Croatian Journal of Education
Vol.28; No.3/2026, pages: 965-990
Original scientific paper
Paper submitted: 27th February 2026
Paper accepted: 8th May 2026
https://doi.org/10.15516/cje.v28i3.41262

Development and Validation of a Scale for Assessing Students' Perceptions of Artificial Intelligence in E-Learning

Marko Marković[1], Dragan Soleša[2] and Petar Ciganović[1]
[1]*University Business Academy in Novi Sad, Faculty of Applied Management, Economics and Finance*
[2]*University Business Academy in Novi Sad, Faculty of Economics and Engineering Management*

Abstract

The increasing integration of artificial intelligence (AI) in higher education highlights the need for valid instruments to assess students' perceptions of its use in e-learning environments. The aim of this study was to develop and validate a psychometric scale for measuring students' perceptions of artificial intelligence in e-learning. A scale development research design was employed on a sample of 225 higher education students. The development process included four phases: item generation based on the technology acceptance model (TAM) and relevant literature, content validation through expert evaluation, pilot testing, and empirical validation. Exploratory factor analysis (EFA) identified a stable three-factor structure consisting of perceived usefulness, efficiency and optimization, and support in teaching. The Kaiser-Meyer-Olkin value (.812) and Bartlett's test of sphericity ($p < .001$) confirmed data adequacy. The scale demonstrated satisfactory reliability, with Cronbach's alpha coefficients of .889, .823, and .767. Discriminant validity was confirmed using an independent samples t-test, while inter-factor correlations supported construct validity. The findings indicate that the developed instrument is a reliable and valid tool for assessing students' perceptions of artificial intelligence in e-learning environments.

Keywords: *artificial intelligence; e-learning; scale development; psychometric validation; factor analysis; student attitudes*

© Author(s) 2026
This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0). https://creativecommons.org/licenses/by-nc/4.0/

Introduction

The teaching process has faced rapid changes in the way activities are conducted in the last few years, which previously required the presence of students and teachers in classrooms. The emergence of e-learning as a new form of instruction brings numerous possibilities and options for modernising the education system, providing the opportunity for place and time to no longer be the main factors in delivering lessons (Jauković Jocić et al., 2021). This kind of flexibility among professors and students offers a significant advantage in their activities, timeliness, and the ability to review certain teaching materials multiple times, which makes it easier for students to master the material (Maričić et al., 2025). Besides these possibilities for distance learning and its high acceptance rate, new, more modern technology has also emerged, changing the process of learning and mastering specific material. Artificial intelligence has also been integrated into modern e-learning systems, initiating a comprehensive transformation of the educational process and the way knowledge is transmitted to the end user (Janković et al., 2025). The process of this transformation is driven by innovative techniques offered by artificial intelligence, starting with content personalisation, adaptability of teaching materials, student engagement and effectiveness, and even the lecturers themselves (Abbas et al., 2023).

Artificial intelligence is enhancing content personalisation systems by tailoring teaching materials to students' needs and abilities. It turns out that artificial intelligence tracks student behaviour, thereby creating a personalised environment based on student models, the content they follow, and their interactions, which allows for the personalisation of materials and creates an environment that increases student engagement and understanding of the teaching material (Zhao, 2024). Sari and Purwanta positively assessed this stance and highlighted that the implementation of artificial intelligence has improved learning and enabled professors to create more effective learning plans (Sari & Purwanta, 2021). This principle is particularly prominent in e-learning systems, where an individual approach can be applied more effectively (Salam et al., 2023). With this approach, it is very easy to implement and monitor students' emotional and cognitive abilities, which can influence the way teaching materials are adapted to ensure better understanding and achieve better results (Jia et al., 2022). Using algorithms, which are a fundamental concept of artificial intelligence systems, interface technologies, and big data processing, a unique pedagogical design for the system is created, guiding students towards an educational environment that is scalable and appropriate for the modern concept of technology and education (Kaban, 2023).

Modern educational systems based on this principle were previously assistive computer services, evolving into today's complex platforms that utilise advanced machine learning techniques, natural language processing techniques, and algorithms that recommend content to the user at any given moment, which provides a high level of personalisation and automation of the administrative process of teaching (Yuskovych-Zhukovska et al., 2022; Dean, 2022). We can use artificial intelligence

as the basis for adaptive learning, allowing the algorithm to independently make decisions about knowledge representation and evaluation. Modelling techniques, including knowledge tracking and student profiling, allow for better prediction (Stošić et al., 2025). Given its interdisciplinary nature, artificial intelligence has a wide range of applications, from classic supervised and unsupervised learning methods to deep learning approaches. The choice between these options depends on user requirements and the type of required data (Dean, 2022). Machine learning represents a set of algorithms that enable systems to improve their task performance. In e-learning systems, student data can be analysed based on their learning habits, grades, research areas, and behaviour, which helps predict student achievement, group students based on research areas or knowledge levels, and discover patterns in the data (Du et al., 2020).

Classical machine learning methods use decision trees to help students make decisions, thus retaining the significance of the data in the training material by using fewer data points and better comparison capabilities with more complex models (Ang et al., 2020). The application of machine learning represents a methodological connection between raw data and useful insights for making informed decisions (Bin, 2023). Deep learning is a subset of machine learning because it uses artificial neural networks to process data in non-linear flows and is known as deep structured learning. Research has shown that deep learning is a powerful driver in advancing perception and sequence modelling (Paramasivam et al., 2023), making it a good procedure for e-learning systems, where it can be very easily implemented in assessing content personalisation. Practice shows that the use of artificial intelligence is transforming e-learning through the application of machine learning, algorithms, and adaptive systems, all with the aim of enabling a more innovative and individualised approach to the educational process. Since this type of technology is viewed as a tutoring system, it's important to emphasise that any feedback it collects is used as a basis for future development. Extensions into more advanced one-on-one pedagogical work models can be expected, which will push the boundaries of generative technology and give users the impression that they are attending traditional classes (Chen et al., 2020).

The traditional way of teaching is being questioned due to the fact that we already have technology that can do it faster and easier. However, we cannot rely entirely on such models because they often depend on the way they are developed and analyse feedback. This requires an introduction of ethical principles and practical risks into implementation, which, if they occur, must be mitigated due to the complexity and role of such a system (Grenander et al., 2021; Igbokwe, 2024). Also, artificial intelligence reduces teachers' workload and facilitates quick evaluation of all student papers and individual feedback for each student. Through automation, teachers' engagement shifts towards other tasks or the creation of more specific lesson plans adapted to all students with the help of artificial intelligence (Çelik et al., 2022). One of the most useful and widely accepted features is virtual assistants,

which are interactive systems that allow for task completion, knowledge acquisition, performance evaluation, and recommendations for the next content that suits the user based on previous results (Fryer et al., 2017). In order to transform education, virtual assistants represent a significant starting point for developing this type of teaching delivery. It is important that virtual assistants complement, but do not replace, human interaction. Even if the students themselves are evaluated, empathy and creativity remain a major problem, as not all students have the same understanding and thinking (Holmes & Tuomi, 2022).

Virtual assistants combine natural language processing (NLP) and automatic speech recognition (ASR) techniques for the most accurate understanding and response to user questions, all within the educational content previously established as the basic starting point for work. Intelligent assistants enable the creation of interactive quizzes and flashcards for material review, which, with the help of gamification, encourages students to engage further and learn adaptively based on previously acquired knowledge and their own progress (Sajja et al., 2024). The increasingly frequent use of such tools enables direct communication between students and the system at any time, which is the definition of e-learning platforms, but with a significant advantage in that a virtual assistant, unlike an LMS system, can answer students' questions or change the way teaching materials are presented to them (Tiwari, 2023). However, the accuracy of the information is questionable, as artificial intelligence often tends to ignore input data and replace it with data that resembles an approximately correct answer to the asked question. The crucial issue is whether virtual assistants can function as reliable educational tools ready to completely replace teachers (Davar et al., 2025). The inclusion of virtual reality has an advantage over solely text or voice options, particularly in inclusive education. In this case, we can use interactive avatars that, with the help of artificial intelligence and virtual reality, will create a learning environment for students with special needs.

This possibility is prone to modifications, so it can be adapted to various levels and individual needs. Hence, it all boils down to content personalisation and automation, which are fundamental concepts of artificial intelligence in such systems. Therefore, the appropriation to the needs of students and their environment is most important and, based on student abilities and feedback, the creation of clear and precise content that is easy to understand. In this way, a virtual assistant can also replace and compensate for the lack of teaching staff in certain areas (Mohamed et al., 2025). However, the adoption of such models depends on several factors, including the perceived usefulness and expected ease of use of the model itself, which only confirms the importance of the virtual assistant's intuitive design, i.e., its optimisation for everyone's use, especially in inclusive environments or to address a shortage of teaching staff (Malešević et al., 2021). Despite all the advantages that artificial intelligence brings to the context of e-learning, we must still be mindful of data privacy. In other words, we should mind the data we enter into these systems, but also verify the model's policy and how it handles our data. Otherwise, student

feedback might be compromised because this data reflects their level of knowledge, preferences, and personal opinions (Marković & Soleša, 2025).

Also, consideration must be given to the teaching materials and the degree of freedom of the model that recommends the teaching units, as these systems can often be biased and perform manipulative actions in providing the materials. When designing such an e-learning system, it is necessary to consider ethical codes, which primarily falls on the programmers, as well as the practical application of artificial intelligence models. Despite all considered perspectives and ethical questions about data protection, these systems have additional limitations. They include problems with consent, academic integrity, and responsible use of student data (Zhai et al., 2021). Besides all their benefits and advantages, as well as the technical aspects of security, questions arise that strictly concern the implementation of artificial intelligence models in the educational environment. Factors influencing the acceptance levels of artificial intelligence among professors and students need to be identified in detail. This raises the issue of technical literacy and readiness to use such models, and in addition, the readiness of educational institution for their implementation alongside online platforms must be considered. However, there is a lack of validated instruments specifically designed to measure these attitudes in regional contexts, which remains a critical research gap. Consequently, this study aimed to develop and psychometrically validate a scale to evaluate students' AI-related perceptions in e-learning, ensuring a reliable methodological framework for future implementation (Krecar & Pavlin-Bernardić, 2026).

Despite the growing body of research on artificial intelligence in education, there is a lack of validated instruments specifically designed to measure students' perceptions of AI in e-learning environments. Existing studies often rely on non-validated or adapted instruments, which limits the reliability and comparability of findings.

Therefore, the aim of this study was to develop and psychometrically validate a scale for assessing students' perceptions of artificial intelligence in e-learning, providing a reliable methodological tool for future research.

Methodology

This study followed a scale development research design rather than a traditional survey-based approach. The primary objective was to construct and validate a psychometric instrument for assessing students' perceptions of artificial intelligence in e-learning environments. To address the requirements for methodological transparency in developing the measurement scale, a systematic four-phase process was implemented. This process ensured that the instrument transitioned from a general questionnaire to a validated psychometric scale, as summarized in Table 1. Each phase represents a necessary step in transforming the initial item pool into a validated measurement instrument.

When creating the initial base of items, a deductive approach was used, which included the combination of a theoretical framework and a systematic literature

review. The basis in this study was the technology acceptance model (TAM), which identified the perceived usefulness and ease of use as key determinants of acceptance. In addition, relevant works on the application of artificial intelligence in e-learning were consulted. Based on this analysis, three factors were created: perceived usefulness, efficiency and optimization, and teaching support. For each of the factors, six to seven items were formulated, which made a total of 20 items, and a 5-point Likert scale was used (1 = strongly disagree to 5 = strongly agree) (Joshi et al., 2015). Clarity, simplicity, and avoidance of double negatives were considered during the formulation of items.

In order to assess the content validity of the scale, a panel of three independent experts analyzed the list of 20 items, rating each on a scale of 1 to 4 in three categories: clarity (whether the item is easy to understand), relevance (whether the item measures the intended construct), and representativeness (whether the item covers the factor domain well). These three experts were from the field of higher education and had extensive experience in using various tools that supported the effective implementation of the educational process. Each of the three experts used various models and tools of artificial intelligence in teaching within three scientific and research fields: management, economics, and informatics.

After collecting the ratings, the item-level content validity index (I-CVI) was calculated as the proportion of experts who rated the item as 3 or 4. According to Lynn's recommendation (1986), items with an I-CVI ≥ 0.78 were retained. Of the 20 initial items, two were excluded (I-CVI = 0.67 and 0.71), while three items were revised based on expert comments (e.g., "virtual assistants" replaced by "artificial intelligence-based systems"). After revision, 18 items remained. The scale-level content validity index (S-CVI/UA – universal agreement) was 0.89, which is considered excellent.

A pilot study was conducted on a sample of 15 students who regularly used e-learning platforms and AI tools in their education (e.g., ChatGPT). The objectives of the pilot study were to check the comprehensibility and clarity of each item, estimate the average completion time and identify possible ambiguities. After completing the questionnaire, the students participated in a short semi-structured interview, which helped to optimize the scale and make it clearer for the main research.

After conducting a pilot study and revising the scale, the final 15 items were obtained, which were formulated to cover all aspects of the research, without repetition or poor wording.

Table 1
The systematic process of scale development

Phase	Activity	Description
Phase I	Item generation	Initial pool of 20 statements derived from the literature and theoretical constructs of AI acceptance
Phase II	Content validity	Review by a panel of experts in educational technology to ensure relevance and clarity of the items
Phase III	Pilot testing	Preliminary run with 15 students to detect linguistic ambiguities and confirm readability
Phase IV	Main study	Final administration of the refined 15-item scale to the target sample (N = 225) for factor analysis

Data analysis

Exploratory factor analysis (EFA) was conducted to determine the underlying factor structure of the scale. Factor extraction was performed using principal component analysis (PCA), followed by Varimax rotation, to achieve a clearer interpretation of the factor structure. To assess internal consistency, Cronbach's alpha coefficients were calculated for each factor. Discriminant validity was evaluated via an independent samples t-test, by which respondents from the upper and lower 27 % of total scores were compared. Additionally, inter-factor correlations were examined to assess construct validity. Prior to conducting the factor analysis, the adequacy of the data was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. The obtained values confirmed the suitability of the dataset for factor analysis.

The sample of 225 students who participated in this study included undergraduate and master's students at the Faculty of Applied Management, Economics and Finance in Belgrade, Republic of Serbia. Students from the following study programs participated: Economics (n = 82), Management (n = 78), and Information Technology (IT) (n = 65). The age range of the participants was between 19 and 26 years (M = 22.0, SD = 2.6), with the following age distribution: 80 participants (35.6 %) were aged 19-21, 110 (48.9 %) were aged 22-24, and 35 (15.6 %) were aged 25-26.

Results and discussion

The scale was administered to a sample of 225 higher-education students who used e-learning platforms and AI tools (see Table 2 for detailed sample characteristics). Participation was voluntary and anonymous, and all respondents provided an informed consent.

These descriptive findings are included solely for contextual purposes and are not interpreted as primary results, as the main objective of this study was the development and validation of the measurement instrument. The results of this study are interpreted exclusively in the context of scale development and psychometric validation. Exploratory factor analysis (EFA) was conducted to examine the underlying structure of the measurement scale. The Kaiser-Meyer-Olkin measure of sampling adequacy was .812, which exceeded the recommended threshold of 0.7. Bartlett's test of sphericity was statistically significant, which indicated that the data were suitable for factor analysis. Factors were extracted using principal component analysis (PCA) followed by Varimax orthogonal rotation to achieve a clearer interpretation of the factor structure. The extracted factors demonstrate clear conceptual differentiation while maintaining theoretical coherence, which supports the construct validity of the scale. The internal consistency of the identified factors was assessed using Cronbach's alpha coefficients. All three dimensions demonstrate satisfactory reliability, with values exceeding the recommended threshold of 0.7 (.889, .823, and .767). Inter-factor correlations indicate moderate positive relationships, suggesting that the dimensions are related but represent distinct aspects of the same construct. The results of the

Table 2
Sample characteristics and contextual descriptive responses

Variable	Category	Frequency	Percentage	Mean	Std. deviation	Min	Max
Gender	Male	132	58.70				
	Female	93	41.30				
Age				22	2.60	19	26
Study program	IT	65	28.89				
	Economics	82	36.44				
	Management	78	34.67				
Are you familiar with the essence and possibilities offered by AI in education?	Yes	102	45.30				
	Partially	87	38.70				
	No	36	16.00				
Have you ever used AI systems in learning (e.g., virtual assistants, adaptive courses)?	Yes	118	52.40				
	Occasionally	64	28.40				
	No	43	19.20				
Do you believe AI will change the way we learn?	Yes	161	71.60				
	No	64	28.40				
Do you believe educational institutions should integrate AI technology into their work?	Yes	142	63.10				
	No	33	14.70				
	I'm not sure	50	22.20				

discriminant validity analysis confirm that the scale successfully differentiates between respondents with high and low levels of the measured construct, further supporting its psychometric robustness. Descriptive statistics are presented only as supporting information and are not interpreted as primary research findings.

Table 3
Factor structure and reliability coefficients

Items	F1	F2	F3
Eigenvalue	5.43	2.91	1.89
Variance explained (%)	36.20	19.40	12.60
Cumulative variance (%)	36.20	55.60	68.20
Cronbach's alpha	0.889	0.823	0.767
Artificial intelligence enables personalised learning tailored to individual needs.	0.692		
Artificial intelligence tools enable faster knowledge evaluation and grading.	0.731		
Students develop greater independence in learning by using virtual assistants.	0.748		

Items	F1	F2	F3
Artificial intelligence systems facilitate communication between professors and students.	0.701		
The development of AI-based educational applications fosters innovative learning methods.	0.776		
Artificial intelligence has the potential to increase the accessibility of education for a wider population.	0.683		
Artificial intelligence tools contribute to the security and protection of educational data.		0.724	
Automation using artificial intelligence reduces the workload of teachers.		0.781	
Artificial intelligence optimises learning time through adaptive courses.		0.763	
AI-based platforms integrate a larger number of courses into a single environment.		0.739	
Artificial intelligence makes it easier to access courses without limitations of space and time.		0.697	
Artificial intelligence generates personalised content recommendations for students.			0.754
Virtual assistants help make teaching more efficient.			0.772
Artificial intelligence-based data analytics leads to better lesson planning.			0.785
Artificial intelligence supports the development of new forms of evaluation and feedback.			0.703

Note: Eigenvalues and percentages of explained variance refer to the initial extraction before rotation (principal component analysis). Factor saturations are shown after Varimax rotation.

To assess the reliability and structure of the scale, items were grouped according to the identified factors: perceived usefulness, efficiency and optimization, and support in teaching. Table 4 details the calculated descriptive statistical dimensions of the items associated with the three obtained factors.

Table 4

Descriptive statistics of items associated with the three obtained factors (n = 225)

Items	Mean	Median	SD	SE	CV	Skew	Kurt
F1 / Perceived usefulness							
Artificial intelligence enables personalised learning tailored to individual needs.	4.12	4.00	0.78	0.05	18.93	-0.52	0.41
Artificial intelligence tools enable faster knowledge evaluation and grading.	3.95	4.00	0.81	0.05	20.50	-0.48	0.36
Students develop greater independence in learning by using virtual assistants.	3.76	3.00	0.92	0.06	24.47	-0.33	0.28

Items	Mean	Median	SD	SE	CV	Skew	Kurt
Artificial intelligence systems facilitate communication between professors and students.	3.58	3.00	0.87	0.06	24.30	-0.41	0.32
The development of AI-based educational applications fosters innovative learning methods.	4.05	4.00	0.83	0.05	20.49	-0.46	0.39
Artificial intelligence has the potential to increase the accessibility of education for a wider population.	4.21	4.00	0.85	0.06	20.19	-0.55	0.47
F2 / Efficiency and optimization of the educational process							
AI tools contribute to the security and protection of educational data.	3.89	4.00	0.91	0.06	23.39	-0.36	0.34
Automation in using artificial intelligence reduces the workload of teachers.	4.07	4.00	0.79	0.05	19.41	-0.49	0.42
Artificial intelligence optimises learning time through adaptive courses.	4.15	4.00	0.82	0.05	19.75	-0.51	0.38
AI-based platforms integrate a larger number of courses into a single environment.	3.97	4.00	0.88	0.06	22.17	-0.37	0.31
Artificial intelligence makes it easier to access courses without limitations of space and time.	3.64	3.00	0.93	0.06	25.55	-0.28	0.26
F3 / Support in teaching							
Artificial intelligence generates personalised content recommendations for students.	3.72	3.00	0.89	0.06	23.92	-0.34	0.29
Virtual assistants help make teaching more efficient.	3.83	4.00	0.91	0.06	23.75	-0.35	0.33
Artificial intelligence-based data analytics leads to better lesson planning.	4.02	4.00	0.84	0.06	20.89	-0.44	0.37
Artificial intelligence supports the development of new forms of evaluation and feedback.	3.68	3.00	0.95	0.06	25.82	-0.29	0.24

To assess the homogeneity of each factor, corrected item-total correlations were calculated for each item within its respective factor. These correlations indicate the degree to which each item is consistent with the other items measuring the same construct. The results are presented in Table 5.

Table 5
Corrected item-total correlations by factor

Items	F1	F2	F3
Artificial intelligence enables personalised learning tailored to individual needs.	0.612		
Artificial intelligence tools enable faster knowledge evaluation and grading.	0.584		
Students develop greater independence in learning by using virtual assistants.	0.551		
Artificial intelligence systems facilitate communication between professors and students.	0.518		
The development of AI-based educational applications fosters innovative learning methods.	0.633		
Artificial intelligence has the potential to increase the accessibility of education for a wider population.	0.572		
Artificial intelligence tools contribute to the security and protection of educational data.		0.534	
Automation in using artificial intelligence reduces the workload of teachers.		0.620	
Artificial intelligence optimises learning time through adaptive courses.		0.591	
AI-based platforms integrate a larger number of courses into a single environment.		0.554	
Artificial intelligence makes it easier to access courses without limitations of space and time.		0.492	
Artificial intelligence generates personalised content recommendations for students.			0.573
Virtual assistants help make teaching more efficient.			0.611
Artificial intelligence-based data analytics leads to better lesson planning.			0.642
Artificial intelligence supports the development of new forms of evaluation and feedback.			0.528

Note: All correlations are statistically significant at $p < .01$. Corrected item-total correlations represent the correlation between each item and the sum of the remaining items within the same factor.

To further examine the internal structure and the relationship between the extracted dimensions, a correlation analysis was performed. As shown in Table 6, all factors demonstrate significant positive correlations, which supports the theoretical integration of the scale.

Table 6
Inter-factor correlation matrix and reliability

Factor	F1	F2	F3	Cronbach's α
F1 - Perceived usefulness	1			0.889
F2 - Efficiency and optimization	0.54*	1		0.823
F3 - Support in teaching	0.48*	0.51*	1	0.767

Discriminant validity was assessed using an independent samples t-test comparing respondents from the upper and lower 27 % of total scores. The results indicate statistically significant differences ($t = 6.18$, $p < 0.001$), which confirms that the scale effectively differentiates between respondents with varying levels of the measured construct.

Table 7
Discriminant validity (comparison of high and low scoring groups)

Group	N	Mean	SD	t	p
Top 27 %	61	4.32	0.41	6.18	<0.001
Bottom 27 %	61	2.87	0.52		

To further examine the discriminant validity at the factor level, independent samples t-tests were conducted for each factor separately, comparing the same top 27 % and bottom 27 % groups (based on total scale scores). The results are shown in Table 8.

Table 8
Discriminant validity by factor: t-test for top and bottom 27 % groups

Factor	Group	N	Mean	SD	t	p
F1 – Perceived usefulness	Top 27 %	61	4.42	0.38	7.38	<0.001
	Bottom 27 %	61	2.68	0.49		
F2 – Efficiency and optimization	Top 27 %	61	4.25	0.42	6.94	<0.001
	Bottom 27 %	61	2.85	0.51		
F3 – Support in teaching	Top 27 %	61	4.19	0.44	6.61	<0.001
	Bottom 27 %	61	2.91	0.53		

Note: Extreme groups (top 27 % and bottom 27 %) were formed based on total scale scores (same split as in Table 7). Means and standard deviations for each factor were then calculated within these groups. All t-values are statistically significant at $p < .001$.

Descriptive statistics are presented solely to support the validation process and are not interpreted as primary research findings. However, these findings are interpreted as contextual support for the validation process rather than as primary evidence of the measured construct. The emphasis of this study remains on the evaluation of the scale's psychometric properties.

Conclusion

Developing a reliable and valid scale that serves as an instrument for assessing students' perception of artificial intelligence in e-learning environments included four important phases, from item generation based on the technology acceptance model (TAM), content validity assessment by our experts, pilot testing on 15 students, and final application on a sample of 225 higher education students. The resulting 15-item scale had a clear three-factor structure. EFA revealed three constructs: perceived usefulness (six items; eigenvalue = 5.43, percentage of explained variance = 36.20 %),

efficiency and optimization (five items; eigenvalue = 2.91, percentage of explained variance = 19.40 %) and teaching support (four items; eigenvalue = 1.89, percentage of explained variance = 12.60 %), which accounted for a total of 68.20 % of variance. The internal consistency reliability coefficients measured via Cronbach's alpha ranged from 0.889 to 0.767. Adjusted item-total correlations ranged between 0.492 and 0.642, exceeding the recommended cut-off point of 0.30. Discriminant validity was tested via independent sample t-tests, where total scores were divided into upper 27 % and lower 27 % groups. The discriminant validity test confirmed statistically significant differences in total scale scores ($t = 6.18$, $p < 0.001$) as well as individual factors' scores ($t = 6.61$-7.38, $p < 0.001$). These results indicate that a reliable scale has been successfully developed and represents a reliable and valid instrument for assessing students' perception of artificial intelligence in e-learning. The scale provides a methodological basis for future research and practical application in creating a modern approach to the educational process. Limitations include the use of a single sample and reliance on only assessed data, which may affect generalizability. Future research should use CFA and test the scale in different educational settings and different samples and populations.

References

Abbas, N., Ali, I., Manzoor, R., Hussain, T., & Al Hussaini, M. H. (2023). Role of artificial intelligence tools in enhancing students' educational performance at higher levels. *Journal of Artificial Intelligence, Machine Learning and Neural Network*, (35), 36-49. https://doi.org/10.55529/jaimlnn.35.36.49

Ang, L., Ge, F., & Seng, K. P. (2020). Big educational data & analytics: survey, architecture and challenges. *IEEE Access*, 8, 116392-116414. https://doi.org/10.1109/access.2020.2994561

Bin, L. (2023). Cognitive web service-based learning analytics in education systems using big data analytics. *International Journal of E-Collaboration*, *19*(2), 1-19. https://doi.org/10.4018/ijec.316658

Çelik, İ., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: a systematic review of research. *TechTrends*, *66*(4), 616-630. https://doi.org/10.1007/s11528-022-00715-y

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: a review. *IEEE Access*, *8,* 75264-75278. https://doi.org/10.1109/access.2020.2988510

Davar, N. F., Dewan, M. A. A., & Zhang, X. (2025). AI chatbots in education: challenges and opportunities. *Information*, *16*(3), 235. https://doi.org/10.3390/info16030235

Dean, J. (2022). A golden decade of deep learning: computing systems & applications. *Daedalus*, *151*(2), 58-74. https://doi.org/10.1162/daed_a_01900

Du, X., Yang, J., Hung, J., & Shelton, B. E. (2020). Educational data mining: a systematic review of research and emerging trends. *Information Discovery and Delivery*, *48*(4), 225- 236. https://doi.org/10.1108/idd-09-2019-0070

Fryer, L. K., Ainley, M., Thompson, A., Gibson, A., & Sherlock, Z. (2017). Stimulating and sustaining interest in a language course: An experimental comparison of Chatbot and Human task partners. *Computers in Human Behavior*, *75*, 461-468. https://doi.org/10.1016/j.chb.2017.05.045

Grenander, M., Belfer, R., Kochmar, E., Serban, I. V., St-Hilaire, F., & Cheung, J. C. K. (2021). Deep discourse analysis for generating personalized feedback in intelligent tutor systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, *35*(17), 15534- 15544. https://doi.org/10.1609/aaai.v35i17.17829

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, 57(4), 542-570. https://doi.org/10.1111/ejed.12533

Igbokwe, I. C. (2024). Artificial intelligence in educational leadership: risks and responsibilities. *European Journal of Arts, Humanities and Social Sciences*, *1*(6), 3-10. https://doi.org/10.59324/ejahss.2024.1(6).01

Janković, A., Radić, M., Tomašević, V., Avdagić, S., Avdagić, S., Mrđa, M., Ristić, V., Brkić, I., Puvača, N., & Prodanović, R. (2025). Management of e-learning in higher education institutions during the COVID-19 pandemic. *Croatian Journal of Education*, *27*(2). https://doi.org/10.15516/cje.v27i2.5855

Jauković Jocić, K., Jocić, G., Karabašević, D., Pucar, Đ., & Veljić, A. (2021). Development of multimedia tools to improve the e-learning program: implementation of the adobe captivate program in the modern teaching system. *Quaestus*, (19), 379-387.

Jia, K., Wang, P., Li, Y., Chen, Z., Jiang, X., Lin, C., & Chin, T. (2022). Research landscape of artificial intelligence and e-learning: a bibliometric research. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.795039

Joshi, A., Kale, S., Chandel, S., & Pal, D. (2015). Likert scale: Explored and explained. *British Journal of Applied Science & Technology*, *7*, 396-403. https://doi.org/10.9734/BJAST/2015/14975

Kaban, A. (2023). Artificial Intelligence in education: A science mapping approach. *International Journal of Education in Mathematics, Science and Technology*, *11*(2), 245- 262. https://doi.org/10.46328/ijemst.3368

Krecar, I. M., & Pavlin-Bernardić, N. (2026). Appropriate and inappropriate use of artificial intelligence language models by students: Teachers' (self-)perceptions and experiences across educational levels. *Croatian Journal of Education*, *27*(3). https://doi.org/10.15516/cje.v27i3.6596

Lynn, M. R. (1986). Determination and quantification of content validity. *Nursing Research, 35*(6), 382–385. https://doi.org/10.1097/00006199-198611000-00017

Malešević, A., Barać, D., Soleša, D., Aleksić, E., & Despotović-Zrakić, M. (2021). Adopting xRM in higher education: E-services outside the classroom. *Sustainability*, *13*(14), 7522. https://doi.org/10.3390/su13147522

Maričić, S., Veljić, A., Jocić, G., & Marković, M. (2025). Electronic portal "Moja srednja škola". *Akademija strukovnih studija „Zapadna Srbija", Odsek Užice*, 56–63.

Marković, M., & Soleša, D. (2025). Security and data protection in artificial intelligence. *Journal of Process Management New Technologies, 13*(1-2), 113-123. https://doi.org/10.5937/jpmnt13-58872

Mohamed, A., Faisal, R., Al-Gindy, A., & Shaalan, K. (2025). Artificial intelligence and immersive technologies: Virtual assistants in AR/VR for special needs learners. *Computers*, *14*(8), 306. https://doi.org/10.3390/computers14080306

Paramasivam, K., Sindha, M. M. R., & Balakrishnan, S. B. (2023). KNN-based machine learning classifier used on deep learned spatial motion features for human action recognition. *Entropy*, *25*(6), 844. https://doi.org/10.3390/e25060844

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, *15*(10), 596. https://doi.org/10.3390/info15100596

Salam, M. Y., Fitri, S., & Zulan, H. (2024). Educational technology based on artificial intelligence in supporting distance learning in Arabic language learning in higher education. *Journal International of Lingua and Technology*, *3*(1), 134-145. https://doi.org/10.55849/jiltech.v3i1.485

Sari, J. M., & Purwanta, E. (2021). The implementation of artificial intelligence in STEM-based creative learning in the society 5.0 era. *Tadris*: *Jurnal Keguruan Dan Ilmu Tarbiyah*, *6*(2), 433-440. https://doi.org/10.24042/tadris.v6i2.10135

Stošić, L., Radonjić, A., Krčadinac, O., Baltezarević, B., & Mikhailova, O. (2025). Personalized learning through artificial intelligence: Opportunities, risks, and policy perspectives. *International Journal of Cognitive Research in Science, Engineering and Education* (IJCRSEE), *13*(2), 541-549. https://doi.org/10.23947/2334-8496-2025-13-2-541-549

Tiwari, R. (2023). The integration of AI and machine learning in education and its potential to personalize and improve student learning experiences. *International Journal of Scientific Research in Engineering and Management*, 07(02). https://doi.org/10.55041/ijsrem17645

Yuskovych-Zhukovska, V., Poplavska, T., Diachenko, O., Misenina, T. M., Topolnyk, Y., & Gurevych, R. (2022). Application of artificial intelligence in education: problems and opportunities for sustainable development. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience,* 13(1). https://doi.org/10.18662/brain/13.1sup1/322

Zhai, X., Chu, X., Chai, C. S., Jong, M. S., Istenic, A., Spector, M., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*(1). https://doi.org/10.1155/2021/8812542

Zhao, C. (2024). Application and prospect of artificial intelligence in personalized learning. *Journal of Innovation and Development*, *8*(3), 24-27. https://doi.org/10.54097/nzxx6z36

Appendix A – Final Scale

Please indicate your level of agreement with the following statements using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Perceived Usefulness

1 Artificial intelligence enables personalised learning tailored to individual needs.

2 Artificial intelligence tools enable faster knowledge evaluation and grading.

3 Students develop greater independence in learning by using virtual assistants.

4 Artificial intelligence systems facilitate communication between professors and students.

5 The development of AI-based educational applications fosters innovative learning methods.
6 Artificial intelligence has the potential to increase the accessibility of education.

Efficiency and Optimization

7 Artificial intelligence tools contribute to the security and protection of educational data.
8 Automation using artificial intelligence reduces the workload of teachers.
9 Artificial intelligence optimises learning time through adaptive courses.
10 AI-based platforms integrate a larger number of courses into a single environment.
11 Artificial intelligence makes it easier to access courses without limitations of space and time.

Support in Teaching

12 Artificial intelligence generates personalised content recommendations for students.
13 Virtual assistants help make teaching more efficient.
14 Artificial intelligence-based data analytics leads to better lesson planning.
15 Artificial intelligence supports the development of new forms of evaluation and feedback.

Marko Marković
University Business Academy in Novi Sad,
Faculty of Applied Management, Economics and Finance
Jevrejska 24, 11000 Belgrade, Serbia
marko.markovic@mef.edu.rs

Dragan Soleša
University Business Academy in Novi Sad,
Faculty of Economics and Engineering Management
Cvećarska 2, 21000 Novi Sad, Serbia
dragan.solesa@fimek.edu.rs

Petar Ciganović
University Business Academy in Novi Sad,
Faculty of Applied Management, Economics and Finance
Jevrejska 24, 11000 Belgrade, Serbia
pciganovic80@gmail.com

Razvoj i validacija skale za procjenu percepcija studenata o primjeni umjetne inteligencije u e-učenju

Sažetak

Sve veća integracija umjetne inteligencije (UI) u visokom obrazovanju naglašava potrebu za valjanim instrumentima za procjenu percepcija studenata o njezinoj primjeni u e-učenju. Cilj je ovoga istraživanja razviti i validirati psihometrijsku skalu za mjerenje percepcija studenata o umjetnoj inteligenciji u e-učenju. Primijenjen je istraživački dizajn razvoja skale na uzorku od 225 studenata visokoga obrazovanja. Proces razvoja obuhvatio je četiri faze: generiranje čestica na temelju modela prihvaćanja tehnologije (TAM) i relevantne literature, validaciju sadržaja putem ekspertne evaluacije, pokusno testiranje te empirijsku validaciju. Eksploratornom faktorskom analizom (EFA) identificirana je stabilna trofaktorska struktura koja uključuje percipiranu korisnost, učinkovitost i optimizaciju te podršku u nastavi. Vrijednost Kaiser-Meyer-Olkinova pokazatelja iznosila je ,812, a Bartlettov test sferičnosti bio je statistički značajan ($p < ,001$), što potvrđuje prikladnost podataka. Skala je pokazala zadovoljavajuću pouzdanost, s Cronbachovim alfa koeficijentima od ,889, ,823 i ,767. Diskriminantna valjanost potvrđena je primjenom t-testa za nezavisne uzorke, dok su korelacije među faktorima podržale konstrukt valjanosti. Rezultati ukazuju na to da razvijeni instrument predstavlja pouzdan i valjan alat za procjenu percepcija studenata o umjetnoj inteligenciji u e-učenju.

Ključne riječi: *e-učenje; faktorska analiza; psihometrijska validacija; razvoj skale; stavovi studenata; umjetna inteligencija*

Uvod

Nastavni proces suočio se s brzim promjenama u načinu na koji se aktivnosti provode u posljednjih nekoliko godina, što je prethodno zahtijevalo prisutnost učenika i učitelja u učionicama. Pojava e-učenja kao nove forme poučavanja donosi brojne mogućnosti i opcije za modernizaciju obrazovnoga sustava, pružajući priliku da mjesto i vrijeme više ne budu glavni faktori u izvođenju nastave (Jauković Jocić i sur., 2021). Ova vrsta fleksibilnosti među profesorima i studentima nudi značajnu

prednost u njihovim aktivnostima, pravovremenosti i mogućnosti višekratnoga pregleda određenih nastavnih materijala, što će studentima olakšati usvajanje gradiva (Maričić i sur., 2025). Osim ovih mogućnosti za učenje na daljinu i visokoga stupnja prihvaćanja istoga, pojavila se i nova, modernija tehnologija koja mijenja proces učenja i usvajanja specifičnoga gradiva. Umjetna inteligencija također je integrirana u moderne sustave e-učenja, pokrećući sveobuhvatnu transformaciju obrazovnoga procesa i način na koji se znanje prenosi krajnjem korisniku (Janković i sur., 2025). Proces ove transformacije pokreću inovativne tehnike koje nudi umjetna inteligencija, počevši od personalizacije sadržaja, prilagodljivosti nastavnih materijala, angažmana i učinkovitosti studenata, pa čak i samih predavača (Abbas i sur., 2023).

Umjetna inteligencija poboljšava sustave personalizacije sadržaja prilagođavanjem nastavnih materijala potrebama i sposobnostima učenika. Ispostavilo se da umjetna inteligencija prati ponašanje studenata, čime stvara personalizirano okružje temeljeno na modelima studenata, sadržaju koji prate i njihovim interakcijama, što omogućuje personalizaciju materijala i stvara okružje koje povećava angažman studenata i razumijevanje nastavnoga gradiva (Zhao, 2024). Sari i Purwanta pozitivno ocjenjuju ovaj stav i ističu da je implementacija umjetne inteligencije poboljšala učenje i omogućila profesorima da kreiraju učinkovitije nastavne planove (Sari i Purwanta, 2021). Ovo načelo posebno je istaknuto u sustavima e-učenja, pri čemu se individualni pristup može učinkovitije primijeniti (Salam i sur., 2023). Ovim pristupom vrlo je lako implementirati i pratiti emocionalne i kognitivne sposobnosti učenika, što može utjecati na način na koji se nastavna sredstva prilagođavaju kako bi se osiguralo bolje razumijevanje i postigli bolji rezultati (Jia i sur., 2022). Korištenjem algoritama, koji su temeljni koncept sustava umjetne inteligencije, sučeljnih tehnologija i obrade velikoga broja podataka, stvara se jedinstveni pedagoški dizajn za sustav, usmjeravajući studente prema obrazovnome okružju koje je skalabilno i prikladno za moderni koncept tehnologije i obrazovanja (Kaban, 2023).

Moderni obrazovni sustavi temeljeni na ovome principu prethodno su bili asistivne računalne usluge, evoluirajući u današnje složene platforme koje se koriste naprednim tehnikama strojnoga učenja, tehnikama obrade prirodnoga jezika i algoritmima koji preporučuju sadržaj korisniku u svakom trenutku, pružajući visoku razinu personalizacije i automatizacije administrativnoga procesa poučavanja (Yuskovych-Zhukovska i sur., 2022; Dean, 2022). Možemo koristiti umjetnu inteligenciju kao temelj za adaptivno učenje, omogućujući algoritmu da neovisno donosi odluke o reprezentaciji i evaluaciji znanja. Tehnike modeliranja, uključujući praćenje znanja i profiliranje studenata, omogućuju bolje predikcije (Stošić i sur., 2025). S obzirom na svoju interdisciplinarnu prirodu, umjetna inteligencija ima širok spektar primjena, od klasičnih metoda nadziranoga i nenadziranoga učenja do pristupa dubokom učenju. Odabir između ovih opcija ovisi o zahtjevima korisnika i vrsti potrebnih podataka (Dean, 2022). Strojno učenje predstavlja skup algoritama koji omogućuju sustavima da poboljšaju svoju učinkovitost u obavljanju zadataka. U sustavima

e-učenja, podatci o studentima mogu se analizirati na temelju njihovih obrazovnih navika, ocjena, područja istraživanja i ponašanja, što pomaže u predviđanju uspjeha studenata, grupiranju studenata prema područjima istraživanja ili razinama znanja te otkrivanju obrazaca u podatcima (Du i sur., 2020).

Klasične metode strojnoga učenja koriste stabla odluka kako bi im pomogle u donošenju odluka, čime zadržavaju važnost podataka u materijalu za obuku koristeći manje podataka i bolje mogućnosti usporedbe sa složenijim modelima (Ang i sur., 2020). Primjenom strojnoga učenja uspostavlja se metodološka povezanost između sirovih podataka i korisnih uvida za donošenje informiranih odluka (Bin, 2023). Duboko učenje jest podskup strojnoga učenja jer koristi umjetne neuronske mreže za obradu podataka u nelinearnim tokovima i poznato je kao duboko strukturirano učenje. Istraživanja su pokazala da je duboko učenje snažan pokretač u unaprjeđenju percepcije i modeliranja sekvenci (Paramasivam i sur., 2023), što ga čini dobrom metodom za sustave e-učenja i može se vrlo lako implementirati u procjeni personalizacije sadržaja. Praksa pokazuje da upotreba umjetne inteligencije transformira e-učenje kakvo trenutačno poznajemo, primjenom strojnoga učenja, algoritama i adaptivnih sustava, sve s ciljem omogućavanja inovativnijega i individualiziranijega pristupa obrazovnome procesu. Budući da se ova vrsta tehnologije temelji na kontinuiranom prikupljanju i analizi podataka, važno je naglasiti da povratni podatci prikupljeni tijekom njezine primjene mogu poslužiti kao osnova za daljnji razvoj sustava i njegovo prilagođavanje potrebama korisnika. Očekuju se proširenja u naprednije modele individualnoga pedagoškog rada, koji će pomaknuti granice generativne tehnologije i korisnicima dati dojam da pohađaju tradicionalnu nastavu (Chen i sur., 2020).

Tradicionalni način poučavanja se dovodi u pitanje ako već imamo tehnologiju koja to može učiniti brže i lakše. Međutim, ne možemo se potpuno osloniti na takav model jer on često ovisi o tome kako je razvijen i kako analizira povratne informacije. To dovodi do potrebe za uvođenjem etičkih načela i praktičnih rizika u implementaciju, koji se, ako se pojave, moraju ublažiti zbog složenosti i uloge takvoga sustava (Grenander i sur., 2021; Igbokwe, 2024). Također, umjetna inteligencija smanjuje opterećenje učitelja i omogućuje brzo ocjenjivanje svih učenikovih radova te pružanje povratnih informacija svakom učeniku pojedinačno. Automatizacijom se angažman učitelja preusmjerava na druge zadatke ili izradu specifičnijih planova lekcija koji će biti prilagođeni svim učenicima pomoću umjetne inteligencije (Çelik i sur., 2022). Jedna od najkorisnijih i najprihvaćenijih značajki su virtualni pomoćnici, koji su interaktivni sustavi koji omogućuju dovršavanje zadataka, stjecanje znanja, ocjenjivanje izvedbe i preporuke za sljedeći sadržaj koji odgovara korisniku na temelju prethodnih rezultata (Fryer i sur., 2017). Kako bi se transformirala edukacija, virtualni pomoćnici predstavljaju značajnu polazišnu točku za razvoj ovogaa tipa nastavnog pristupa. Važno je da virtualni pomoćnici nadopunjuju, ali ne zamjenjuju, ljudsku interakciju. Čak i kada se sami učenici

ocjenjuju, veliki problem je empatija i kreativnost,jer ne razumiju i ne razmišljaju svi učenici na isti način (Holmes i Tuomi, 2022).

Virtualni pomoćnici kombiniraju tehnike obrade prirodnoga jezika (NLP) i automatskoga prepoznavanja govora (ASR) za najpreciznije razumijevanje i odgovaranje na korisnička pitanja, sve unutar obrazovnoga sadržaja prethodno utvrđenoga kao osnovna polazišna točka za rad. Inteligentni pomoćnici omogućuju kreiranje interaktivnih kvizova i kartica za pregled gradiva što, pomoću gamifikacije, potiče studente na daljnje angažiranje i adaptivno učenje temeljeno na prethodno stečenom znanju i vlastitom napretku (Sajja i sur., 2024). Sve učestalija upotreba takvih alata omogućuje izravnu komunikaciju između studenata i sustava u bilo kojem trenutku, što je definicija e-učenja, ali sa značajnom prednošću u tome što virtualni pomoćnik, za razliku od LMS sustava, može odgovarati na pitanja studenata ili promijeniti način na koji im se predstavljaju nastavni materijali (Tiwari, 2023). Međutim, točnost informacija je upitna jer umjetna inteligencija često zanemaruje ulazne podatke i zamjenjuje ih podatcima koji nalikuju odgovoru koji se čini približno točnim u odnosu na postavljeno pitanje. Ključno je pitanje mogu li virtualni pomoćnici funkcionirati kao pouzdani obrazovni alati spremni potpuno zamijeniti učitelje (Davar i sur., 2025). Prednost u odnosu na tekstualne i glasovne opcije širi se kako bi uključila virtualnu stvarnost, posebno u inkluzivnom obrazovanju. U ovome slučaju možemo koristiti interaktivne avatare koji će, pomoću umjetne inteligencije i virtualne stvarnosti, stvoriti okružje koje učenici s posebnim potrebama mogu koristiti.

Ova je mogućnost podložna izmjenama, tako da se može prilagoditi različitim razinama i individualnim potrebama. Zaključujemo da se sve svodi na personalizaciju sadržaja i automatizaciju, što su temeljni koncepti umjetne inteligencije u takvim sustavima. Stoga je, radi prilagodbe potrebama studenata i njihovu okružju, te na temelju uvida u njihove sposobnosti i povratne informacije, potrebno oblikovati sadržaj koji je jasan, točan, precizan i lako razumljiv. Tako virtualni pomoćnik može pridonijeti ublažavanju nedostatka nastavnoga osoblja u određenim područjima koja se suočavaju s manjkom stručnih kadrova (Mohamed i sur., 2025). Međutim, usvajanje takvih modela ovisi o nekoliko faktora, uključujući percipiranu korisnost i očekivanu jednostavnost korištenja samoga modela, što samo potvrđuje važnost intuitivnoga dizajna virtualnoga pomoćnika – da bude optimiziran tako da ga svi mogu koristiti, posebno u inkluzivnim okružjima ili za rješavanje nedostatka nastavnoga osoblja (Malešević i sur., 2021). Unatoč svim tim prednostima koje umjetna inteligencija donosi u kontekstu e-učenja, moramo i dalje biti svjesni privatnosti podataka. Drugim riječima, moramo biti oprezni s podatcima koje unosimo u te sustave, ali također trebamo provjeriti politiku modela i kako on postupa s našim podatcima. Rizik se odnosi na zaštitu povratnih informacija studenata jer ti podatci odražavaju njihovu razinu znanja, preferencije i osobna mišljenja (Marković i Soleša, 2025).

Također je potrebno je uzeti u obzir kvalitetu nastavnih materijala i razinu autonomije modela koji preporučuje nastavne jedinice budući da takvi sustavi mogu

pokazivati pristranost prema određenim sadržajima ili izvorima te utjecati na način oblikovanja i prezentiranja nastavnih materijala. Prilikom dizajniranja takvoga sustava e-učenja, potrebno je uzeti u obzir etičke kodekse, koji se ponajprije odnose na programere, kao i praktičnu primjenu modela umjetne inteligencije. Unatoč svim perspektivama, kao i etičkim pitanjima o zaštiti podataka, ovi sustavi imaju dodatna ograničenja. Pitanja povezana s pristankom, akademskim integritetom i odgovornim korištenjem podataka studenata često se ističu kao važni izazovi u implementaciji umjetne inteligencije u obrazovanju (Zhai i sur., 2021). Osim svih prednosti i koristi koje nam nudi, kao i tehničkih aspekata sigurnosti, postavljaju se pitanja koja se isključivo odnose na implementaciju modela umjetne inteligencije u obrazovnom okružju. Faktori koji utječu na razinu prihvaćanja umjetne inteligencije među profesorima i studentima trebaju se detaljno identificirati. Time se otvara pitanje tehničke pismenosti i spremnosti za korištenje takvih modela, a osim toga, treba razmotriti jesu li obrazovne institucije spremne za implementaciju UI-a uz *online* platforme. Međutim, nedostaje validiranih instrumenata posebno dizajniranih za mjerenje tih stavova u regionalnim kontekstima, što ostaje kritična istraživačka praznina. Stoga ova studija ima za cilj razviti i psihometrijski validirati skalu za procjenu percepcija studenata o umjetnoj inteligenciji u e-učenju, osiguravajući pouzdan metodološki okvir za buduću primjenu (Krecar i Pavlin-Bernardić, 2026).

Unatoč rastućem broju istraživanja o umjetnoj inteligenciji u obrazovanju, nedostaje validiranih instrumenata posebno dizajniranih za mjerenje percepcije studenata o UI-u u e-učenju. Postojeće studije često se oslanjaju na nevalidirane ili prilagođene instrumente, što ograničava pouzdanost i usporedivost nalaza.

Stoga je cilj ove studije razviti i psihometrijski validirati skalu za procjenu percepcije studenata o umjetnoj inteligenciji u e-učenju, pružajući pouzdan metodološki alat za buduća istraživanja.

Metodologija

Ova studija slijedi istraživački dizajn razvoja skale umjesto tradicionalnoga pristupa temeljenoga na anketama. Primarni je cilj konstruirati i validirati psihometrijski instrument za procjenu percepcija studenata o umjetnoj inteligenciji u e-učenju. Kako bi se zadovoljili zahtjevi za metodološkom transparentnošću u razvoju mjernoga instrumenta, proveden je sustavni proces u četiri faze. Ovaj proces osigurao je da instrument prijeđe iz općega upitnika u validiranu psihometrijsku skalu, kako je sažeto prikazano u Tablici 1. Svaka faza predstavlja nužan korak u transformaciji početnoga skupa stavki u validirani mjerni instrument.

Prilikom stvaranja početne baze stavki, korišten je deduktivni pristup, koji je uključivao kombiniranje teorijskoga okvira i sustavnoga pregleda literature. Kao osnova korišten je TAM (model prihvaćanja tehnologije), koji identificira percipiranu korisnost i percipiranu jednostavnost korištenja kao ključne odrednice prihvaćanja. Osim toga, konzultirani su relevantni radovi o primjeni umjetne inteligencije u e-učenju. Na temelju

ove analize stvorena su tri faktora: percipirana korisnost, učinkovitost i optimizacija te podrška u poučavanju. Za svaki od faktora formulirano je 6-7 stavki, što je ukupno činilo 20 stavki. Prilikom formuliranja korištena je 5-stupanjska Likertova skala (1 = uopće se ne slažem do 5 = u potpunosti se slažem) (Joshi i sur., 2015). Tijekom formulacije razmatrali su se jasnoća, jednostavnost i izbjegavanje dvostrukih negacija.

Kako bi se procijenila sadržajna valjanost ljestvice, formirano je povjerenstvo od tri neovisna stručnjaka koji su analizirali popis od 20 stavki, ocjenjujući svaku na skali od 1 do 4 u tri kategorije: jasnoća (je li stavka lako razumljiva), relevantnost (mjeri li stavka namjenski konstrukt) i reprezentativnost (pokriva li stavka dobro domenu faktora). Ova tri stručnjaka dolaze iz područja visokoga obrazovanja i imaju bogato iskustvo u korištenju različitih alata koji podržavaju učinkovitu provedbu obrazovnoga procesa. Svaki od ovih triju stručnjaka koristio je različite modele i alate umjetne inteligencije u nastavi, oni su stručnjaci iz triju znanstvenih i istraživačkih područja: menadžmenta, ekonomije i informatike.

Nakon prikupljanja ocjena, indeks sadržajne valjanosti na razini stavke (I-CVI) izračunat je kao omjer stručnjaka koji su stavku ocijenili s 3 ili 4. Prema preporuci Lynna (1986), zadržani su stavci s I-CVI ≥ 0,78. Od 20 inicijalnih stavki, dvije su isključene (I-CVI = 0,67 i 0,71), dok su tri stavke revidirane na temelju komentara stručnjaka (npr. „virtualni pomoćnici" zamijenjeni su sa „sustavima temeljenim na umjetnoj inteligenciji"). Nakon revizije ostalo je 18 stavki. Indeks valjanosti sadržaja na razini skale (S-CVI/UA – univerzalni sporazum) iznosio je 0,89, što se smatra izvrsnim.

Pokusna studija provedena je na uzorku od 15 studenata koji redovito koriste e-učenje i alate umjetne inteligencije u svojemu obrazovanju (npr. ChatGPT). Ciljevi pokusne studije bili su provjeriti razumljivost i jasnoću svake stavke, procijeniti prosječno vrijeme dovršetka i identificirati moguće nejasnoće. Nakon što su ispunili upitnik, studenti su sudjelovali u kratkom polustrukturiranom intervjuu koji je pomogao u optimizaciji ljestvice i učinio je jasnijom za glavno istraživanje.

Nakon provedbe pokusnoga istraživanja i revizije ljestvice, dobiveno je konačnih 15 stavki koje su formulirane kako bi obuhvatile sve aspekte istraživanja, bez ponavljanja ili lošega izražavanja.

Tablica 1

Analiza podataka

Provedena je eksploratorna faktorska analiza (EFA) kako bi se odredila temeljna faktorska struktura skale. Ekstrakcija faktora provedena je korištenjem analize glavnih komponenti (PCA), nakon čega je uslijedila Varimax rotacija da bi se postigla jasnija interpretacija strukture faktora. Kako bi se procijenila interna dosljednost, izračunati su Cronbachovi alfa koeficijenti za svaki faktor. Diskriminantna valjanost procijenjena je korištenjem t-testa za neovisne uzorke, uspoređujući ispitanike iz gornjih i donjih 27 % ukupnih rezultata. Dodatno, ispitane su međufaktorske korelacije kako bi se

procijenila konstruktna valjanost. Prije provođenja faktorske analize, adekvatnost podataka procijenjena je korištenjem Kaiser-Meyer-Olkinove (KMO) mjere i Bartlettova testa sferičnosti. Dobivene vrijednosti potvrdile su prikladnost skupa podataka za faktorsku analizu.

Uzorak od 225 studenata koji su sudjelovali u ovome istraživanju uključivao je studente preddiplomskoge i diplomskoge studija na Fakultetu primijenjenoga menadžmenta, ekonomije i financija u Beogradu, Republika Srbija. Sudjelovali su studenti sljedećih studijskih programa: Ekonomija (n = 82), Menadžment (n = 78) i Informacijske tehnologije (IT) (n = 65). Dob sudionika bila je između 19 i 26 godina (M = 22,0; SD = 2,6), sa sljedećom dobnom distribucijom: 80 sudionika (35,6 %) bilo je u dobi od 19 do 21 godine, 110 (48,9 %) bilo je u dobi od 22 do 24 godine, a 35 (15,6 %) bilo je u dobi od 25 do 26 godina.

Rezultati i diskusija

Skala je primijenjena na uzorku od 225 studenata visokoga obrazovanja koji koriste platforme e-učenja i alate umjetne inteligencije (vidjeti Tablicu 2 za detaljne karakteristike uzorka). Sudjelovanje je bilo dobrovoljno i anonimno, a svi ispitanici su dali informirani pristanak.

Tablica 2

Ova deskriptivna saznanja uključena su isključivo u svrhu konteksta i ne tumače se kao primarni rezultati jer je glavni cilj ove studije razvoj i validacija mjernoga instrumenta. Rezultati ove studije tumače se isključivo u kontekstu razvoja ljestvice i psihometrijske validacije. Eksploratorna faktorska analiza (EFA) provedena je kako bi se ispitala temeljna struktura mjernoga instrumenta. Kaiser-Meyer-Olkinov pokazatelj adekvatnosti uzorka iznosio je ,812, što premašuje preporučeni prag od 0,7. Bartlettov test sferičnosti bio je statistički značajan, što ukazuje na to da su podatci bili prikladni za faktorsku analizu. Faktori su izdvojeni korištenjem analize glavnih komponenti (PCA), nakon čega je uslijedila Varimax ortogonalna rotacija kako bi se postigla jasnija interpretacija strukture faktora. Izdvojeni faktori pokazuju jasnu konceptualnu diferencijaciju uz održavanje teorijske koherentnosti, podržavajući konstruktnu valjanost skale. Interna dosljednost identificiranih faktora procijenjena je korištenjem Cronbachovih alfa koeficijenata. Sve tri dimenzije pokazale su zadovoljavajuću pouzdanost, s vrijednostima koje premašuju preporučeni prag od 0,7 (,889; ,823 i ,767). Međufaktorske korelacije ukazuju na umjerene pozitivne odnose, sugerirajući da su dimenzije povezane, ali predstavljaju različite aspekte istoga konstrukta. Rezultati analize diskriminantne valjanosti potvrđuju da skala uspješno razlikuje ispitanike s visokim i niskim razinama mjerenoga konstrukta, dodatno potkrepljujući njezinu psihometrijsku robusnost. Deskriptivna statistika prikazana je samo kao podržavajuća informacija i ne tumači se kao primarni istraživački nalazi.

Tablica 3

Napomena: Svojstvene vrijednosti i postotci objašnjene varijance odnose se na početnu ekstrakciju prije rotacije (analiza glavnih komponenti). Zasićenja faktora prikazana su nakon Varimax rotacije.

Kako bi se procijenila pouzdanost i struktura ljestvice, stavke su grupirane prema identificiranim faktorima: percipirana korisnost, učinkovitost i optimizacija i podrška u poučavanju. Tablica 4 detaljno prikazuje izračunate deskriptivne statističke dimenzije stavki povezanih s tri dobivena faktora.

Tablica 4

Kako bi se procijenila homogenost svakog faktora, izračunate su korigirane korelacije stavke i ukupnoga rezultata za svaku stavku unutar njezina odgovarajućega faktora. Ove korelacije ukazuju na stupanj u kojem je svaka stavka dosljedna ostalim stavkama koje mjere isti konstrukt. Rezultati su prikazani u Tablici 5.

Tablica 5

Napomena: sve korelacije su statistički značajne na $p < ,01$. Korigirane korelacije stavki s ukupnim rezultatom predstavljaju korelaciju između svake stavke i zbroja preostalih stavki unutar istoga faktora.

Kako bismo dodatno ispitali unutarnju strukturu i odnos između izvučenih dimenzija, provedena je analiza korelacija. Kao što je prikazano u Tablici 6, svi faktori pokazuju značajne pozitivne korelacije, što podržava teorijsku integraciju skale.

Tablica 6

Diskriminantna valjanost procijenjena je korištenjem t-testa za neovisne uzorke, uspoređujući ispitanike iz gornjih i donjih 27 % ukupnih rezultata. Rezultati ukazuju na statistički značajne razlike ($t = 6,18$; $p < 0,001$), potvrđujući da skala učinkovito razlikuje ispitanike s različitim razinama mjerenoga konstrukta.

Tablica 7

Kako bi se dodatno ispitala diskriminantna valjanost na razini faktora, provedeni su t-testovi nezavisnih uzoraka za svaki faktor zasebno, uspoređujući iste skupine gornjih 27 % i donjih 27 % (na temelju ukupnih rezultata na skali). Rezultati su prikazani u Tablici 8.

Tablica 8

Napomena: ekstremne skupine (gornjih 27 % i donjih 27 %) formirane su na temelju ukupnih rezultata skale (ista podjela kao u Tablici 7). Zatim su unutar tih skupina izračunate srednje vrijednosti i standardne devijacije za svaki faktor. Sve t-vrijednosti su statistički značajne pri $p < 0,001$.

Deskriptivna statistika prikazana je isključivo radi podrške procesu validacije i ne tumači se kao primarni nalazi istraživanja. Međutim, ovi se nalazi tumače kao kontekstualna podrška procesu validacije, a ne kao primarni dokaz izmjerenoga konstrukta. Naglasak ove studije ostaje na procjeni psihometrijskih svojstava skale.

Zaključak

Razvoj pouzdane i valjane skale koja služi kao instrument za procjenu studentske percepcije umjetne inteligencije u okružjima e-učenja uključivao je četiri važne faze, od generiranja pitanja na temelju modela prihvaćanja tehnologije (TAM), procjene valjanosti sadržaja naših stručnjaka, pokusno testiranja na 15 studenata i konačne primjene na uzorku od 225 studenata visokoga obrazovanja. Dobivena skala od 15 pitanja imala je jasnu strukturu s tri faktora. EFA je otkrila tri konstrukta: percipirana korisnost (šest pitanja, svojstvena vrijednost = 5,43, postotak objašnjene varijance = 36,20 %), učinkovitost i optimizacija (pet pitanja, svojstvena vrijednost = 2,91, postotak objašnjene varijance = 19,40 %) te podrška u nastavi (četiri pitanja, svojstvena vrijednost = 1,89, postotak objašnjene varijance = 12,60 %), što čini ukupno 68,20 % varijance. Koeficijenti pouzdanosti unutarnje konzistentnosti mjereni Cronbachovim alfa koeficijentom kretali su se od 0,889 do 0,767. Korigirane korelacije između stavki i ukupnoga rezultata kretale su se između 0,492 i 0,642, što prelazi preporučenu graničnu vrijednost od 0,30. Diskriminantna valjanost testirana je t-testovima neovisnih uzoraka, pri čemu su ukupni rezultati podijeljeni u skupine od gornjih 27 % i donjih 27 %. Test diskriminantne valjanosti potvrdio je statistički značajne razlike u ukupnim rezultatima skale ($t = 6,18$; $p < 0,001$) kao i u rezultatima pojedinačnih faktora ($t = 6,61–7,38$; $p < 0,001$). Ovi rezultati ukazuju na to da je uspješno razvijena pouzdana skala koja predstavlja pouzdan i valjan instrument za procjenu studentske percepcije umjetne inteligencije u e-učenju. Ova skala pruža metodološku osnovu za buduća istraživanja i praktičnu primjenu u stvaranju modernoga pristupa obrazovnom procesu. Ograničenja uključuju korištenje jednoga uzorka i oslanjanje samo na samoprocijenjene podatke, što može utjecati na generalizaciju. Buduća istraživanja trebala bi koristiti CFA i testirati skalu u različitim obrazovnim okružjima te na različitim uzorcima i populacijama.

Dodatak A - Konačna skala

Molimo vas da naznačite svoj stupanj slaganja sa sljedećim tvrdnjama koristeći Likertovu skalu od 5 stupnjeva (1 = u potpunosti se ne slažem, 5 = u potpunosti se slažem).

Percipirana korisnost

1. Umjetna inteligencija omogućuje personalizirano učenje prilagođeno individualnim potrebama.
2. Alati umjetne inteligencije omogućuju bržu procjenu znanja i ocjenjivanje.
3. Korištenjem virtualnih pomoćnika studenti razvijaju veću neovisnost u učenju.
4. Sustavi umjetne inteligencije olakšavaju komunikaciju između nastavnika i studenata.
5. Razvoj obrazovnih aplikacija temeljenih na umjetnoj inteligenciji potiče inovativne metode učenja.
6. Umjetna inteligencija ima potencijal povećati dostupnost obrazovanja.

Učinkovitost i optimizacija

7. Alati umjetne inteligencije doprinose sigurnosti i zaštiti obrazovnih podataka.
8. Automatizacija pomoću umjetne inteligencije smanjuje radno opterećenje nastavnika.
9. Umjetna inteligencija optimizira vrijeme učenja primjenom adaptivnih tečajeva.
10. Platforme temeljene na umjetnoj inteligenciji integriraju veći broj tečajeva u jedno okružje.
11. Umjetna inteligencija olakšava pristup tečajevima bez ograničenja prostora i vremena.

Podrška u poučavanju

12. Umjetna inteligencija generira personalizirane preporuke sadržaja za studente.
13. Virtualni pomoćnici doprinose učinkovitijem poučavanju.
14. Analitika podataka temeljena na umjetnoj inteligenciji doprinosi boljem planiranju nastave.
15. Umjetna inteligencija podržava razvoj novih oblika evaluacije i povratnih informacija.