Adapting the Student Attitudes Toward Artificial Intelligence (SATAI) Scale for Higher Education Contexts

Neslihan Köse, Bartın University, Türkiye
İlknur Civan Biçer, Anadolu University, Türkiye

The European Conference on Education 2025
Official Conference Proceedings

Abstract

The growing integration of artificial intelligence into educational environments underscores the need for valid and reliable tools to assess students' attitudes toward AI across different educational levels. The purpose of this study is to adapt the Students' Attitudes towards Artificial Intelligence (SATAI) Scale, developed by Suh and Ahn (2022) for primary and secondary education, for higher education contexts. The participants in the study were 535 undergraduate students from English Language Teaching departments at two different universities in Türkiye. Data were collected through Google Forms in two rounds: the first round for exploratory factor analysis ($n_1 = 325$) and the second round for confirmatory factor analysis ($n_2 = 210$). The exploratory factor analysis confirmed the original three-factor structure of the scale, which includes cognitive, affective, and behavioral components. Following this analysis, nine items were removed for the confirmatory factor analysis. The results of the confirmatory factor analysis showed a good fit, supporting the three-factor structure. Therefore, the SATAI Scale for higher education contexts (SATAI-HE) is validated as a reliable tool for measuring the attitudes of higher education students toward artificial intelligence. This study contributes to the field by offering a relevant assessment tool that can guide AI-related educational practices, policy decisions, and curriculum development in higher education.

Keywords: AI, higher education, scale adaptation, validity, reliability

Introduction

AI technology dates back to the 1940s and 1950s, and its definition was initially coined by McCarthy in 1956, emphasizing its component of intelligence. Especially after COVID-19, technology became an indispensable part of education. ICT tools have had many applications in teaching and learning for many years, and it has also been transformed on a big scale with the rise of AI in education, including its rapid integration in higher education (Zawacki-Richter et al., 2019).

AI in education has a long history, and it has a controversial one for educators (Konecki et al., 2024). Its use is becoming increasingly popular and widespread. While AI has the potential to significantly enhance teaching and learning, its growing presence in higher education also raises new dangers and ethical concerns (Zawacki-Richter et al., 2019). In their study, Almaraz-López et al. (2023) found that most students employed AI technologies for learning purposes and, while their opinions on its use, limitations, and possible hazards were clear due to lack of training in AI. Therefore, understanding student attitudes regarding the use of AI is crucial since it has become very popular and has promising functions for universities to guarantee successful adoption and alignment with their educational objectives. Also, the educational landscape is changing, especially in higher education, thanks to the use of AI (Holmes, 2019).

AI is not always welcome by researchers or educators (Chrisinger, 2019), and it has dual facets that can present both benefits and drawbacks for the educational process (Humble & Mozelius, 2022; K. Zhang & Aslan, 2021). On the other hand, the study conducted by Johnson et al. (2024), revealed that university students use AI for various purposes and they suggest, instead of prohibiting students from using AI technologies, HE institutions must find ways to integrate it in their educational system and to teach their students how to use it effectively and ethically, as it presents a great number of advantages.

Nevertheless, how AI affects education is still a grey area, and that needs further investigation from different perspectives, specifically from teacher candidates' perspectives, so as to get deeper and more detailed ideas about their attitudes and even tendencies towards it. In addition, it holds significance to identify young people's attitudes towards the use of AI in education as they are engaged with it more than others (Luckin, 2018) due to their complex skills and exploring desires (Turgut & Kunuroğlu, 2025). Therefore, preservice teachers are important figures, and their attitudes can influence the use of AI for pedagogical purposes (Gao et al., 2025). Therefore, the current study aims to provide researchers, educators, curriculum developers, and policymakers with a reliable instrument to reveal teacher candidates' perceptions towards the use of AI in higher education. It will also contribute to the growing body of literature on AI in higher education and offer evidence and insights from the higher education context by focusing on the perceptions of English Language Teaching (ELT) undergraduate students in Türkiye.

Literature Review

AI has been widely used in various fields today. It is used in practically every aspect of education, for various educational purposes such as tutoring, mentoring, personalizing learning, testing, translation, gaming, etc. (Alam, 2022; Chen et al., 2020; Fitria, 2021). Technology advancements have made it feasible to modify AI systems to do nearly anything, from simple to complex tasks. The way students study and reach information has changed as a result of the widespread use of AI technologies in higher education. The use of AI in education is increasing, and it is changing tertiary education through various applications of AI in education, such as virtual assistants, grading, researching, etc. (Zawacki-Richter et al., 2019).

The reason why AI has widespread applications in many fields, and its use in education is increasing and catching the spotlight every year (Chen et al., 2020) in today's world might be that people's opinions towards AI have changed significantly over time, and the topic remains debatable. Especially, teachers' ideas about AI tools and their applications play a crucial role in determining whether they are approved or not (Gao et al., 2025; Ghimire et al., 2024) because this might increase the potential of their acceptance by individuals.

The concept of attitude is important in education, and it has been of interest for many years even though attitudes towards the use of AI in education are a relatively new topic on the agenda. One of the early definitions of attitude was made by Allport (1967) focusing on its being a mental state and an individual response to different things. It also refers to specific inclination (Ajzen & Fishbein, 2000). It has been touched upon from various perspectives and technology use is one of the popular topics that have been addressed by researchers (e.g. Ardies et al., 2015; Kemp et al., 2019; Svenningsson et al., 2022).

Attitudes towards the use of AI, other than education, have been interestingly influenced by the term "AI" itself (Cojean et al., 2023). However, it should be borne in mind that teachers have a lot to learn and do while using AI in the classroom because it offers many advantages, but also difficulties.

Even if AI has the potential to greatly enhance teaching and learning, the growth of AI applications in HE also brings with it possible hazards and ethical issues (Zawacki-Richter et al., 2019). In order to ensure successful alignment, it is crucial to comprehend students' attitudes toward AI as institutions use these tools more and more. Students' desire to use AI tools is influenced by their attitudes, and they include cognitive, affective, and behavioral aspects. These attitudes also affect how they view the ethical and pedagogical consequences of AI (Teo, 2011; B. Zhang & Dafoe, 2019), and their attitudes are likely to impact the adoption and implementation (Suh & Ahn, 2022).

With a coherent purpose, the development and validation of SATAI-HE scale in a higher education context targets to investigate tertiary-level students' attitudes towards AI from multidimensionally significant aspects, since AI has been pervasively adopted by university students for various educational purposes. Also, it aims to contribute to the gap in HE context with a practical implication to integrate AI successfully by assessing their perceptions.

Method

Quantitative in nature, this research is structured as a cross-sectional survey. Data were collected from undergraduate students studying English Language Teaching in Türkiye during January-March 2025 after the ethical board approval from the ethics committee of Bartın University Decision no: 2024-SBB-0960. Those students who agreed to voluntarily participate in the survey filled in the online questionnaire without including any identifiable information.

Original Scale

Originally developed by Suh and Ahn (2022), SATAI is developed for primary and secondary school students. SATAI is a 5-point Likert scale and has a three-factor structure, with cognitive, affective, and behavioral factors, and consists of 26 items. The items range from 1 (strongly disagree) to 5 (strongly agree). The cognitive factor includes 4 questions, while the affective factor includes 10 questions, and the behavioral factor includes 12 questions. Specifically designed for AI education, SATAI allows educators to assess and quantify students' attitudes toward artificial intelligence.

Participants

Comrey and Lee (2013) indicate that the reliability of factor analysis results is significantly affected by sample size, with larger samples yielding more reliable correlations, and a sample size of 200 is considered fair. In our study, the sample size was decided according to the items being analyzed. In the first round, we surveyed 325 undergraduate students, and in the second round, we included 210 students. Before data collection, we obtained informed consent from the participants in both rounds.

In the first round, the participants consisted of 325 freshmen, sophomores, juniors, and seniors studying English Language Teaching at two different universities in Türkiye. Among these participants, 225 (69.2%) were female, 89 (27.4%) were male, and 11 (3.4%) preferred not to disclose their gender. Additionally, the distribution of participants by class year was as follows: 127 (39.1%) were freshmen, 108 (33.2%) were sophomores, 43 (13.2%) were juniors, and 47 (14.5%) were seniors. Table 1 shows the frequencies of gender and class year in the first round.

Table 1
Frequencies of Gender and Class Year in the First Round

Gender	Counts	% of Total
Female	225	69.2%
Male	89	27.4%
Preferred not to disclose	11	3.4%
Class year	**Counts**	**% of Total**
Freshman	127	39.1%
Sophomore	108	33.2%
Junior	43	13.2%
Senior	47	14.5%

In the second round, participants were 210 undergraduate students. The participants included 129 (61,4%) females, 75 (35.7%) males, 9 males and 6 (2.9%) who preferred not to disclose their gender. Additionally, the distribution of participants by class year was as follows: 11 (5.2 %) were freshmen, 111 (52.9 %) were sophomores, 58 (27.6 %) were juniors, and 30 (14.3%) were seniors. Table 2 shows the frequencies of gender and class year in the second round.

Table 2
Frequencies of Gender and Class Year in the Second Round

Gender	**Counts**	**% of Total**
Female	129	61.4%
Male	75	35.7%
Preferred not to disclose	6	2.9%
Class year	**Counts**	**% of Total**
Freshman	11	5.2%
Sophomore	111	52.9%
Junior	58	27.6%
Senior	30	14.3%

Data Analysis

The initial 325 students' data were used to run EFA. Initially, the data collected through Google forms were transferred to Jamovi 2.4.12 (The Jamovi Project, 2024) for descriptive statistics, and then EFA was conducted on Jamovi with initial 26 items from 325 participants for construct validity and factor structure. After conducting EFA, the factor loadings were checked, and the number of items was reduced to 17.

In the second round, CFA was conducted again using Jamovi version 2.4.12 with the remaining 17 items and with the data collected from a sample of 210 students. The model's fit was evaluated by various fit indices. The chi-square/degrees of freedom ratio (df), comparative fit index (CFI) and Tucker-Lewis Index (TLI) were C) were used to evaluate the model data fit. The results of EFA and CFA are presented under the "Results" section of the paper.

Results

Results From EFA

We conducted EFA to see whether the adaptation of the SATAI Scale keeps the original three-construct structure and to identify the specific items associated with each construct. Before proceeding, we assessed the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity for assumption checks and both assumptions were met to continue with EFA. Overall KMO value was found as 0.916, which indicates "marvelous" sampling adequacy for conducting EFA (Kaiser, 1974). Also, Bartlett's Test of Sphericity [$\chi 2(2922) = 136$, $p < 0.001$], was significant.

First of all, descriptive statistics of the items were checked out and they are given in Table 3 below.

Table 3
Descriptive Statistics

Items	Mean	Median	SD	Skewness	Kurtosis
Item 1	4.25	4	0.736	-0.670	-0.0808
Item 2	3.91	4	0.849	-0.535	0.0767
Item 3	4.07	4	0.794	-0.605	0.182
Item 4	3.94	4	0.848	-0.536	-0.0953
Item 5	3.63	4	1.04	-0.557	-0.183
Item 6	3.90	4	0.848	-0.777	0.652
Item 7	3.49	4	0.915	-0.345	-0.177
Item 8	3.54	4	1.04	-0.570	-0.273
Item 9	3.46	4	1.09	-0.445	-0.567
Item 10	3.96	4	0.929	-1.09	1.42
Item 11	3.28	3	1.09	-0.307	-0.575
Item 12	3.41	3	0.940	-0.362	0.102
Item 13	4.00	4	0.747	-0.853	1.59
Item 14	4.14	4	0.758	-0.847	1.07
Item 15	2.79	3	1.11	0.225	-0.644
Item 16	2.51	2	0.977	0.341	-0.099
Item 17	2.88	3	1.12	0.138	-0.768
Item 18	3.42	4	0.977	-0.576	0.049
Item 19	3.83	4	0.832	-0.800	1.270
Item 20	3.81	4	0.837	-0.736	1.103
Item 21	3.09	3	1.106	-0.205	-0.751
Item 22	3.28	3	1.039	-0.256	-0.444
Item 23	3.46	4	1.028	-0.564	-0.153
Item 24	4.02	4	0.782	-0.969	1.966
Item 25	3.58	4	0.939	-0.614	0.371
Item 26	3.67	4	0.886	-0.370	-0.167

Principal Axis Factoring in combination with oblimin rotation was employed as the extraction method to identify the underlying factor structure. The analysis extracted a three-factor structure (Table 4). As can be seen in Table 4, 16 items had high factor loadings. Factors 1-3 cumulatively explained 54,8 % of the total variance. Specifically, Factor 1 explained 23.6%, Factor 2 explained 16.9%, and Factor 3 explained 14.3% of the variance, respectively.

Table 4
Factor Loadings

	Factor			
	1	2	3	Uniqueness
1		0.763		0.419
2		0.744		0.418
3		0.872		0.280
4		0.695		0.391
7			0.542	0.533
8			0.871	0.324
9			0.734	0.385
10			0.559	0.588
11				0.653
16	0.703			0.537
17	0.853			0.394
18	0.518			0.446
19	0.569			0.510
20	0.558			0.388
21	0.671			0.506
22	0.709			0.416
23	0.699			0.497

Note. "Principal axis factoring" extraction method was used in combination with a "oblimin" rotation

Results From CFA

In the second round, we ran CFA to test the factor structure results from EFA. Descriptive statistics of each item were calculated and presented in Table 5.

Table 5
Descriptive Statistics

Items	Mean	Median	SD	Skewness	Kurtosis
Item 1	4.24	4.00	0.843	-1.452	2.982
Item 2	4.02	4.00	0.904	-0.949	1.053
Item 3	4.08	4.00	0.832	-1.049	1.749
Item 4	4.07	4.00	0.891	-1.042	1.186
Item 7	3.69	4.00	1.010	-0.714	0.352
Item 8	3.80	4.00	1.066	-0.860	0.355
Item 9	3.79	4.00	1.032	-0.887	0.404
Item 10	4.12	4.00	0.849	-0.902	0.861
Item 11	3.48	3.00	1.374	4.428	43.898
Item 16	2.60	2.00	1.032	0.574	-0.044
Item 17	2.89	3.00	1.152	0.169	-0.809
Item 18	4.00	4.00	1.050	-0.476	-0.208
Item 19	4.00	4.00	0.833	-0.865	1.268
Item 20	4.00	4.00	0.884	-0.843	1.136
Item 21	3.21	3.00	1.108	-0.232	-0.692
Item 22	3.36	3.00	1.045	-0.174	-0.649
Item 23	3.54	4.00	1.049	-0.503	-0.231

We ran CFA to look into the factor structure of SATAI-HE. All factor loadings were statistically significant ($p < 0.001$). This shows that the items strongly indicate the structure. The results of CFA, including standardized estimates, are presented in Table 6.

Table 6
Results From CFA

Factor	Indicator	Estimate	SE	Z	p	Stand. Estimate
Cognitive	**1**	0.692	0.0484	14.32	< .001	0.823
	2	0.751	0.0516	14.55	< .001	0.832
	3	0.748	0.0452	16.56	< .001	0.901
	4	0.805	0.0482	16.70	< .001	0.905
Affective	**7**	0.641	0.0637	10.06	< .001	0.636
	8	1.016	0.0556	18.27	< .001	0.955
	9	0.936	0.0556	16.83	< .001	0.909
	10	0.567	0.0527	10.76	< .001	0.669
	11	0.425	0.0953	4.46	< .001	0.310
Behavioral	**16**	0.606	0.0676	8.97	< .001	0.589
	17	0.750	0.0734	10.21	< .001	0.653
	18	0.818	0.0627	13.04	< .001	0.781
	19	0.623	0.0506	12.30	< .001	0.750

20	0.714	0.0519	13.76	< .001	0.810
21	0.771	0.0692	11.14	< .001	0.697
22	0.769	0.0639	12.04	< .001	0.738
23	0.705	0.0664	10.62	< .001	0.673

The chi-square/degrees of freedom ratio ($\chi2$/df), the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) were used to test model fit. Table 7 shows the criteria for good and acceptable model data fit.

Table 7
Fit Values of the CFA Model

Fit values	Good fit	Acceptable fit	SATAI-HE Scale Fit Values	Reference
$X^{2/}$df	$0 \leq \chi2/df \leq 2$	$2 \leq \chi2/df \leq 3$	2.06	Kline (2011)
CFI	.95 ≤ CFI ≤ 1.00	90 ≤ CFI ≤ .95	.942	Baumgartner & Homburg (1996)
TLI	.95 ≤TLI ≤ 1.00	90 ≤ TLI ≤ .95	.932	Baumgartner & Homburg (1996)

The three-factor model provided an acceptable fit for the data with the following indices: $\chi2 = 240$ (df = 116, $p < .01$) CFI = .942; and TLI = .932. The CFI and the TLI were CFI = 0.942, TLI = 0.932, both exceeding the acceptable threshold of 0.90, indicating good fit. Additionally, the Root Mean Square Error of Approximation (RMSEA) was 0.0714, and the Standardized Root Mean Square Residual (SRMR) was 0.0738, both within acceptable limits. All factor loadings in the final model were statistically significant ($p < .001$). These results support the construct validity of the scale with a three-factor structure: Cognitive, Affective, and Behavioral.

Reliability

Cronbach's alpha (α) was used to test the reliability of the SATAI-HE scale in both rounds. In the first round, Cronbach's α for the overall scale was .938; .866 for the first factor; .851 for the second factor and .913 for the third factor, respectively.

The Cronbach alpha (α) reliability coefficients was used to analyze the reliability of the final version of the scale. Cronbach's α for the final scale was .920 for the overall scale; .922 for the first factor; .853 for the second factor and .883 for the third factor. Table 8 shows the overall and factor reliabilities.

Table 8

Reliability Coefficients in the Final Version of SATAI-HE Scale

Factor Name	Reliability coefficients
Overall	.938
Cognitive	.866
Affective	.851
Behavioral	.913
Factor Name	Reliability coefficients
Overall	.920
Cognitive	.922
Affective	.853
Behavioral	.883

Discussion and Conclusion

Our study aimed to adapt the SATAI scale for use in higher education environments and to assess its psychometric characteristics. The results from both EFA and CFA demonstrate strong evidence that the original three-factor structure of the SATAI scale- comprising cognitive, affective, and behavioral dimensions- was maintained in the adapted version. This outcome underscores the continued relevance and theoretical soundness of the original scale when applied to university-level populations, reinforcing its conceptual applicability across diverse educational contexts.

Furthermore, the reliability analysis demonstrated consistently high internal consistency across both study rounds. In the first round, Cronbach's alpha values for the total scale and its subscales ranged from .851 to .938, while in the second round, they ranged from .853 to .922. These findings confirm that the items within each dimension are closely aligned and that the scale provides a stable measurement of students' attitudes toward artificial intelligence across cognitive, emotional, and behavioral aspects. Additionally, factor loadings between .518 and .872 further validate the construct integrity of the adapted instrument.

The current study contributes to the growing body of literature on AI in education by offering a reliable and valid instrument tailored for the higher education context. As Almaraz-López et al. (2023) found that tertiary-level students have mostly positive attitudes towards the use of AI and are eager to learn more. Still, they are also aware of its potential risks, which were also found in our study. Similarly, Katsantonis and Katsantonis (2024) identified positive attitudes among university students from the social sciences towards the use of AI, using SATAI in a Greek context. This finding aligns with our study in terms of research motivation, higher education context, and results. Turgut and Kunuroğlu (2025), in their study, adapted SATAI into Turkish. The findings showed high consistency, reliability and validity of the scale to be used in HE context, which shows accordance with our study. Derinalp and Özyurt (2024), from a similar perspective, used and adapted SATAI in Turkish K12 context (middle and high school). They found the scale was reliable and valid to be used to find out secondary and high school students' attitudes towards AI. In addition, it showed significant resemblance to the original study.

As AI tools are increasingly incorporated into university teaching, learning, and administrative functions, it is essential to grasp students' perceptions and interactions with these technologies. The SATAI-HE can be an important resource for researchers and educators looking to evaluate students' readiness, concerns, and expectations about AI, which can help shape the development of AI-integrated curricula and support structures.

The study offers a strong multidimensional tool (SATAI-HE) for future research, institutional planning, and curriculum development in AI integration in education by confirming the scale's structure and reliability using both exploratory and confirmatory factor analyses with a sample of ELT undergraduates in Türkiye. Additionally, university students typically might possess more developed viewpoints about AI than younger students. As a result, the scale used in this study takes into account the unique characteristics of these learners in educational environments.

The study is not without limitations. Our sample was limited to undergraduate students from a specific context - country and department- which may affect the generalizability of the findings. Cultural, institutional, or disciplinary differences could influence students' attitudes toward AI, and future research could test the SATAI-HE in more diverse populations, including students from different faculties and departments, graduate students, or students from different countries. In addition, further research could focus on the potential risks or negative attitudes towards AI as it possesses a blurry area in people's minds and needs further and deeper investigation.

In conclusion, the SATAI-HE is a valid and reliable scale for measuring students' cognitive, affective, and behavioral attitudes toward AI in higher education. Its strong psychometric properties make it a useful instrument for both research and practical applications in educational settings where AI continues to gain prominence.

References

Ajzen, I., & Fishbein, M. (2000). Attitudes and the attitude-behavior relation: Reasoned and automatic processes. *European review of social psychology, 11*(1), 1-33.

Alam, A. (2022). Employing adaptive learning and intelligent tutoring robots for virtual classrooms and smart campuses: reforming education in the age of artificial intelligence. In Advanced computing and intelligent technologies: Proceedings of ICACIT 2022 (pp. 395-406). Singapore: Springer Nature Singapore.

Allport, G. (1967). Attitudes. In M. Fishbein (Ed.), Readings in attitude theory and measurement (pp. 1-13). New York: John Wiley & Sons.

Almaraz-López, C., Almaraz-Menéndez, F., & López-Esteban, C. (2023). Comparative study of the attitudes and perceptions of university students in business administration and management and in education toward artificial intelligence. *Education Sciences, 13*(6), 609.

Ardies, J., De Maeyer, S., Gijbels, D., & van Keulen, H. (2015). Students' attitudes towards technology. International Journal of Technology and Design.

Baumgartner, H., & Homburg, C. (1996). Applications of structural equation modeling in marketing and consumer research: A review. *International Journal of Research in Marketing, 13*(2), 139-161. https://doi.org/10.1016/0167-8116(95)00038-0

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. Ieee Access, 8, 75264-75278.

Chrisinger, D. (2019). The solution lies in education: Artificial intelligence & the skills gap. On the Horizon, 27(1), 1–4. https://doi.org/10.1108/OTH-03-2019-096

Cojean, S., Brun, L., Amadieu, F., & Dessus, P. (2023). Teachers' attitudes towards AI: what is the difference with non-AI technologies?. In Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 45, No. 45).

Comrey, A. L., & Lee, H. B. (2013). A first course in factor analysis. Psychology Press. https://doi.org/10.4324/9781315827506

Derinalp, P., & Ozyurt, M. (2025). Adaptation of the Student Attitudes Toward Artificial Intelligence Scale to the Turkish Context: Validity and Reliability Study. *International Journal of Human-Computer Interaction*, 41(8), 4653-4667. https://doi.org/10.1080/10447318.2024.2352921

Fitria, T. N. (2021, December). Artificial intelligence (AI) in education: Using AI tools for teaching and learning process. In Prosiding Seminar Nasional & Call for Paper STIE AAS (pp. 134-147).

Gao, M., Zhang, H., Dong, Y., & Li, J. (2025). Embracing generative AI in education: an experiential study on preservice teachers' acceptance and attitudes. Educational Studies, 1-20.

Ghimire, A., Pather, J., & Edwards, J. (2024). Generative AI in education: A study of Educators' awareness, sentiments, and influencing factors. In 2024 IEEE Frontiers in Education Conference (FIE) (pp. 1-9). IEEE.

Holmes, W. (2019). Artificial Intelligence in Education. In: Tatnall, A. (eds) Encyclopedia of Education and Information Technologies. Springer, Cham. https://doi.org/10.1007/978-3-319-60013-0_107-1

Humble, N., & Mozelius, P. (2022). The threat, hype, and promise of artificial intelligence in education. Discover Artificial Intelligence, 2(1), 22.

The Jamovi Project. (2024). Jamovi (Version 2.4.12) [Computer software]. https://www.jamovi.org

Johnson, N., Seaman, J., & Seaman, J. (2024). The Anticipated Impact of Artificial Intelligence on US Higher Education: A National Study. *Online Learning, 28*(3), 9-33.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

Katsantonis, A., & Katsantonis, I. G. (2024). University students' attitudes toward artificial intelligence: An exploratory study of the cognitive, emotional, and behavioural dimensions of AI attitudes. *Education Sciences, 14*(9), 988. https://doi.org/10.3390/educsci14090988

Kemp, A., Palmer, E., & Strelan, P. (2019). A taxonomy of factors affecting attitudes towards educational technologies for use with technology acceptance models. *British Journal of Educational Technology, 50*(5), 2394-2413.

Kline, R. B. (2011). Principles and practice of structural equation modeling. New York: Guilford Press.

Konecki, M., Baksa, T., & Konecki, M. (2024). Teachers' Perception of AI and Their Attitudes Towards AI. CSEDU (1), 564, 568.

Luckin, R. (2018). Machine learning and human intelligence: The future of education for the 21st century. UCL IOE Press.

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 (Original work published 2022)

Svenningsson, J., Höst, G., Hultén, M., & Hallström, J. (2022). Students' attitudes toward technology: exploring the relationship among affective, cognitive and behavioral components of the attitude construct. *International Journal of Technology and Design Education, 32*(3), 1531-1551.

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432-2440.

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*, 1-11. https://doi.org/10.1080/10447318.2025.2474474

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zhang, B., & Dafoe, A. (2019). Artificial intelligence: American attitudes and trends. Available at SSRN 3312874.

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. Computers and education: Artificial intelligence, 2, 100025.

Contact emails: neslihankose@bartin.edu.tr
neslihannnkose@gmail.com