

Psychometric Properties of the Turkish Version of the AI Mindset Scale

Barzan Batuk¹  Nuri Türk^{2*}  , Oğuzhan Yıldırım³ 

¹ Department of Educational Sciences, Faculty of Education, Siirt University, Türkiye

² Faculty of Education, Siirt University, Türkiye

³ School of Health Sciences, Kahramanmaraş Sutcu Imam University, Türkiye

ABSTRACT

One of the fields where Artificial Intelligence (AI) is most widely used is higher education. Among the factors that determine university students' acceptance and effective use of AI tools is the AI mindset. This study aimed to adapt the AI Mindset Scale to Turkish culture. The study sample consisted of 285 university students (aged 18 and above). The study's data collection tools included the AI Mindset Scale, the AI Acceptance Scale, and the AI Attitude Scale. The results of the reliability analysis conducted on the AI Mindset Scale showed that Cronbach's alpha and McDonald's omega values were at good levels. According to the findings of the Confirmatory Factor Analysis (CFA) conducted within the scope of validity, the fit indices of the AI Mindset Scale were found to be at acceptable levels. Furthermore, the scale's high values in item factor loadings and its provided item discriminant and convergent validity strengthened its construct validity. Criterion validity findings revealed significant positive correlations between AI acceptance and AI attitudes, and AI mindsets. In conclusion, all analyses conducted in the study show that the AI Mindset Scale is a valid and reliable measurement tool that can be used in Turkey. Therefore, it is expected that these research findings will lead to studies on the AI mindset both in Turkish culture and across cultures.

Keywords: Artificial Intelligence, mindset, AI accept, AI attitude

* Corresponding Author's email: nuri.turk@siirt.edu.tr

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1. INTRODUCTION

Since the early 21st century, AI has been at the forefront of technological developments (Adaş & Erbay, 2022). Artificial intelligence (AI) encompasses digital technology that is rapidly spreading in the data, robotics, technology, cloud computing and energy sectors (Lyu & Liu, 2021). AI can successfully perform operations such as comparison, evaluation, and prediction. Furthermore, It can also perform tasks such as mathematical calculations in a shorter time than humans (Khaleel et al., 2023). In addition to mathematical calculations, conversational AI has the ability to comprehend various languages, recognize, and understand speech (Huynh-The et al., 2023). AI, which has the potential to change our perspective, has the capacity to shift existing paradigms (Bozkurt, 2023). Deep Blue, an AI-based computer that defeated world chess champion Kasparov, and Sophia, the AI robot developed by Hanson Robotics, have increased the recognition and influence of AI (Adaş & Erbay, 2022). Today, current AI robots and programs continue to increase this recognition and impact.

Scientific and technological advances are leading to social, moral, and legal changes (Jiang et al., 2022). In this context, users have serious concerns about ChatGPT, one of the most popular AI applications (Karakoç-Keskin, 2023). It also raises certain concerns about privacy and data security (Koçyiğit & Darı, 2023). Furthermore, when use of AI becomes persistent, it can get out of control and lead to risky behaviors such as suicide (Akkaya et al., 2021; Campbell et al., 2025). In the context of providing psychological and emotional support, AI may be inadequate in terms of sincerity and healthy communication (Yorgancioğlu-Tarcan, et al., 2024).

Another important issue related to AI is ethics. One of the most critical issues that will determine the future importance of AI is its ethical success. Scientists, engineers, philosophers, policymakers, and users all have important roles to play in this regard (Huang et al., 2023). While individuals' adaptation to AI is important, identifying ethical concerns and usage criteria is critical. Understanding individuals' concerns and facilitating their adaptation to technology can ensure the functional use of AI tools (Akkaya et al., 2021). In this context, uncovering the positive effects of AI, minimizing the impact of usage concerns, and ensuring equal opportunities are crucial (Mannuru et al., 2023).

AI applications have high potential for understanding human emotions (Zhao et al., 2022). According to psychology students, AI ease of use and perceived usefulness are important factors influencing attitudes toward AI (Gado et al., 2022). AI plays a significant role in embracing innovative developments in psychology, supporting individuals' mental health, and enhancing their well-being (Oladimeji et al., 2023). AI is also effective in diagnosing psychological disorders (Zhou et al., 2022). AI-powered chatbots, which aim to provide psychological support to individuals experiencing distress, have been found to be successful in reducing anxiety. Accessible and low-cost robots can help address gaps in mental health services during crises (Spytska, 2025). However, AI may also have potential negative impacts on mental health (Bond et al., 2025). AI can facilitate diagnosis and decision-making in the therapeutic process through the analysis of clients' behaviors, clinical histories, and social media data. Therefore, it is anticipated that valuable studies combining the fields of psychology and artificial intelligence will be conducted in the future (Prasad & Kalavakolanu, 2023).

AI plays a critical role in terms of hardware and software in the science, social sciences, mathematics, medicine, and engineering (Gültekin et al., 2022). Furthermore, AI has the potential to influence the fundamental dynamics of the educational process (Alan et al., 2024). AI is expected to play an active role in school and classroom management in the near future (Üstün, 2024). AI in the teacher role is expected to avoid negative emotions and attitudes such as impatience, anger, forgetfulness, and conflict.

However, AI has disadvantages in teaching students core values such as religion, culture, and history, serving as appropriate role models for students, ensuring data security, and being reliable (Çetin & Aktaş, 2021). One of the active roles of artificial intelligence in the educational process is providing individualized learning applications. Applications such as the Khan Academy Platform and Duolingo have the function of detecting the student's level and providing exercises (Otahanova, 2025). AI has a functional role in the educational process by providing online education and learning opportunities, acting as virtual teacher assistants, and developing intelligent teaching systems (İncemen & Öztürk, 2024).

AI tools are actively used by academics and university students in higher education (Hashmi et al., 2024). However, the use of AI tools is influenced by students' attitudes and mindsets toward AI (Ibrahim et al., 2025; Türk et al., 2025). Therefore, studies are needed to examine students' positive/negative attitudes toward AI, their concerns/expectations about AI, and their trust in AI. To carry out these studies, scales developed (Alan et al., 2024) and adapted (Akkaya et al., 2021) for AI are required. Existing research suggests that there are data collection tools such as AI Literacy Scale (Erdoğan & Ekşioğlu, 2024), AI Anxiety Scale (Akkaya et al., 2021), threats of AI Scale (Kaya et al., 2024), AI Attitude Scale (Türk et al., 2025), the AI Self-Efficacy Scale (Türk et al., 2025) and the AI Acceptance Scale (Batuk et al., 2025) in Türkiye.

There is no Turkish-language scale that measures individuals' perspectives/mindsets toward AI. The Artificial Intelligence Mindset Scale (Ibrahim et al., 2025), adapted to Turkish for this study, differs from other scales in terms of structure and features. This scale aims to reveal individuals' beliefs about whether AI enhances their abilities, skills, and intelligence. The idea of influencing AI's compatibility, integration, acceptance, and use is related to the AI mindset (Ibrahim et al., 2025). The AI Mindset Scale consists of two subscales: growth and deskilling. The growth dimension consists of four items reflecting a positive perspective, while the deskilling dimension includes four items reflecting a negative perspective. This scale aims to reveal holistic attitudes and perceptions regarding the positive and negative characteristics of AI. Therefore, it is anticipated that the Turkish adaptation of this scale will play a pivotal role in the development of the field.

2.METHOD

2.1. Study Design and Participants

This scale adaptation study utilized a quantitative research design (Karasar, 2012). Data for the study, planned according to a relational survey design, were collected cross-sectionally. Ethical permission was obtained from the Siirt University Ethics Committee before data collection began (decision number: 10492). Data were collected in a classroom setting using Google Forms.

The research was conducted with a sample of 305 education faculty students studying at the university in November 2025. However, due to missing data and duplicate responses among the sample's responses to the scale items, 20 participants were excluded from the data analysis process, and analyses were conducted on 285 participants. The research data was collected through convenience sampling. Table 1 presents the sociodemographic characteristic profiles of the respondents:

Table 1. Sociodemographic Characteristics of Participants

Variables	Categories	n	%
Gender	Male	65	22.8
	Female	220	77.2
Socioeconomic level	Low	42	14.7
	Medium	238	83.5
	High	5	1.8
Grade level	1st	94	32.9
	2nd	35	12.3
	3rd	69	24.2
	4th	87	30.6
Total		285	100

Data presented in Table 1 demonstrate that 22.8% of the participants are male and 77.2% are female. 14.7% of participants perceive their income level as low, 83.5% as medium, and 1.8% as high. 32.9% of participants are first-grade students, 12.3% are second-grade students, 24.2% are third-grade students, and 30.6% are fourth-grade students.

2.2. Data Collection Tool

2.2.1. AI Mindset Scale: The AI Mindset Scale was used to assess participants' AI mindset levels. Items on the scale (e.g., "Using AI programs weakens my skills") are rated on a six-point Likert scale from 1 (Strongly disagree) to 6 (Strongly agree). The scale has been developed by Ibrahim et al. (2025) and consists of two subscales: Growth and Deskilling. It has eight items: four Growth items and four Deskilling items. Reliability coefficients for the original scale indicate good internal consistency (Cronbach's $\alpha=0.82$, McDonald's $\omega=0.91$).

2.2.2. AI Attitude Scale (AIAS-4): The AI Attitude Scale was used to assess participants' AI attitude levels. Items on the scale (e.g., "I believe artificial intelligence tools will make my life easier") are rated on a 10-point Likert scale from 1 (Strongly disagree) to 10 (Strongly agree). This study used a scale developed by Grassini (2023) and adapted into Turkish by Türk et al. (2025) to measure general attitudes towards artificial intelligence. The single-factor, scale consists of four items. High scores indicate a high general attitude towards artificial intelligence. The Cronbach's alpha acquired from the scale was .89. In this study, the Cronbach's alpha internal consistency coefficient for the scale was calculated to be 0.87.

2.2.3. AI Acceptance Scale: The AI Acceptance Scale was used to assess participants' AI acceptance. Items on the scale (e.g., "I find AI programs useful for answering my questions") were rated on a five-point Likert scale from 1 (Strongly disagree) to 5 (Strongly agree). This scale, developed by De Winter et al. (2024) to measure acceptance of artificial intelligence, includes six items. The scale includes reverse-coded items (4, 5, and 6). The Cronbach's alpha acquired from the scale adapted by Batuk et al. (2025), was .76. In this study, the Cronbach Alpha internal consistency coefficient of the scale was estimated as .72.

2.3. Language Validity

To tailor AI Mindset scale to cultural characteristics of Turkish society, the scale's authors were first contacted via e-mail, and permissions for use and adaptation were approved. Ethical approval for the study was then acquired from the Ethics Board of XXX University (xxxxxxxx). At the beginning of the adaptation process, the researchers examined the scale and its items. The findings indicated that AI

Mindset scale and its items were appropriate for the selected population. The procedures for translating the scale were executed using the method recommended by Brislin et al. (1973).

Two field experts who are fluent in both Turkish and English carried out Turkish translation of AI Mindset scale questions. Three field reviewed the translation for clarity of the questions and cultural appropriateness of the sentence structures. The translated scale was translated into English by two faculty members from the English department for grammatical analysis. It was observed that the translation procedures did not cause any loss of meaning. Two Turkish teachers checked the suitability of the measurement tool for Turkish. Necessary corrections were made based on the feedback. AI Mindset questionnaire was administered to 12 students registered in the Turkish Language Teaching Department. It was concluded that no of the items ambiguous in terms of meaning. In the final phase, the scale was administered to 305 education faculty students accessed through online platforms via Google Form.

2.4. Data Analysis

The study data were tested employing SSPS 27 and AMOS 25 programs. The significance threshold was established at $p<0.05$. Validity analyses included first-level multifactor CFA, convergent validity, item discrimination, and language and content validity. Cronbach's Alpha and McDonald's Omega reliability coefficients were used to determine the scale's reliability. Model fit criteria, comparative fit indices, absolute fit values, and residual fit values were used for CFA. The internal validity of the scale was tested using a t-test for the item mean scores between the upper 27% and lower 27% groups. Because the scale yields a total score, it was evaluated both overall and within each subscale.

3. FINDINGS

Descriptive statistics, validity and reliability results of the adapted AI Mindset Scale are included in this section.

Table 2. AI Mindset Scale's Descriptive Statistics and Item Analysis Output

Items	Mean	Standart Deviation	Skewness	Kurtosis	Item Total Correlations	Common Factor Variances
Item 1	2,89	1,35	,31	-,62	.73	.70
Item 2	3,01	1,40	,35	-,60	.76	.81
Item 3	2,55	1,39	,73	-,29	.72	.51
Item 4	2,49	1,38	,77	-,13	.65	.40
Item 5	4,38	1,26	-,66	-,32	.68	.42
Item 6	4,13	1,18	-,29	-,38	.83	.67
Item 7	3,90	1,30	-,22	-,55	.81	.88
Item 8	3,97	1,35	-,20	-,66	.72	.64

Table 2 provides evidence that the corrected item-total correlation coefficients range from .65 to .83. The obtained values above 0.30 are considered acceptable (Büyüköztürk, 2018). The common variance values range from .41 to .88. Common variance is expected to be no lower than 0.20 (Büyüköztürk et al., 2014). The skewness and kurtosis values of the items range from -.66 to .77. According to Kline (2011), for the normality assumption to be met, the skewness and kurtosis values must be less than 3.

3.1. Findings Related to Validity Analysis

The 8-item, two-factor structure of the AI Mindset Scale was tested using CFA. The measurement values of the CFA results confirming the two-factor structure of the scale are shown in Figure 1. Factor loadings

for Deskilling ranged from .63 to .90, and for Growth, from .65 to .94. The validity of the confirmatory factor analysis results was assessed using model fit indices (χ^2/df , CFI, NFI, RFI, IFI, RMSEA, GFI, AGFI). The references cited by Tabachnick and Fidell (2007), Bayram (2013), and Karagöz (2017) were considered to interpret AI Mindset Scale's fit values. Table 2 below shows the good, acceptable, and CFA model fit values obtained.

Table 3. AI Mindset Fit Values

	χ^2/df	CFI	IFI	RFI	AGFI	GFI	RMSEA	NFI	TLI	SRMR
Good Fit	≤ 3	$\geq .95$	$\geq .95$	$\geq .95$	$\geq .90$	$\geq .95$	$\leq .05$	$\geq .95$	$\geq .95$	$\leq .05$
Accepted Fit	$3 < \chi^2/\text{df} < 5$	$\geq .90$	$\geq .90$	$\geq .90$	$\geq .85$	$\geq .90$	$\leq .08$	$\geq .90$	$\geq .90$	$\leq .08$
AI Mindset Fit Values	2.83	.98	.98	.95	0.91	.96	.08	.95	.96	.04

As shown in Table 3, the data indicate that the χ^2/df (2.83) value is below 3. The values of other fit indices are CFI=.98, IFI=.98, RFI=.95, AGFI=.91, GFI=.96, RMSEA=.08, NFI=.95, TLI=.96 and SRMR=.04. χ^2/df , CFI, IFI, RFI, AGFI, GFI, TLI, NFI, SRMR and RMSEA values indicate a good fit.

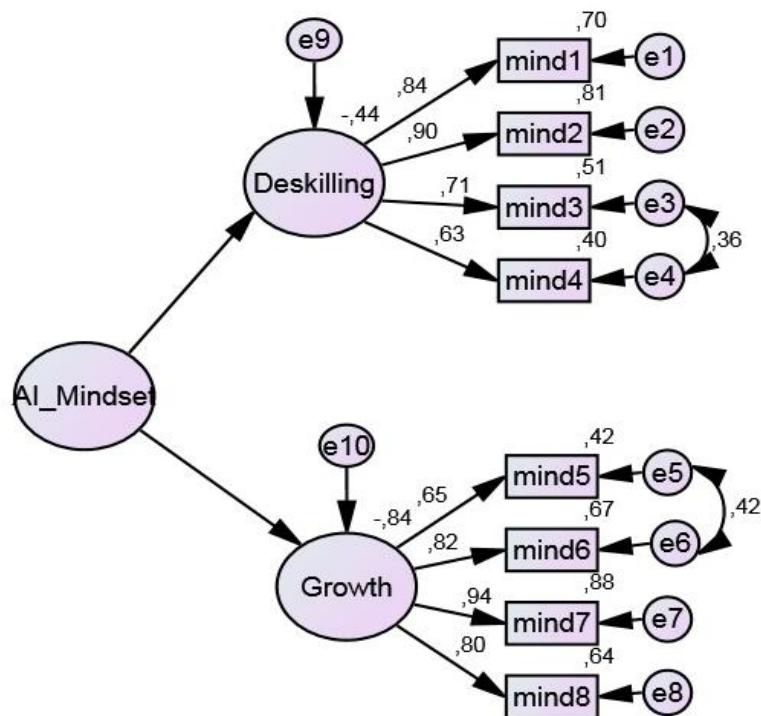


Figure 1. Second Order Confirmatory Factor Analysis of AI Mindset Scale

Convergent Validity: The assessment of convergent validity involves examining the CR and AVE values. Some sources require an AVE value above .50 (Shrestha, 2021) and the CR > AVE condition (Hair et al., 2014). However, convergent validity is considered to be achieved when AVE is < 0.50 and CR is > 0.60 (Fornell & Larcker, 1981; Shrestha, 2021).

Table 4. Convergent Validity of The Adapted Scale

	CR	AVE
Growth	.85	.60
Deskilling	.88	.65

As seen in Table 4, CR values were above .60 for the overall scale and all dimensions. High CR values for the overall scale and its subdimensions indicate good internal consistency reliability. Furthermore, AVE values ranged from .60 to .93, supporting the scale's convergent validity. In light of these results, it may be concluded that the scale achieved convergent validity.

3.2. Item Discrimination

One of the methods for examining the reliability of a data collection tool is to compare upper and lower groups. The analysis is projected to identify distinctions between participants who possess and do not possess the desired characteristic. In order to achieve this, total scores are arranged from highest to lowest, and the 27% groups are divided into lower and upper 27% groups. To assess the scale's internal validity, an independent samples t-test was used to examine the significance of the differences between the lower and upper 27% groups. The means of these two groups were then compared using an independent samples t-test. A significant analysis indicates that the test has high discriminative power (Can, 2020). In this study, 77 participants with the lowest and highest scores were divided into upper and lower groups. The average score of the upper group was found to be 32.66, while the average score of the lower group was 22.18.

Table 6. Independent Samples t-Test for Lower and Upper Groups of the AI Mindset Scale

Measurement Tool	Group	n	Mean	sd	t	p
AI Mindset Scale	Lower group	77	22.18	3.04	-24.64	00*
	Upper group	77	32.66	2.17		

$N_{Alt\%27}=77$ ve $N_{Üst\%27}=77$

Table 6 reveals a statistically significant difference between the AI Mindset Scale scores of the lower and upper groups ($p<0.01$). In this context, the scale can be considered highly reliable.

3.3. Criterion Validity

At this stage, data collected from 285-population was examined to assess the criterion validity of the AI Mindset scale. In this context, the relationships between the AI Mindset scale scores and the one-dimensional AI General Attitude and two-dimensional AI Acceptance scale scores (Effectiveness and Concerns) were examined using Pearson correlation analysis.

Table 7. Descriptive statistics and correlation data of the AI Mindset Scale

Değişkenler	N	Mean	Sd	1	2	3	4	5
1.AI Mindset	285	33.44	7.99					
2.Growth	285	17.05	4.67	-.88**				
3. Deskilling	285	16.40	4.44	-.87**	-.54**			
4.AI Attitude	285	28.52	7.83	.48**	.29**	-.56**		
5.AI Acceptance	285	20.62	4.34	.61**	.49**	-.58**	.61**	

*p<0.05, **P<0.01

Table 7 reveals a positive and significant relationship between AI Mindset and AI Attitude ($r = .48$) and AI Acceptance ($r = .61$). A positive and significant relationship is reported between Growth and AI Attitude ($r = .29$) and AI Acceptance ($r = .49$). A negative and significant relationship is recorded between Deskilling and AI Attitude ($r = -.56$) and AI Acceptance ($r = -.58$). These findings demonstrate that the AI Mindset scale meets criterion validity.

3.4. Findings Related to Reliability Analyses

The McDonald's Omega and Cronbach's Alpha internal consistency were adapted to verify the reliability of the adapted scale. The findings are displayed in Table 8.

Table 8. AI Mindset Scale's Cronbach's Alpha and McDonald's Omega value

Factors	Cronbach Alfa	McDonald's Omega
Growth	.87	.87
Deskilling	.89	.89
Scale Total	.88	.88

Table 8 reveals that Cronbach's alpha and omega values for all dimensions are 0.87 and above. These measurement results demonstrate that the AI Mindset Scale is a reliable measurement tool.

4. DISCUSSION

This study aimed to adapt the AI Mindset Scale (Ibrahim et al., 2025) to Turkish culture. The Turkish version of the AI Mindset Scale validated the study, which consisted of a sample of university students. The reliability analysis results of the study showed that Cronbach's alpha and McDonald's omega values for the scale's sub-dimensions, Growth and Deskilling, were .87 and .89, respectively. Furthermore, Cronbach's alpha and Omega values for the AI mindset were found to be .88. Similarly, in the original study (Ibrahim et al., 2025), it was observed that Cronbach's alpha and McDonald's omega values for both the sub-dimensions and the overall scale ranged from .82 to .91. The findings of the study show that the AI Mindset scale provides reliability.

The item-total correlation values of the AI Mindset Scale, which ranged from .65 to .83, proved that it was within an acceptable range. Furthermore, the fact that the AI Mindset scale item factor loadings are between .63 and .90 indicates that the construct validity is achieved (DeVellis, 2017). CFA results for the scale indicate that the fit indices are good. The convergent validity results of the AI Mindset Scale (AVE=.60-.65, CR=.85-.88) were also found to be good. The results of the 27% upper-lower groups analysis conducted to determine item discrimination show that the scale has a high level of item discrimination (Can, 2020). In conclusion, all analyses proved that the AI Mindset Scale, consisting of two sub-dimensions and a total of 8 items, can be used as a valid and reliable measurement tool in Turkish culture.

To examine the criterion validity of the AI Mindset Scale, the Short Form of the AI Acceptance Scale and the Short Form of the AI Attitude Scale were used. The analyses revealed that both the sub-dimensions and the overall scale had significant relationships with AI acceptance and AI attitude. While there is a significant positive relationship between AI acceptance and AI mindset and growth, there is a negative significant relationship with deskilling. Similarly, a significant positive relationship was found between AI attitude and AI mindset and growth, while a significant negative relationship was found

with deskilling. A significant negative relationship was also found between the sub-dimensions of the AI mindset scale. The original study of the scale (Ibrahim et al., 2025) also found significant positive relationships between AI acceptance, AI attitude, and AI mindset. Therefore, it can be said that as individuals' AI acceptance and attitude rates increase, they develop an enhancing mindset towards AI. Similarly, as the enhancing mindset of AI increases, AI acceptance is expected to become easier. Furthermore, it can be said that these findings are valid for both university students and adults. Indeed, the sample of the original study of the scale included adults in addition to university students.

University students with high digital competencies and cognitive flexibility develop more positive attitudes towards AI tools (Karaoglan Yilmaz & Yilmaz, 2025). University students who have a positive attitude towards artificial intelligence are more likely to use AI tools in their academic tasks and research (Nemt-Allah et al., 2024). However, the extent to which university students use AI tools in their academic assignments is determined by the academics' perspective on AI. Some academics actively use AI tools with their students in their courses and recommend that students use AI tools in assignments. However, most academics prohibit students from using AI tools in academic assignments due to concerns about plagiarism (Nikolic et al., 2024). This prevents students from developing AI self-efficacy and competence. Therefore, there is a need for comprehensive ethical regulations regarding the use of AI tools in academia. In this context, future studies could address the relationship between AI mindset and AI ethical awareness.

This scale adaptation study has several limitations. The fact that the study sample consists only of university students prevents its generalizability to other education levels and age groups. Future studies could expand the scope of the scale by including primary and secondary education levels, as well as older age groups. In this way, the causes and consequences of the AI enhancing and debilitating mindset can be understood in depth among a wider audience. While the study employed various analyses, including convergent validity, future studies could utilize methods such as measurement invariance and Rasch analysis. Furthermore, the data were collected using self-report instruments. Therefore, future studies could also utilize techniques such as observation and interviews to avoid established method bias. The development of the AI Mindset Scale was conducted with a German sample. Following the development study, the scale's first adaptation in a different culture was conducted in Turkish. Therefore, it has been demonstrated that the AI Mindset Scale can be used as a valid and reliable measurement tool across different languages and cultures. Future adaptation studies will enable the scale to be used globally, enabling cross-cultural comparative studies.

5. STATEMENTS

5. 1. Conflict of Interest

There is no conflict of interest in this study.

5. 2. Contributions

Each of the author contributed equally to all study.

5. 3. Ethical Considerations

Ethical permission was obtained from the Siirt University Ethics Committee before data collection began (decision number: 10492)

REFERENCES

Adaş, E., & Erbay, B. (2022). Yapay zekâ sosyolojisi üzerine bir değerlendirme. *Gaziantep University Journal of Social Sciences*, 21(1), 326-337. <https://doi.org/10.21547/jss.991383>

Ak, M. (2022). Yapay zekâ kaygısının kariyer kararlılığına etkisine yönelik bir araştırma: Ondokuz Mayıs Üniversitesi öğrencileri örneği. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 27(3), 477-491.

Akkaya, B., Özkan, A., & Özkan, H. (2021). Yapay zekâ kaygı (YZK) ölçeği: Türkçeye uyarlama, geçerlik ve güvenilirlik çalışması. *Alanya Akademik Bakış*, 5(2), 1125-1146. <https://doi.org/10.29023/alanyaakademik.833668>

Alan, B., Zengin, F. K., & Keçeci, G. (2024). Artificial Intelligence Attitude Scale (AIAS): Validity and Reliability Study. *Cumhuriyet International Journal of Education*, 13(4), 789-800. <https://dx.doi.org/10.30703/cije.1327949>

Batuk, B., Aktu, Y., & Türk, N. (2025). Yapay Zeka Kabul Ölçeği Kısa Formu'nun psikometrik özelliklerinin incelenmesi. *Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 34(Özel Sayı), 438-451. <https://doi.org/10.35379/cusosbil.1695975>

Bayram, N. (2013). *Yapısal eşitlik modellemesine giriş* (3.baskı). Ezgi Kitapevi.

Bond, R. R., Ennis, E., & Mulvenna, M. D. (2025). How artificial intelligence may affect our mental wellbeing. *Behaviour & Information Technology*, 44(10), 2093-2100. <https://doi.org/10.1080/0144929X.2025.2520593>

Bozkurt, A. (2023). ChatGPT, üretken yapay zeka ve algoritmik paradigma değişikliği. *Alanyazın*, 4(1), 63-72. <https://doi.org/10.59320/alanyazin.1283282>

Brislin, R. W., Lonner, W. J., & Thorndike, R. M. (1973). *Cross-cultural research methods*. John Wiley & Sons

Büyüköztürk, Ş., Çakmak, E. K., Akgün, Ö. E., Karadeniz, Ş., Demirel, F. (2014). *Bilimsel araştırma yöntemleri* (18th ed.). Pegem Akademi.

Büyüköztürk, Ş. (2018). Faktör analizi: Temel kavamlar ve ölçek geliştirmede kullanımı. *Kuram ve Uygulamada Eğitim Yönetimi*, 32(32), 470-483.

Campbell, L. O., Babb, K., Lambie, G. W., & Hayes, B. G. (2025). An Examination of Generative AI Response to Suicide Inquires: Content Analysis. *JMIR Mental Health*, 12, e73623.

Can, A. (2020). *Spss ile Bilimsel Araştırma Sürecinde Nicel Veri Analizi* (9th Ed.). Ankara: Pegem Akademi.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, 14(3), 464-504. <https://doi.org/10.1080/10705510701301834>

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, 9(2), 233-255. https://doi.org/10.1207/S15328007SEM0902_5

Çetin, M., & Aktaş, A. (2021). Yapay zeka ve eğitimde gelecek senaryoları. *OPUS International Journal of Society Researches*, 18 (Eğitim Bilimleri Özel Sayısı), 4225-4268. <https://doi.org/10.26466/opus.911444>

DeVellis, R.F. (2017). *Scale development: Theory and applications*. Sage Publications.

De Winter, J., Dodou, D., & Eisma, Y. B. (2024). Personality and acceptance as predictors of ChatGPT use. *Discover Psychology*, 4(1), 57. <https://doi.org/10.1007/s44202-024-00161-2>

Erdoğan, T. E., & Ekşioğlu, S. (2024). Yapay Zekâ Okuryazarlığı Ölçeği'nin Türkçeye uyarlanması. *Türk Eğitim Bilimleri Dergisi*, 22(2), 1196-1211. <https://doi.org/10.37217/tebd.1496716>

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. <https://doi.org/10.1177/002224378101800104>

Gado, S., Kempen, R., Lingelbach, K., & Bipp, T. (2022). Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence?. *Psychology Learning & Teaching*, 21(1), 37-56. <https://doi.org/10.1177/14757257211037149>

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>

Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2014). *Exploratory factor analysis. Multivariate data analysis*. Prentice Hall.

Huang, C., Zhang, Z., Mao, B., & Yao, X. (2022). An overview of artificial intelligence ethics. *IEEE Transactions on Artificial Intelligence*, 4(4), 799-819. <https://doi.org/10.1109/TAI.2022.3194503>

Huynh-The, T., Pham, Q. V., Pham, X. Q., Nguyen, T. T., Han, Z., & Kim, D. S. (2023). Artificial intelligence for the metaverse: A survey. *Engineering Applications of Artificial Intelligence*, 117, 105581. <https://doi.org/10.1016/j.engappai.2022.105581>

Ibrahim, F., Telle, N. T., Herzberg, P. Y., & Münscher, J. C. (2025). The construction and Validation of the AI mindset Scale (AIMS). *Computers in Human Behavior: Artificial Humans*, 100220. <https://doi.org/10.1016/j.chbah.2025.100220>

İncemen, S., & Öztürk, G. (2024). Farklı eğitim alanlarında yapay zekâ: Uygulama örnekleri. *International Journal of Computers in Education*, 7(1), 27-49. <https://doi.org/10.5281/zenodo.12600022>

Jiang, Y., Li, X., Luo, H., Yin, S., & Kaynak, O. (2022). Quo vadis artificial intelligence?. *Discover Artificial Intelligence*, 2(4), 1-19. <https://doi.org/10.1007/s44163-022-00022-8>

Karagöz, Y. (2021). *Bilimsel araştırma yöntemleri ve yayın etiği* (3.Baskı). Nobel.

Karakoç-Keskin, E. (2023). Yapay zekâ sohbet robotu ChatGPT ve Türkiye internet gündeminde oluşturduğu temalar. *Yeni Medya Elektronik Dergisi*, 7(2), 114-131.

Karaoglan Yilmaz, F. G., & Yilmaz, R. (2025). Exploring the role of self-regulated learnings skills, cognitive flexibility, and metacognitive awareness on generative artificial intelligence attitude. *Innovations in Education and Teaching International*, 1-14. <https://doi.org/10.1080/14703297.2025.2484613>

Karasar, N. (2012). *Bilimsel araştırma yöntemi*. Nobel Yayınevi.

Kaya, F., Yetisensoy, O., Aydin, F., & Kaya, M. D. (2024). Yapay Zekâ Korkusu Ölçeğinin Türkçe'ye uyarlanması. *Ordu Üniversitesi Sosyal Bilimler Enstitüsü Sosyal Bilimler Araştırmaları Dergisi*, 14(2), 554-567. <https://doi.org/10.48146/odusobiad.1264103>

Khaleel, M., Ahmed, A. A., & Alsharif, A. (2023). Artificial intelligence in engineering. *Brilliance: Research of Artificial Intelligence*, 3(1), 32-42. <https://doi.org/10.47709/brilliance.v3i1.2170>

Koçyiğit, A. & Darı, A. B. (2023). Yapay zekâ iletişiminde ChatGPT: İnsanlaşan dijitalleşmenin geleceği. *Stratejik ve Sosyal Araştırmalar Dergisi*, 7(2), 427-438. <https://doi.org/10.30692/sisad.1311336>

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. NY: The Guilford Press.

Lyu, W., & Liu, J. (2021). Artificial Intelligence and emerging digital technologies in the energy sector. *Applied Energy*, 303, 117615. <https://doi.org/10.1016/j.apenergy.2021.117615>

Mannuru, N. R., Shahriar, S., Teel, Z. A., Wang, T., Lund, B. D., Tijani, S., ... & Vaidya, P. (2025). Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) Technologies for development. *Information Development*, 41(3), 1036-1054. <https://doi.org/10.1177/0266669231200628>

Nemt-Allah, M., Khalifa, W., Badawy, M., Elbably, Y., & Ibrahim, A. (2024). Validating the ChatGPT Usage Scale: psychometric properties and factor structures among postgraduate students. *BMC Psychology*, 12(1), 497. <https://doi.org/10.1186/s40359-024-01983-4>

Nikolic, S., Wentworth, I., Sheridan, L., Moss, S., Duursma, E., Jones, R. A., ... & Middleton, R. (2024). A systematic literature review of attitudes, intentions and behaviours of teaching academics pertaining to AI and generative AI (GenAI) in higher education: An analysis of GenAI adoption using the UTAUT framework. *Australasian Journal of Educational Technology*, 40(6), 56-75. <https://doi.org/10.14742/ajet.9643>

Hashmi, N., & Bal, A. S. (2024). Generative AI in higher education and beyond. *Business Horizons*, 67(5), 607-614. <https://doi.org/10.1016/j.bushor.2024.05.005>

Oladimeji, K. E., Nyatela, A., Gumede, S., Dwarka, D., & Lalla-Edward, S. T. (2023). Impact of artificial intelligence (AI) on psychological and mental health promotion: an opinion piece. *New Voices in Psychology*, 13, 1-12. <https://doi.org/10.25159/2958-3918/14548>

Otahanova, S. (2025). The concept of artificial intelligence and its role in education. *International Journal of Artificial Intelligence*, 1(4), 3-6.

Prasad, K., & Kalavakolanu, S. (2023). The study of cognitive psychology in conjunction with artificial intelligence. *Conhecimento & Diversidade*, 15(36), 271-287.

Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics*, 9(1), 4-11

Spytska, L. (2025). The use of artificial intelligence in psychotherapy: Development of intelligent therapeutic systems. *BMC Psychology*, 13(175). <https://doi.org/10.1186/s40359-025-02491-9>

Tabachnick, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics*. Allyn and Bacon

Üstün, A. B. (2024). Applications of Artificial Intelligence in Education: A Systematic Review of Postgraduate Theses. *Journal of Information and Communication Technologies*, 6(2), 95-112. <https://doi.org/10.53694/bited.1593139>

Türk, N., Batuk, B., Kaya, A., & Yıldırım, O. (2025). What makes university students accept generative artificial intelligence? A moderated mediation model. *BMC Psychology*, 13, 1257. <https://doi.org/10.1186/s40359-025-03559-2>

Turgut, D., & Kunuroglu, F. (2025). Adaptation of the Student Attitudes toward Artificial Intelligence Scale (SATAI) to the Turkish context: A sample of emerging adults. *International Journal of Human-Computer Interaction*, 41(21) 13505-13515. <https://doi.org/10.1080/10447318.2025.2474474>

Yorgancıoğlu-Tarcan, G., Balçık, P. Y., & Sebik, N. B. (2024). Türkiye ve dünyada sağlık hizmetlerinde yapay zekâ. *Mersin Üniversitesi Tip Fakültesi Lokman Hekim Tip Tarihi ve Folklorik Tip Dergisi*, 14(1), 50-60. <https://doi.org/10.31020/mutftd.1278529>

Zhao, J., Wu, M., Zhou, L., Wang, X., & Jia, J. (2022). Cognitive psychology-based artificial intelligence review. *Frontiers in Neuroscience*, 16, 1024316. <https://doi.org/10.3389/fnins.2022.1024316>

Zhou, S., Zhao, J., & Zhang, L. (2022). Application of artificial intelligence on psychological interventions and diagnosis: An overview. *Frontiers in Psychiatry*, 13, 811665. <https://doi.org/10.3389/fpsyg.2022.811665>



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