

EXPLORING THE FACTOR STRUCTURE OF THE GENERAL ATTITUDES TOWARDS ARTIFICIAL INTELLIGENCE SCALE

BEATRICE ADRIANA BALGIU*

National University of Science and Technology Politehnica Bucharest

Abstract

This study aimed to investigate the factorial structure of the General Attitudes Towards Artificial Intelligence Scale (GAAIS) in a sample of Romanian adults (N=480; 220 females; Mean age=28.26). The scale assesses attitudes towards Artificial Intelligence (AI), comprising two factors in the original version: positive and negative attitudes regarding AI. To analyze how the scale is structured, the sample was split into two equal parts: the first part was used for exploratory factor analysis (EFA), and the confirmatory factor analysis (CFA) and multi-group CFA for gender invariance were performed on the second group. McDonald's omega and Cronbach's alpha coefficients were calculated to assess the internal consistency of the scale. The results indicate that, unlike the original two-factor structure, the Romanian version comprises three factors: two reflecting positive attitudes (perceived benefits of AI and superiority of AI over Human Intelligence) and one representing negative attitudes. Internal consistency was high, with α and ω values ranging between 0.742 and 0.890. In addition, discriminant validity was confirmed using heterotrait monotrait ratio (HTMT). The three-factor version of the GAAIS is a valid and reliable instrument for assessing attitudes towards AI in Romanian populations and can be used to analyze attitudes towards AI in different domains.

Cuvinte-cheie: inteligența artificială, atitudini, beneficii, superioritatea percepută a AI, structura factorială, validare

Keywords: artificial intelligence, attitudes, benefits, perceived AI superiority, factorial structure, validation

1. INTRODUCTION

A broad definition of AI describes it as a technology capable of performing tasks and activities that would be commonly considered typical of human cognition and reasoning (Triberti, 2024). AI systems can imitate, match, and even surpass human cognitive tasks in specific fields (Dwivedi *et al.*, 2023). The progress of artificial intelligence-based technologies has led to their dominance in most sectors of economic and social life, including education, healthcare, public administration, and business (Huang *et al.*, 2023; Mah and Grass, 2024). The benefits of these technologies are considerable, as AI helps automate repetitive and complex tasks, thereby improving efficiency and quality of work. For example, 91% of sales employees believe that automation has improved their work-life balance and increased job satisfaction (Perryman, 2024). Artificial Intelligence is expected to

* National University of Science and Technology Politehnica Bucharest, Department of Career and Educational Training, Splaiul Independenței, 313, București, RO-060042, E-mail: beatrice.balgiu@upb.ro.

enhance productivity, generate new opportunities, minimize human error, address complex problems, and automate repetitive tasks (Hartwig, 2021). Strategic AI alignment ensures sustainable growth and competitive advantages (Gupta *et al.*, 2024).

However, many companies face barriers to implementing AI in organisations due to negative employee attitudes (Lichtenthaler, 2020; Arslan *et al.*, 2022). These resistances in adopting AI arise from fears related to the loss of professional autonomy (Jussupow *et al.*, 2021), lack of trust in technology, scepticism regarding the accuracy of AI algorithms, and the culture of resistance within organisations (Deloitte Report, 2024), fear of loss of control (Monod *et al.*, 2024), and technological complexity (Vrontis *et al.*, 2022). In summary, AI resistance incorporates employee fears, inefficiencies, and aversions to AI (Golgeci *et al.*, 2025). In addition, it should be noted that organisations often face issues related to the quality, availability, and access to data that are vital for AI systems to function effectively. Moreover, data protection regulations and the lack of coherent legislative frameworks – frequently encountered in the context of the novelty of the phenomenon – further complicate the management and sharing of data essential for the functioning of AI algorithms (Radhakrishnan *et al.*, 2022).

With the adoption of the National Strategy for Artificial Intelligence 2024–2027, Romania has set ambitious goals: driving economic growth, enhancing social well-being, strengthening national security, and accelerating digital transformation. Despite these intentions, the strategy has yet to reveal a tangible impact on practical research. At the same time, more and more Romanian organisations are turning to AI-based solutions—not only to streamline operations and improve decision-making in business (Iuga and Brad, 2022), but also to enhance public administration services (Androniceanu, 2024) and to advance diagnostics and treatment planning in healthcare (Fitzeke, 2024), among other areas.

Moreover, there is a need to understand how different populations perceive and interact with AI. A correct assessment of the attitudes and values of different groups towards the involvement of AI in their professional domains would contribute to a better acceptance of AI-based technologies. In this regard, General Attitudes Towards Artificial Intelligence Scale was developed to measure individuals' attitudes towards AI in different contexts (Schepman and Rodaway, 2020, 2022). Since people's adoption or resistance to AI can be influenced by cultural differences in the acceptability of the technology, we aimed to adapt the GAAIS in the Romanian context. In the absence of culturally validated instruments in Romania, the present study aims to contribute to this endeavour through a comprehensive and scientific assessment framework. The choice of the GAAIS in the validation study is based on the fact that it reflects essential dimensions such as interest, concerns and willingness to accept AI in everyday life. Given the purpose of our study, to understand favourable perceptions and psychological barriers to AI adoption, this scale provides a comprehensive and validated framework to capture individual perceptions of AI. On the other hand, it is considered that attitudes towards AI should be assessed regularly, given the rapid development of these technologies and their profound impact on society (Schepman and Rodway, 2020).

2. GENERAL ATTITUDES TOWARDS ARTIFICIAL INTELLIGENCE SCALE

The General Attitudes Towards Artificial Intelligence Scale (GAAIS) was developed to assess individuals' perceptions of artificial intelligence (AI) from cognitive, affective, and behavioral perspectives. According to the authors, the construction of the GAAIS is based on an empirical-inductive approach through which the items were formulated starting from recurring themes identified in academic literature and public discourse (Schepman and Rodway, 2020). This strategy for constructing the instrument reflects the authors' intent to draw on both general sets of positive (e.g., efficiency, superiority of repetitive tasks, economic benefit) and negative (e.g., surveillance, loss of control, the presence of errors) attitudes. Thus, GAAIS offers an inclusive framework for studying attitudes towards AI across varied environments, without restricting interpretation to any deterministic theory framework.

The scale comprises two factors: positive and negative attitudes respectively (Schepman and Rodway, 2020, 2022). The positive attitudes factor captures perceptions of the social and personal benefits of AI, preferences for AI use in various contexts (e.g., routine transactions), and emotional responses (e.g., AI is exciting, impressive, or enhances well-being). In contrast, the negative attitudes factor is dominated by emotional aspects (e.g., AI is sinister, dangerous, creates discomfort, suffering, etc.) and includes unrealistic opinions on the use of AI (AI is unethical, prone to errors, takes over control, espionage, etc.).

In the validation studies, the GAAIS has been shown to have convergent validity with all scales from the Technology Readiness Index (Lam *et al.*, 2008), which measures readiness for consumer technologies, and with the Corporate Distrust Scale (Adams *et al.*, 2010), which measures distrust towards corporations. Regarding the personality traits in the Big Five model, some studies have found that positive GAAIS correlates negatively with extraversion, meaning that introverted people have more positive attitudes towards AI than extraverts (Schepman and Rodway, 2023). Other studies have found that negative attitudes toward AI correlate with extraversion, emotional stability, agreeableness, and openness (Kaya *et al.*, 2024). In different studies, the scale has demonstrated good internal consistency: Cronbach's alpha 0.88 for Positive GAAIS and 0.83 for Negative GAAIS, 0.87 for the entire scale (Schepman and Rodway, 2020), between 0.82 and 0.88 (Schepman and Rodway, 2023), 0.82 for the Positive GAAIS and 0.84 for the Negative GAAIS in the Turkish cultural model (Kaya *et al.*, 2024). The scale, validated for the Turkish language in the general population using a convenience sample, also showed a two-dimensional structure and good psychometric properties (Kaya *et al.*, 2024).

Although this research provides promising evidence regarding the reliability and validity of the GAAIS, further studies are needed to investigate the scale's performance in various cultural contexts and on diverse samples. Drawing on existing literature, the present study hypothesizes that: 1) the scale will preserve its two-factor structure and 2) exhibit good internal consistency in the Romanian cultural setting.

3. METHOD

3.1. Cultural and linguistic adaptation of the scale

The cross-cultural adaptation of the General Attitudes towards Artificial Intelligence Scale (GAAIS) into Romanian followed the methodological process in

accordance with established international guidelines for instrument translation and validation (Gudmundson, 2009). The original scale was independently translated into Romanian by two bilingual translators with expertise in psychology and academic English. A preliminary Romanian version was then produced by synthesizing these two translations. A third independent bilingual translator then performed a back-translation while being blinded to the scale's initial version. The purpose of this step was to confirm that the translated content matched the items' original meaning. Small changes were made to ensure that some AI-related terms and concepts were understood in the context of Romanian culture and technology. Subsequently, a convenience sample of 16 students participated in a pilot study to assess face validity, comprehensibility, and clarity. Additional changes were made in response to feedback from the pilot participants, especially to improve the fluency of the Romanian version and simplify some phrases. None of the items were removed or reworded.

3.2. Procedure and participants

Data were collected through a cross-sectional study conducted between December 21, 2024, and, March 15, 2025, using a convenience sample of the general adult population. The data collection was facilitated via an online survey developed using Google Forms, which included GAAIS along with a brief sociodemographic questionnaire. A commonly accepted criterion for factor analysis is to have a sample size of at least 10 participants per item and a minimum of 200 participants in total, to ensure stable psychometric results (International Test Commission, 2017). To increase the statistical power of the analyses, it is generally recommended to recruit more participants when possible. In total, 500 people were invited to participate and 480 completed questionnaires were ultimately returned, achieving a robust sample size. The sampling technique used was the snowball sampling method, a non-probability sampling technique that offers the advantages of providing access to hard-to-reach populations, reducing data collection costs and time, and increasing response rates, and was chosen because it allows access to different categories of employees (Ting *et al.*, 2025). The time required to complete the questionnaire was estimated at 5-6 minutes. In the introduction to the questionnaire, an informative text was presented detailing the purpose of the study, informing participants of confidentiality and the absence of risks, and mentioning the lack of rewards for participation. According to Schepman and Rodway's (2020) recommendation, the text defining AI was added to the preamble of the questionnaire: „We are interested in your attitudes towards artificial intelligence. By artificial intelligence, we refer to devices that can perform tasks that would usually require human intelligence. Please note that these can be computers, robots, or other hardware devices, possibly augmented with sensors or cameras, etc.” Participants were recruited from social media (WhatsApp) and an undergraduate psychology course at a technical university.

3.3. Measures

1. General Attitudes towards Artificial Intelligence Scale (GAAIS) (Schepman and Rodway, 2020) consists of 20 items, 12 of which measure positive attitudes towards AI (e.g., There are many beneficial applications of Artificial Intelligence). The next eight items measured negative attitudes towards AI (e.g., I think Artificial Intelligence is dangerous). Items are rated on a scale from 1 – *strongly disagree* to 5 – *strongly agree* for subscale 1 (positive) with reversed

scoring for items in subscale 2 (negative). Higher scores on the positive subscale indicate pro-AI attitudes, and higher scores (before reversal) on the negative subscale indicate anti-AI attitudes. As recommended by the scale authors, items were presented in a randomized order to prevent the detection of content patterns and reduce response bias.

2. Questionnaire to collect sociodemographic data: (i) age; (ii) gender; (iii) education; (iv) experience in using digital technologies; (v) residence and work environment (urban/rural); (vi) work sector (public/private/freelancer); (vii) field of activity; (viii) geographical region.

3.4. Data analysis

The construct validity of the scale was tested through exploratory factor analysis (EFA) to identify the latent structure of the scale in the context of the first cultural validation and confirmatory factor analysis (CFA) for its verification. Thus, the general sample was divided into two relatively equal sub-samples: the first one (N=238) was used for EFA and the second (N=242) for CFA. For EFA a maximum-likelihood extraction method with direct varimax rotation was used. Kaiser-Meyer-Olkin (KMO) and Bartlett's test were used to examine whether the participant-to-item ratio and sample size were appropriate for EFA (Hair et al., 2019). In the case of CFA (maximum-likelihood estimation method), in order to determine the statistical fit of the model, we used the coefficients χ^2 (chi-square), df (degrees of freedom), χ^2/df (criterion chi-squared/df), CFI (comparative fit index), TLI (Tucker-Lewis index), RMSEA (root mean squared error of approximation), SRMR (standardized root mean square residual), and AIC (Akaike's Information Criterion). For these indices, we considered the following cut-off level: the value of χ^2/df is acceptable if it is <3 (Schermelleh-Engel *et al.*, 2003). CFI, GFI, and TLI values close to 0.90 or greater are acceptable to good (Schumacher and Lomax, 2016). RMSEA and SRMR have good values if they are almost 0.06 (Brown, 2015); AIC, used to compare the models of measuring CFA, deems the model with the lowest value of the AIC indicator to be statistically adequate (Schermelleh-Engel *et al.*, 2003). Invariance criteria imply insignificant changes in absolute fit indices: ΔCFI and $\Delta RMSEA$ <0.010 (Nouredine et al., 2025). The reliability was examined using Cronbach's alpha and McDonald's omega, considered to be good when they are ≥ 0.70 (De Vellis and Thorpe, 2021). We calculated the scale's composite reliability (CR) on the factor loading and convergent validity on the Average Variance Extracted (AVE). The minimum AVE level is 0.50 (Hair et al., 2019), while for CR it is 0.70 (Chin, 2010). Discriminant validity was calculated using a robust Heterotrait monotrait ratio (HTMT). A lower AIC indicates a better fit. All data were analyzed using JASP 0.19.1.0 (Amsterdam University, Amsterdam, The Netherlands).

4. RESULTS

4.1. Sociodemographic analysis of the sample

The analyzed group consisted of 480 participants, of which 260 (54%) are men and 220 (46%) are women, with an average age of $M=28.26$ ($SD=11.99$). In terms of the environment in which they work, 95.6% of the participants work in urban areas, while 4.4% work in rural areas. In terms of educational level, 78.95% of the respondents have university degrees, 18.75% have postgraduate studies (master's and/or doctoral), and 2.29% have high school education. Among these, 27.08%

work in the public sector, 39.37% come from the private sector, 11.5% are freelancers, and 25% are students. Experience in using technology varies considerably, from 0-5 years (12.3%) to over 15 years (31.4%). The geographical area from which most respondents come is Bucharest-Ilfov (68.2%), followed by participants from the South-East (10.7%), South Muntenia (7.7%) and 13.4% from other regions of the country. The field of activity varies: most are from I.T. (13.54%), medical (7.5%), entrepreneurship (3.75%), education (8.33%), banking (4.37%), telecommunications (6.25%), automotive industry (5.62%), research (2.5%), marketing (1.66%), hospitality (1.87%), pharmacies (3.33%), and public administration (6.25%) plus a percentage that falls into other fields of activity (10.03%). A group of first and second-year students (25%) has been added.

4.2. Factorial structure

4.2.1. Exploratory factor analysis

Exploratory factor analysis (EFA) revealed a three-factor structure underlying the scale. The factorability of the correlation matrix was supported by a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.892, which exceeds the minimum requirement of 0.50, suggesting that the sample size was suitable for factor analysis. Additionally, Bartlett's test of sphericity was statistically significant, $\chi^2(190)=2189.689$, $p<0.001$ confirming that the correlation matrix is appropriate for factor analysis.

A principal component analysis with varimax rotation identified three components, which together accounted for 56.83% of the total variance explained by the scale. The first factor includes seven items with factor loadings between 0.618 and 0.849 (variance 32.947%), the second factor consists of 4 items with factor loadings between 0.633 and 0.741 (variance 6.901%), and the third factor includes 8 items with factor loadings between 0.579 and 0.749 (variance 14.295%). The scree plot analysis supported a three-dimensional factorial solution (Figure 1).

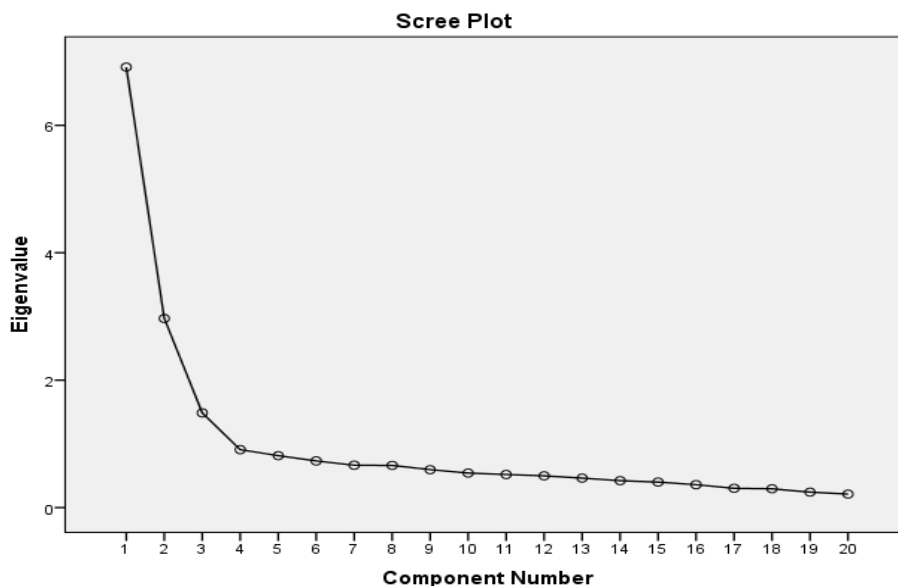


Figure no.1. Scree Plot of GAAIS

All factors contained items with loadings greater than 0.40 (Tabachnik and Fidell, 2013) (Table no. 1).

Table no 1.
Exploratory factor analysis of GAAIS (N=238)

Items	Factors		
	1	2	3
1. I am interested in using artificially intelligent systems in my daily life.	0.794	0.139	0.180
2. There are many beneficial applications of Artificial Intelligence.	0.849	0.067	0.074
3. Artificial Intelligence is exciting.	0.774	0.230	0.084
4. Artificial Intelligence can provide new economic opportunities for this country.	0.732	0.244	0.103
5. I would like to use Artificial Intelligence in my own job.	0.662	0.300	0.174
6. An artificially intelligent agent would be better than an employee in many routine jobs.	0.276	0.721	0.071
7. I am impressed by what Artificial Intelligence can do.	0.660	0.358	0.008
8. Artificial Intelligence can have positive impacts on people's wellbeing.	0.618	0.449	0.198
9. Artificially intelligent systems can help people feel happier.	0.370	0.655	0.123
10. Artificially intelligent systems can perform better than humans.	0.164	0.761	0.113
11. Much of society will benefit from a future full of Artificial Intelligence.	0.405	0.503	0.074
12. For routine transactions, I would rather interact with an artificially intelligent system than with a human.	0.215	0.633	0.097
13. I think Artificial Intelligence is dangerous.	0.142	0.230	0.598
14. Organisations use Artificial Intelligence unethically.	-0.063	0.218	0.579
15. I find Artificial Intelligence sinister.	0.296	-0.028	0.749
16. Artificial Intelligence is used to spy on people.	-0.003	-0.048	0.725
17. I shiver with discomfort when I think about future uses of Artificial Intelligence.	0.245	-0.086	0.767
18. Artificial Intelligence might take control of people.	0.180	-0.003	0.743
19. I think artificially intelligent systems make many errors.	-0.075	0.372	0.602
20. People like me will suffer if Artificial Intelligence is used more and more.	0.095	0.209	0.687

As item 11 is cross-loading, which indicates conceptual ambiguity. According to a recommendation by Comrey and Lee (2013), items that had loadings ≥ 0.33 on more than one factor should be omitted. Consequently, we decided to eliminate this item with cross-loading. The analysis of the factors split from the original factor of positive attitudes indicates that the first factor focuses on the benefits offered by

AI, and the second factor on the superiority of AI compared to human intelligence. Factor 3 remained unchanged, and comprised all items related to negative attitudes.

Consequently, the first factor was named perceived benefits of AI, the second was the superiority of AI compared to human intelligence, and the third, was negative attitudes towards AI.

4.2.2. *Confirmatory factor analysis*

To verify the dimensional structure of the GAAIS scale identified in the exploratory factor analysis (EFA), we conducted a confirmatory factor analysis (CFA) on a second sample (N=242). The assumption of multivariate normality was violated, as the distributions of scores were not normal, indicating substantial skewness (30.382) and kurtosis (456.482), with a critical ratio of 22.306. As a result, a robust estimation method by bootstrapping (2000 subsamples) was used. Three structural models for the GAAIS were tested: a unifactorial model, a bifactorial model (positive and negative attitudes) and a trifactorial model, resulting from the EFA analysis. Based on the AIC criterion, the three-factor model demonstrated the best fit to the data. The goodness-of-fit indices for the three-factorial model are: $\chi^2=310.003$; $df=140$; $\chi^2/df=2.214$; CFI=0.953; TLI=0.984; RMSEA=0.051 [90%CI: 0.043-0.058]; SRMR=0.051; $p<0.001$. The three-factor model provides a significantly better fit and adequate theoretical interpretability (Table no 2).

Table no 2.

Goodness-of-fit indices of the alternative models in CFA (N=242)

Models	χ^2	df	χ^2/df	CFI	TLI	RMSEA [90%CI]	SRMR	AIC
M1: one factor	1429.571	170	8.409	0.666	0.626	0.125 [0.119-0.131]	0.115	28076.019
M2: two-factors	612.438	169	3.623	0.882	0.868	0.074 [0.008-0.080]	0.058	27260.886
M2: three-factors	310.003	140	2.214	0.953	0.984	0.051 [0.043-0.058]	0.051	25595.489

The factor loading for the first extracted factor is between 0.666 (item 8 – Artificial Intelligence can have positive impacts on people’s wellbeing) and 0.779 (item 2 – There are many beneficial applications of Artificial Intelligence). Factor 2 has a factor loading between 0.471 (item 12 – For routine transactions, I would rather interact with an artificially intelligent system than with a human) and 0.772 (item 6 – An artificially intelligent agent would be better than an employee in many routine jobs), and factor 3 regarding negative attitudes has a factor loading between 0.310 (item 19 – I think artificially intelligent systems make many errors) and 0.792 (item 16 – Artificial Intelligence is used to spy on people). In conclusion, Hypothesis 1, which predicted a two-dimensional structure of the scale (positive and negative attitudes), is not supported by the data obtained from EFA and CFA.

4.3. *Gender invariance*

Next, gender invariance was performed for the respective group. The values of the scores for ΔCFI and $\Delta RMSEA$ are below the critical thresholds of 0.010, which suggests that invariance can be accepted. The model fit indices were all within an

acceptable range, with all ΔCFI and $\Delta RMSEA$ values less than 0.010 and 0.015, respectively, suggesting a stable and comparable factorial structure across genders (Table no 3).

Table no 3.
The gender invariance for GAAIS

Models	Indices					Comparative Fit Indices	
	χ^2	df	χ^2/df	CFI	RMSEA	ΔCFI	$\Delta RMSEA$
Configural	472.293	282	1.67	0.944	0.055 [0.046-0.061]	–	–
Metric	482381	298	1.61	0.946	0.052 [0.044-0.061]	-0.002	0.003
Scalar	503660	314	1.60	0.944	0.052 [0.043-0.060]	0.000	0.000
Strict	555649	341	1.62	0.937	0.053 [0.044-0.061]	0.007	0.003

4.4. Descriptive analysis

The descriptive statistics of the items are presented in Table 4. The highest mean scores are for items 2 ($M=4.043$; $SD=0.98$) and 7 ($M=4.016$; $SD=1.04$).

The distributions of the responses do not suggest major deviations from normality. Regarding the corrected item-total correlation, all items are above the recommended minimum value of 0.40 (Wang, 2003) except for item 19 (0.389) which is a borderline value and may require revision. Alpha if an item is deleted has values between 0.680 and 0.875, confirming good internal consistency.

4.5. Gender differences

Gender differences are not the main focus of the study. In line with previous studies, we found that male respondents are more likely to express positive attitudes towards AI compared to females (Sinderman *et al.*, 2021; Park and Woo, 2022; Méndez-Suárez *et al.*, 2024). Table no 5 reveals that the perception of the benefits of AI is similar between genders.

The perception of the superiority of AI (vs. human intelligence) is higher in males than in females, which may reflect a more technophilic attitude or a greater trust in the power of technology. Negative attitudes (e.g., fear, distrust, anxiety) are present in both groups in a balanced way.

Table no 4.
The descriptive statistics of the items

Items	M	SD	Min.- Max.	Skewness	Kurtosis	α if item deleted	Corrected item- total correlation
1	3.583	1.14	1-5	-0.468	-0.439	0.868	0.720
2	4.043	0.98	1-5	-0.928	0.461	0.866	0.750
3	3.659	1.09	1-5	-0.453	-0.457	0.868	0.718
4	3.759	1.10	1-5	-0.698	-0.112	0.874	0.668
5	3.497	1.28	1-5	-0.507	-0.801	0.875	0.675
6	2.679	1.26	1-5	0.322	-0.880	0.657	0.577
7	4.016	1.04	1-5	-0.988	0.546	0.881	0.608
8	3.374	1.08	1-5	-0.181	-0.526	0.875	0.661
9	2.891	1.24	1-5	0.084	-0.907	0.686	0.527
10	2.782	1.18	1-5	0.138	-0.735	0.680	0.539
12	2.686	1.30	1-5	0.256	-1.013	0.705	0.510
13	2.989	1.24	1-5	-0.019	-0.879	0.816	0.474
14	2.882	1.07	1-5	-0.028	-0.366	0.820	0.441

15	3.186	1.28	1-5	-0.088	-0.998	0.791	0.659
16	3.083	1.26	1-5	0.029	-0.952	0.802	0.578
17	3.338	1.36	1-5	-0.275	-1.064	0.795	0.627
18	3.167	1.35	1-5	-0.072	-1.175	0.794	0.634
19	2.786	1.11	1-5	0.073	-0.606	0.826	0.389
20	3.062	1.25	1-5	-0.036	-0.936	0.802	0.583

Note: M-Mean; *SD*-Standard deviation; item 11 has been removed

Table no 5.

Gender differences

Variables	males		females		t	p
	M	SD	M	SD		
Positive attitudes (benefits)	3.75	0.89	3.66	0.82	1.165	0.245
Positive attitudes (superiority)	2.88	0.98	2.65	0.92	2.784	0.006
Negative attitudes	3.53	0.96	3.46	0.95	0.827	0.409

4.6. Reliability

All three factors highlight good internal consistency, with α and ω values above 0.742, which confirms Hypothesis 2 which predicted good internal consistency. Inter-item correlations were within acceptable ranges, supporting item homogeneity

without indicating significant redundancy (Table no 6).

Table no 6.

Internal consistency, averages, standard deviations and correlations

Factors	M*	SD	α [95%CI]	ω [95%CI]	Range interitem correlation
F1	3.705	0.858	0.889[0.873-0.903]	0.890[0.875-0.905]	0.425-0.669
F2	2.759	0.940	0.742 [0.701-0.777]	0.742[0.705-0.780]	0.383-0.475
F3	3.499	0.958	0.826[0.802-0.848]	0.833[0.810-0.855]	0.260-0.595

*The total score obtained for every scale was divided by the number of scale items

4.7. Convergent and discriminant validity

The results regarding the convergent validity indicate satisfactory values for all three factors: the composite reliability (CR) coefficient exceeds the recommended threshold of 0.70, and the average variance extracted (AVE) is acceptable, even if marginal in the case of factor 1. According to Malhotra and Dash (2011), an AVE value below 0.50 is not necessarily a major problem if the CR is >0.70). The discriminant validity, assessed by HTMT, was also confirmed, with all values being below the conservative threshold of 0.85. These results support the adequacy of the factorial structure and the conceptual distinction between the dimensions of the adapted scale (Table no 7).

Table no 7.

Convergent and discriminant validity					
Factors			Heterotrait-monotrait ratio		
	CR	AVE	1	2	3
F1	0.831	0.497	-		
F2	0.825	0.551	0.756	-	
F3	0.921	0.627	0.373	0.301	-

5. DISCUSSION

The main purpose of this study was the structural and psychometric validation of the Romanian-adapted version of the General Attitudes towards Artificial Intelligence Scale (GAAIS). To ensure the validity of the responses, the standard cross-cultural adaptation was employed, including translation and back-translation by bilingual expert translators, comprehensibility assessment through a pilot study, as well as the clear and neutral formulation of items. In addition, a mixed presentation of both positive and negative items was adopted to reduce response bias and enhance content validity. EFA and CFA established construct validity, and convergent and discriminant validity were also statistically confirmed by the CR, AVE, and HTMT coefficients, which were also within the specified limits (Hair *et al.*, 2019).

The use of both EFA and CFA provided comprehensive empirical support for the scale's three-factorial structure. Unlike previous studies that identified a bi-dimensional structure (Schepman and Rodway, 2020, 2022; Kaya *et al.*, 2024), the present study highlights a three-dimensional structure. In the present study, the factor corresponding to positive attitudes was split into two subfactors, one focused on the benefits of AI, and the other on the adoption of AI due to its superiority over human intelligence. This factor includes 4 items (items 6, 9, 10, 12). The identification of this distinct factor related to the benefits of AI aligns with the Technology Acceptance Model (Davis *et al.*, 1989; Aldraiweesh and Alturki, 2025), which posits that perceived usefulness is fundamental to developing favorable attitudes toward technology adoption. When users believe that AI will enhance their performance or provide significant benefits, they are more likely to develop favorable attitudes towards its adoption. The third factor, corresponding to negative attitudes, remains unchanged from the original structure in terms of the items included. Item 11 (Much of society will benefit from a future full of Artificial Intelligence) was eliminated. This decision is justified by its significant loading on several factors, thus affecting dimensional clarity. In two other previous validations, item 11 obtained moderate factor loading (0.49 – Schepman and Rodway, 2020) and 0.50 (Kaya *et al.*, 2024) in comparison to the other items. However, in another context, the respective item has a factor loading of 0.836 (Schepman and Rodway, 2022). Also, in the original study (Schepman and Rodway, 2020), items 9 (Artificially intelligent systems can help people feel happier) and 10 (Artificially intelligent systems can perform better than humans) have moderate factor loadings (0.494). In the case of EFA, the items' factor loadings are higher than the values obtained in previous studies by Schepman and Rodway (2022) and Kaya *et al.* (2024). In comparison, the loading values in previous studies range between 0.47–0.78 for positive attitudes and 0.41–0.76 for negative ones, which confirms the general consistency of the structure (Schepman and Rodway, 2022). For the Turkish version, the estimates are 0.40–0.71 for

positive GAAIS and 0.41–0.72 for negative GAAIS (Kaya *et al.*, 2024). Another item whose potential needs to be reviewed is item 19 due to the marginally corrected item-total correlation.

In the process of testing gender invariance, all indicators (ΔCFI and $\Delta RMSEA$) were below the critical thresholds (<0.01), supporting the configural, metric, scalar and strict equivalence of the scale across genders. Thus, the factorial structure is robust and comparable across the analysed subgroups.

High scores for items such as „Artificial Intelligence can provide new economic opportunities for this country” ($M=3.759$, $SD=1.10$) suggest a positive perception of AI regarding its role in improving work efficiency. The presence of negative attitudes (e.g., „Artificial Intelligence might take control of people”) indicates the existence of fears regarding loss of control and the ethics of AI use in organisations. This ambivalence regarding AI suggests that it is perceived simultaneously as a facilitator of progress, but also as a source of vulnerability.

The results obtained support both the internal consistency and the convergent and discriminant validity of the three factors identified in the present study: positive attitudes towards the benefits of AI (F1), perception of AI superiority (F2) and negative attitudes (F3). The internal reliability analysis indicated high values of the α and ω coefficients for all three factors, ranging between 0.742 and 0.890, which demonstrates a good internal consistency of the scale. In particular, the factor capturing positive attitudes towards the benefits of AI recorded the highest mean scores and high-reliability coefficients, suggesting a clear and homogeneous representation of this dimension.

Convergent validity was supported by CR and AVE values, which were above the minimum recommended thresholds ($CR>0.70$; $AVE>0.50$). Discriminant validity was confirmed by HTMT values, all below 0.85, indicating adequate differentiation between the three dimensions.

Regarding gender differences, only the factor „perception of AI superiority” yielded significantly higher scores among men, suggesting greater openness to AI. This result is in line with other research (Zawacki-Richter *et al.*, 2019; Kovačević and Demić, 2024), which identified that men have a higher interest in emerging technologies, even if the level of knowledge and general attitudes remain similar between genders. Along the same lines, other studies have demonstrated more accepting attitudes in men than in women in the general adult population (Park and Woo, 2022). However, some studies have indicated that, among university students, there was no statistically significant difference in attitudes toward AI between males and females (Haja and Gahir, 2024; Vo and Nguyen, 2024), suggesting that these attitudes, for students, actually depend on their experience with artificial intelligence (Sun and Zhou, 2024).

Limitations of the study: One limitation is that concurrent validity was not assessed. It would have been important to associate the GAAIS with other instruments that measure motivations, attitudes, and values toward AI. Future research could consider associating the GAAIS with other scales assessing attitudes toward AI, such as the five-item Attitude Towards Artificial Intelligence (ATAI) scale, which comprises negatively associated factors assessing (1) acceptance and (2) fear of artificial intelligence (Sinderman *et al.*, 2021). It can also be correlated with motivation scales of using AI (e.g., the Questionnaire of AI Use Motives – QAIUM; Yurt and Kasarci, 2024). Such associations may contribute to understanding how attitudes toward AI influence technology acceptance in educational, occupational, or clinical contexts. It would also be useful in the future

to investigate criterion validity by correlating GAAIS scores with concrete behaviors related to AI use (e.g., frequency of use of chatbots, AI-based educational platforms, or medically assisted diagnostic tools). This approach would allow for a better understanding of how stated attitudes translate into actual behaviors. Also, it is important to further explore how specific categories of tasks (e.g., creative, repetitive, interpersonal) affect people's acceptance or rejection of AI, as this may have significant implications for technology integration across various domains. Additionally, stability over time was not experimentally verified for the current study through test-retest validity. Future longitudinal studies are recommended to assess the stability of responses over time, especially considering how rapidly AI technologies are evolving and how easily public opinion can fluctuate. The factor structure is robustly supported by psychometric analyses, especially EFA and CFA, although the design precludes any conclusion of causality or temporal stability. Also as a future direction, replication of the study with other samples of respondents is required. Finally, we also mention the need for qualitative research to deepen the nuances of the factor of „superiority of AI over human intelligence” in the Romanian context.

6. CONCLUSIONS

According to the comprehensive content and construct validity results obtained, the three factors GAAIS is a valid instrument for Romanian adults. The finding of three factors instead of two suggests that the structure of attitudes toward AI is more complex than previously thought. Thus, the original model may require conceptual reassessment, especially in cultural contexts different from the one in which it was developed. Second, the role of perceived AI superiority as a distinct dimension requires some discussion. This dimension highlights a more radical line of thinking that deserves investigation as a potential predictor of automatic technology adoption behaviors or even uncritical trust in AI. The differences from previous validation studies of the GAAIS in the UK and Turkey highlight the fact that perceptions of AI are culturally influenced, and the validation of the GAAIS in other languages must take these nuances into account. The result obtained allows us to conclude that the scale can be used to assess the readiness of employees to work with AI systems, and to personalize familiarization interventions with new technologies. GAAIS can provide indications of how open employees are and what reservations and fears they have about adopting AI. In education, the instrument can support the assessment of the openness of students or teachers to the integration of AI in the teaching process. In organisations, the study's findings can inform the design of more user-friendly and acceptable AI interfaces. By understanding the factors that drive positive and negative attitudes, designers can create systems that enhance user experience and foster trust. Emphasis should be placed on clearly communicating the benefits of AI and designing systems that promote a sense of user control, thereby alleviating anxieties about perceived AI dominance. Further research could investigate how attitudes toward AI vary across application domains and task types, providing insights into optimizing AI integration in specific contexts. A more comprehensive picture of the barriers and facilitators to AI adoption in various fields, especially in education and research, would also include the ethical dimension of AI usage. Therefore, we propose the use of validated tools (for example, the AI Assessment Scale developed by Perkins *et al.*, 2023) or the development of subscales that explicitly evaluate perceptions and ethical concerns regarding AI, in line with ethical integration policies from

universities (Dabis and Csáki, 2024) and the ethical perceptions of students (Mumtaz *et al.*, 2024). The integration of subscales that evaluate aspects such as privacy and data protection, algorithm transparency, responsible AI use, or decision-making autonomy could provide more complex results and useful guidelines regarding the adoption and rejection of AI in different fields.

Received: 5.06.2025

REFERENCES

1. ADAMS, J. E., HIGHHOUSE, S., ZICKAR, M. J., *Understanding general distrust of corporations*, Corporate Reputation Review, **13**, 1, 2010, p. 38–51. <https://doi.org/10.1057/crr.2010.6>
2. ALDRAIWEESH, A.A., ALTURKI, U., The Influence of Social Support Theory on AI Acceptance: Examining Educational Support and Perceived Usefulness using SEM analysis, IEE Access, **13**, 2025, p. 18366–18385. DOI 10.1109/ACCESS.2025.3534099
3. ANDRONICEANU, A., *Generative artificial intelligence, present and perspectives in public administration*, Administrație și Management Public, **43**, 2024, p. 105–119. <https://doi.org/10.24818/amp/2024.43-06>
4. ARSLAN, A., COOPER, C., KHAN, Z., GOLGECI, I., ALI, I., *Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies*, International Journal of Manpower, **43**, 1, 2022, p. 75–88. <https://doi.org/10.1108/IJM-01-2021-0052>
5. BROWN, T.A., *Confirmatory factor analysis for applied research*, 2nd ed., New York, The Guilford Press, 2015.
6. COMREY, A.L., LEE, H.B., *A first course in factor analysis*, 2nd ed., New York, Psychology Press, 2013. <https://doi.org/10.4324/9781315827506>
7. CHIN W.W., *How to write up and report PLS analyses* in ESPOSITO VINZI, V., CHIN, W., HENSELER, J., WANG, H. (eds.), *Handbook of Partial Least Squares*, Berlin, Springer, 2010, p. 655–690.
8. DABIS, A., CSÁKI, C., *AI and ethics: Investigating the first policy responses of higher education institutions to the challenge of generative AI*, Humanities and Social Sciences Communications, **11**, 2024, 1006. <https://doi.org/10.1057/s41599-024-03526-z>
9. DAVIS, F.D., BAGOZZI, R.P., WARSHAW, P.R., *User acceptance of computer technology: A comparison of two theoretical models*, Management Science, **35**, 8, 1989, p. 982–1003.
10. DELOITTE REPORT, *The State of Generative AI in the Enterprise*, 2024, <https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-generative-ai-in-enterprise.html>
11. De VELLIS, R., THORPE, C., *Scale development: Theory and applications*, Sage Publications, Thousand Oaks, 2021.
12. DWIVEDI, Y.K., SHARMA, A., RANA, N.P., GIANNAKIS, M., GOEL, P., et al., *Evolution of artificial intelligence research in technological forecasting and social change: Research topics, trends, and future directions*, Technological Forecasting and Social Change, **192**, 2023, 122579. <https://doi.org/10.1016/j.techfore.2023.122579>
13. FITZEK, S., *Ethical challenges and transformative potential: examining the impact of artificial intelligence on patient care, data security, and the healthcare workforce in Romania*, Journal of Community Positive Practices, **1**, 2024, p. 59–85. DOI: <https://doi.org/10.35782/JCPP.2024.1.04>
14. GOLGECI, I., RITALA, P., ARSLAN, A., MCKENNA, B., ALI, I., *Confronting and alleviating AI resistance in the workplace: An integrative review and a process*

- framework, *Human Resource Management Review*, **35**, 2, 2025, 101075. <https://doi.org/10.1016/j.hrmr.2024.101075>
15. GUDMUNDSSON, E., *Guidelines for translating and adapting psychological instruments*, *Nordic Psychology*, **61**, 2009, p. 29–45. <http://dx.doi.org/10.1027/1901-2276.61.2.29>
 16. GUPTA, R.D., BISWAS, D., RONTY, A.P., KAPALI, S., KHAN S.M., *Empowering digital transformation: the strategic role of Artificial Intelligence in enterprise innovation*, *European Journal of Theoretical and Applied Sciences*, **2**, 6, 2024, p. 210–218. [https://doi.org/10.59324/ejtas.2024.2\(6\).16](https://doi.org/10.59324/ejtas.2024.2(6).16)
 17. HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, R.E., *Multivariate data analysis*, 8th ed. Essex: Pearson Education Limited, 2019.
 18. HUANG, A.Y., LU, O.H., YANG, S.J., *Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom*, *Computers & Education*, **194**, 2023, 104684, <https://doi.org/10.1016/j.compedu.2022.104684>
 19. HARTWIG, B., *Benefits of Artificial Intelligence*. Hackr.io. 2021, Retrieved at: <https://hackr.io/blog/benefits-ofartificial-intelligence> (accessed on 12 April 2024).
 20. INTERNATIONAL TEST COMMISSION, *The ITC guidelines for translating and adapting tests (Second edition)*, 2017, Retrieved at: https://www.intestcom.org/files/guideline_test_adaptation_2ed.pdf
 21. IUGA, M., BRAD, S., *Adoption of artificial intelligence in Romania: Innovative policies to overpass vulnerabilities with TRIZ and deep-thinking tools*, In: NOWAK, R., CHRZĄSZCZ, J., BRAD, S. (eds.), *Systematic Innovation Partnerships with Artificial Intelligence and Information Technology*. TFC 2022. IFIP Advances in Information and Communication Technology, **655**, Springer, Cham. https://doi.org/10.1007/978-3-031-17288-5_26
 22. JUSSUPOW, E., SPOHRER, K., HEINZL, A., GAWLITZA, J., *Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence*, *Information Systems Journal*, **32**, 3, 2012, p. 394–432. <https://doi.org/10.1287/isre.2020.0980>
 23. KOVAČEVIĆ A., DEMIĆ E., *The Impact of Gender, Seniority, Knowledge, and Interest on Attitudes to Artificial Intelligence*, in *IEEE Access*, 12, 2024, p. 129765–129775. doi: 10.1109/ACCESS.2024.3454801.
 24. LAM, S. Y., CHIANG, J., PARASURAMAN, A., *The effects of the dimensions of technology readiness on technology acceptance: An empirical analysis*, *Journal of Interactive Marketing*, **22**, 4, 2008, p. 19–39. <https://doi.org/10.1002/dir.20119>
 25. LICHTENTHALER, U., *Extremes of acceptance: employee attitudes toward artificial intelligence*, *Journal of Business Strategy*, **41**, 5, 2020, p. 39–45. <https://doi.org/10.1108/JBS-12-2018-0204>
 26. MAH, D.K., GROß, N., *Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs*, *International Journal of Educational Technology in Higher Education*, **21**, 58, 2024. <https://doi.org/10.1186/s41239-024-00490-1>
 27. MALHOTRA, N.K., DASH, S., *Marketing research an applied orientation*, London, Pearson Publishing, 2011.
 28. MÉNDEZ-SUÁREZ, M., DELBELLO, L., DE VEGA DE UNCETA, A., ORTEGA LARREA, A.L., *Factors affecting consumers' attitudes towards Artificial Intelligence*, *Journal of Promotion Management*, **30**, 7, 2024, p. 1141–1158. <https://doi.org/10.1080/10496491.2024.2367203>
 29. MUMTAZ, S., CARMICHAEL, J., WEISS, M., NIMON-PETERS, A., *Ethical use of artificial intelligence-based tools in higher education: are future business leaders ready?*, *Education and Information Technology*, **30**, 2025, p. 7293–7319. <https://doi.org/10.1007/s10639-024-13099-8>
 30. NOUREDDINE, D., MALAEB, S., EL KHATIB, M., DABBOUS, M., SAKR, F., ALI, A.M., et al., *Psychometric properties of an Arabic translation of the 13-item*

- short mood and feelings questionnaire- parent version (SMFQ-P) to screen for depression in children*, BMC Psychiatry, **25**, 1, 2025, 2. <https://doi.org/10.1186/s12888-024-06433-4>
31. PARK, J., WOO, S.E., *Who likes artificial intelligence? Personality predictors of attitudes toward artificial intelligence*, The Journal of Psychology, **156**, 1, 2022, p. 68–94. <https://doi.org/10.1080/00223980.2021.2012109>
 32. PERKINS, M., FURZE, L., ROE, J., MACVAUGH, J., *The Artificial Intelligence Assessment Scale (AIAS): A framework for ethical integration of generative AI in educational assessment*, Journal of University Teaching and Learning Practice, **21**, 6, 2024. <https://doi.org/10.53761/q3azde36>
 33. PERRYMAN, D., *Embracing AI in the Workplace*, 2024, Retrieved at: <https://news.hr.ncsu.edu/2024/07/embracing-ai-in-the-workplace/>
 34. RADHAKRISHNAN, J., GUPTA, S., PRASHAR, S., *Understanding organisations' Artificial Intelligence journey: A qualitative approach*, Pacific Asia Journal of the Association for Information Systems, **14**, 6, 2022, p. 43–77. DOI: 10.17705/1pais.14602
 35. SCHEPMAN, A., RODWAY, P., *Initial validation of the general attitudes towards Artificial Intelligence Scale*, Computers in Human Behavior Reports, **1**, 2020, 100014. <https://doi.org/10.1016/j.chbr.2020.100014>
 36. SCHEPMAN, A., RODWAY, P., *The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory validation and associations with personality, corporate distrust, and general trust*, International Journal of Human–Computer Interaction, 2022, p. 1–18. <https://doi.org/10.1080/10447318.2022.2085400>
 37. SCHERMELLEH-ENGEL, K., MOOSBRUGGER, H., MÜLLER, H., *Evaluating the fit of structural equation models: tests of significance and descriptive goodness-of-fit measures*, MPR-Online, **8**, 2003, p.23–74. Retrieved at https://www.stats.ox.ac.uk/~snijders/mpr_Schermelleh.pdf
 38. SCHUMACKER, R.E., LOMAX, R.G., *A beginner's guide to structural equation modeling*, 4th Ed., New York, Taylor & Francis, 2016.
 39. SINDERMAN, C., SHA, P., ZHOU, M., WERNICKE, J., SCHMITT, H.S., LI, M., et al., *Assessing the attitude towards artificial intelligence: Introduction of a short measure in German, Chinese, and English language*, Künstliche Intelligenz, **35**, 2021, p. 109–118, <https://doi.org/10.1007/s13218-020-00689-0>
 40. STRATEGIA NAȚIONALĂ ÎN DOMENIUL INTELIGENȚEI ARTIFICIALE 2024-2027 [National Strategy in the Field of Artificial Intelligence 2024-2027], Retrieved at: <https://www.adr.gov.ro/wp-content/uploads/2024/03/Strategie-Inteligenta-Artificiala-22012024-1.pdf>
 41. SUN, L., ZHOU, L., *Generative artificial intelligence attitude analysis of undergraduate students and their precise improvement strategies: A differential analysis of multifactorial influences*, Education and Information Technology, 2024. <https://doi.org/10.1007/s10639-024-13236-3>
 42. TABACHNICK, B.G., FIDELL, L.S., *Using multivariate statistics*, 6th ed. Boston, Pearson, 2013.
 43. TING, H., MEMON, M.A., THURASAMY, R., CHEAH, J.H., *Snowball sampling: A review and guidelines for survey research*, Asian Journal of Business Research, **15**, 1, 2025. <https://doi.org/10.14707/ajbr.250186>
 44. TRIBERTI, S., DI FUCCIO, R., SCUOTTO, C., MARSICO, E., LIMONE, P., *„Better than my professor?” How to develop artificial intelligence tools for higher education*, Frontiers in Artificial Intelligence, **7**, 2024, 329605. <https://doi.org/10.3389/frai.2024.1329605>
 45. VO, A., NGUYEN, H., *Generative artificial intelligence and ChatGPT in language learning: EFL students' perceptions of technology acceptance*, Journal of University Teaching and Learning Practice, **21**, 6, 2024, p. 199–218. <https://doi.org/10.53761/fr1rkj58>

46. VRONTIS, D., CHRISTOFI, M., PEREIRA, V., TARBA, S., MAKRIDES, A., TRICHINA, E., *Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review*, The International Journal of Human Resource Management, **32**, 6, 2022, p. 1237–1266.
47. WANG, Y.S., *Assessment of learner satisfaction with asynchronous electronic learning systems*, Information & Management, **41**, 1, 2003, p. 75–86. [https://doi.org/10.1016/S0378-7206\(03\)00028-4](https://doi.org/10.1016/S0378-7206(03)00028-4)
48. YURT, E., KASARCI, I., *A questionnaire of Artificial Intelligence use motives: A contribution to investigating the connection between AI and motivation*, International Journal of Technology in Education (IJTE), **7**, 2, 2024, p. 308–325. <https://doi.org/10.46328/ijte.72>
49. ZAWACKI-RICHTER, O., MARÍN, V.I., BOND, M., GOUVERNEUR, F., *Systematic review of research on artificial intelligence applications in higher education – where are the educators?*, International Journal of Educational Technology in Higher Education, **16**, 2019, 39. <https://doi.org/10.1186/s41239-019-0171-0>