of Soc Robotics 13*, 1563–1577 (2021). https://doi.org/10.1007/s12369-020-00734-w

Kim, S. W., & Lee, Y. (2022). The Artificial Intelligence Literacy Scale for Middle School Students., *Journal of The Korea Society of Computer and Information, 27(*3), 225-238. https://doi.org/10.9708/jksci.2022.27.03.225

Kurudayıcıoğlu, M., & Tüzel, S. (2010). The types of literacy of the 21st century, changing text comprehension and Turkish teaching. *Türklük Bilimi Araştırmaları, 28*, 281-298.

Laupichler, M. C., Aster, A., & Raupach, T. (2023a). Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' AI literacy. *Computers and Education: Artificial Intelligence, 4*. https://doi.org/10.1016/j.caeai.2023.100126

Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023b). Development of the "Scale for the assessment of non-experts' AI literacy" – An exploratory factor analysis. *Computers in Human Behavior Reports, 12*. https://doi.org/10.1016/j.chbr.2023.100338

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. Education Sciences, *13*(4), 410-425. https://doi.org/10.3390/educsci13040410

Long, D., & Magerko, B. (23 Nisan 2020). *What is AI literacy? Competencies and design considerations*. CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. Honolulu, USA: Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

McDermid, J. A., Jia, Y., Porter, Z., & Habli, I. (2021). Artificial intelligence explainability: the technical and ethical dimensions. *Philosophical Transactions: Mathematical, Physical and Engineering Sciences,* 379(2207), Article 20200363. Advance online publication. https://doi.org/10.1098/rsta.2020.0363

Mohajan, H. K. (2017). Two criteria for good measurements in research: Validity and reliability. Annals of Spiru Haret University. *Economic Series, 17*(4), 59–82. https://doi.org/10.26458/1746

Muenjohn, Dr. N., & Armstrong, Prof. A. (2008). Evaluating the structural validity of the Multifactor Leadership Questionnaire (MLQ), capturing the leadership factors of transformational-transactional leadership. *Contemporary Management Research, 4*(1). https://doi.org/10.7903/cmr.704

Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin*, *105*(3), 430–445. https://doi.org/10.1037/0033-2909.105.3.430

Öztürk, K., & Şahin, M. E. (2018). A general view of artificial neural networks and artificial intelligence. *Takvim-i Vekayi*, *6(*2), 25-36.

Panayides, P. (2013). Coefficient alpha: Interpret with caution. *Europe's Journal of Psychology*, *9*(4), 687–696. https://doi.org/10.5964/ejop.v9i4.653

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37–40. https://doi.org/10.1590/0101-60830000000081

Pinski, M., & Benlian, A. (2023). *AI literacy-towards measuring human competency in artificial intelligence*. https:// scholarspace.manoa.hawaii.edu/handle/10125/102649

Precedence Research. (2023). *Artificial intelligence (AI) market*. https://www.precedenceresearch.com/artificial-intelligence-market#:~:text=The%20global%20artificial%20intelligence%20(AI,19%25%20from%202023%20to%202032.

Rosemann, A., & Zhang, X. (2022). Exploring the social, ethical, legal, and responsibility dimensions of artificial intelligence for health-a new column in Intelligent Medicine. I*ntelligent Medicine, 2*(2), 103-109. https://doi.org/10.1016/j.imed.2021.12.002

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. *Computers in Human Behavior Reports,* 1, 1-18. https://doi.org/10.1016/j.chbr.2020.100014

Schermelleh-Engel, K., & Moosbrugger, 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.

Suh, W., & Ahn, S. (2022). Development and Validation of a Scale Measuring Student Attitudes Toward Artificial Intelligence. *SAGE Open, 12*(2). https://doi.org/10.1177/21582440221100463

Taasoobshirazi, G., & Wang, S. (2016). The performance of the SRMR, RMSEA, CFI, and TLI: An examination of sample size, path size, and degrees of freedom. *Journal of Applied Quantitative Methods, 11*(3), 31–39.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. I*nternational Journal of Medical Education, 2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Terzi, R. (2020). An adaptation of Artificial Intelligence Anxiety Scale into Turkish: Reliability and validity study, *International Online Journal of Education and Teaching, 7*(4), 1501-1515.

Thanasegaran, G. (2009). Reliability and validity issues in research. *Integration and Dissemination Research Bulletin*, 4, 35–40.

Topal, Ç. (2017). Sociological imagination of Alan Turing: artificial intelligence as social imaginary. *Ankara University Journal of the Faculty of Languages and History-Geography, 57*(2), 1340-1364. https://doi.org/10.1501/Dtcfder_0000001565

Turing, A. (1950). Computing machinery and intelligence. Mind, *LIX*(236), 433-460. https://doi.org/10.1093/mind/LIX.236.433

Wang, B., Rau, P.-L. P., & Yuan, T. (2022). 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

Wilson, M., Scalise, K., & Gochyyev, P. (2015). Rethinking ICT literacy: From computer skills to social network settings. *Thinking Skills and Creativity, 18*, 65-80. https://doi.org/10.1016/j.tsc.2015.05.001

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods, 51*(1), 409–428. https://doi.org/10.3758/s13428-018-1055-2

Yavuz Aksakal, N., & Ülgen, B. (2021). Artificial intelligence and jobs of the future. *TRT Akademi, 6*(13), 834-852. https://doi.org/10.37679/trta.969285

6. Appendix

Madde No	YAPAY ZEKÂ OKURYAZARLIĞI ÖLÇEĞİ	Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Kararsızım	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
Farkındalık								
1	Akıllı cihazlar ile akıllı olmayan cihazları birbirinden ayırt edebilirim.	1	2	3	4	5	6	7
2	Yapay zekâ teknolojisinin bana nasıl yardımcı olacağını bilmiyorum. [T]	1	2	3	4	5	6	7
3	Kullandığım uygulama ve ürünlerde kullanılan yapay zekâ teknolojisini tanımlayabilirim.	1	2	3	4	5	6	7
Kullanım								
4	Günlük işlerimde bana yardımcı olması için yapay zekâ uygulamalarını veya ürünlerini ustalıkla kullanabilirim.	1	2	3	4	5	6	7
5	Yeni bir yapay zekâ uygulamasını veya ürününü kullanmayı öğrenmek benim için genellikle zordur. [T]	1	2	3	4	5	6	7
6	İş verimliliğimi artırmak için yapay zekâ uygulamalarını veya ürünlerini kullanabilirim.	1	2	3	4	5	6	7
Değerlendirme								
7	Bir yapay zekâ uygulamasını veya ürününü bir süre kullandıktan sonra kapasitesini ve sınırlarını değerlendirebilirim.	1	2	3	4	5	6	7
8	Belirli bir görev için çeşitli yapay zekâ uygulamaları veya ürünleri arasından en uygun olanını seçebilirim.	1	2	3	4	5	6	7
9	Yapay zekâ tarafından sunulan çeşitli çözümler arasından uygun olanını seçebilirim.	1	2	3	4	5	6	7
Etik								
10	Yapay zekâ uygulamalarını veya ürünlerini kullanırken her zaman etik ilkelere uyarım.	1	2	3	4	5	6	7
11	Yapay zekâ uygulamalarını veya ürünlerini kullanırken gizlilik ve bilgi güvenliği konularına asla dikkat etmem. [T]	1	2	3	4	5	6	7
12	Yapay zekâ teknolojisinin kötü amaçlı kullanılmaması için her zaman dikkatliyimdir.	1	2	3	4	5	6	7