UDC: 378.091.279.7:004.8
Professional paper

EVALUATION OF THE SCALE FOR THE ASSESSMENT OF THE ATTITUDE AND PERCEPTION OF ARTIFICIAL INTELLIGENCE IN THE STUDENT POPULATION

Qufli OSMANI[1],Teuta IDRIZI[1], Fjolla VESELI[1]

[1]*UT-University of Tetova, Faculty of Philosophy*
qufli.osmani@unite.edu.mk t.idrizi210216@unite.edu.mk, f.veseli210316@unite.edu.mk

Abstract

This study aimed to develop and validate an indigenous assessment unit for measuring AI attitude and perception, focusing on its psychometric properties. The presented results are from the first study, conducted in three phases. In Phase I, internal consistency and dimensionality of the construct were assessed using a sample of 474 students (381 girls and 95 boys) aged 18-28 years, selected through convenience sampling. Exploratory factor analysis (EFA) was employed, generating items for the AI attitude and perception scale based on a 5-point Likert scale. In Phase II, the factor structure from Phase I was confirmed through structural equation modeling, yielding a 12-factor structure with 65.87% explanatory variance. Phase III established the scale's convergent validity by correlating its items with those of a predefined scale (SPAI). The final scale comprised 34 items across 5 discriminative factors, demonstrating robust psychometric properties. This scale is a significant tool for assessing AI attitudes and perceptions, particularly among student

Keywords: Artificial Intelligence, Humanoid Intelligence, perception, attitudes

1. Introduction

The AI perspective goes beyond the current design framework. It is predicted to become more and more widespread as the technology develops, revolutionizing various sectors such as healthcare, education, various professions and transportation.
AI and the field of energy fusion, Helion, PC and communication intership are just some of the fields in which, according to company leaders and AI researchers, AI increasingly finds prominent applicability. The spectrum of the fusion of AI and the need for AI made researchers from different fields (not only those of IT, but also psychologists, neuroscientists, etc.) turn this "process" into a "need for need". AI turns the future into the present and vice versa. The ever-increasing applicability of AI in domains that were previously unimaginable prompts different attitudes among the wider mass. Therefore, the aim of the authors was to operationalize the personal attitude towards what IA predicts today, respectively to develop a questionnaire on the attitude and individual perception about IA.

1.1. Artificial Intelligence: The theoretical definition is important not only for the correct understanding of the notion but first of all for the process of its operationalization itself. In this context, the consulted literature highlighted some definitions and settings of AI. The cultural dimensions theory on artificial intelligence (AI) defines it as the ability of a system to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation. According to the theory, AI is categorized into: analytical, human-inspired and humanized. While analytical AI possesses characteristics that match only cognitive intelligence, artificial, human-inspired AI has elements such as cognitive as well as emotional intelligence. Humanized AI in the context of competence is defined as multidimensional competence (i.e., because it simultaneously incorporates elements of

https://doi.org/10.62792/ut.philosophica.v11.i22-23.p2731

cognitive, emotional and social intelligence) with which it is able to be aware in its interactions. According theory AI was followed by several "summers" and "winters", metaphorically alluding to AI's later ups and downs Andreas&Haenlein, 2019).
Relevant research on AI is numerous as is the applicability of AI itself in many domains and spheres. Such is the study of artificial emotional intelligence in the field of health care. Today's emotional AI uses an integrated approach to cognitive elements, synthesizes them with programming skills in a very clear way to detect emotions in human beings including fear, disgust, happiness, sadness, surprise and even neutrality. The capabilities of emotional AI go beyond those of humans, to the extent that microprojectors are able to detect micro-expressions that are difficult to notice with the human eye. Predictions are that emotional AI has the health care sector to flourish. Another area of its application is "sensing" to observe the cardiac status (heart rate and breathing) of a person non-invasively, using devices such as cameras. Emotional AI can be used in the diagnosis and prognosis of disorders such as anxiety, major depression, bipolar disorders, and autism. (Ahuja, 2023)
Philosopher John Haugeland (1985) falls into the Human/Reasoning quadrant when he says that AI is "*The exciting new attempt to make computers think ... machines with minds, in the full and literal sense*" (Haugeland, 1985). By far, this is the quadrant most popular narratives assert and explore. The recent television series Westworld is a powerful case in point.) Luger and Stubblefield seem to fall into the Ideal/Act quadrant when they point out that: "*the branch of computer science dealing with the automation of intelligent behavior*" (Stubblefield, 1993) The Human/Act position is mostly occupied by Turing, whose test is passed only by those systems that are able to act sufficiently like a human.
Russell sees AI as a field dedicated to building intelligent agents, which are functions that receive as input bundles of perceptions from the external environment and produce behaviors (actions) based on these perceptions.
John McCarthy defined the term "artificial intelligence" as "*the science and engineering of creating intelligent machines*" (McCarthy at all, 2022). Alan Turing, who wrote "Computing Machinery and Intelligence" in 1950, discussed the conditions under which a machine can be considered intelligent (Turing, 1950). Today, AI is commonly used to facilitate early disease detection, understand disease progression, optimize drug selection and dosing, and discover new treatments. (Topol, 2019)
Artificial Intelligence (AI), is the ability of a digital computer or computer-controlled robot to perform tasks normally associated with intelligent beings. The term is often used for the project of developing systems equipped with intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize, or learn from past experience. (Copeland, n.d.)
The expansion of the capacities and possibilities of AI, then the ever-increasing applicability of AI in domains that were previously "science fiction" produce varying degrees of perceptions and expectations about AI. The spectrum of attitudes moves from one extreme to the other, from a positive attitude towards AI to a negative one, perceiving AI as a serious threat to jobs.

1.2.Attitudes: In the Cambridge Dictionary, attitudes are defined as "*a feeling or opinion about something or someone, or a way of behaving that is caused by...*" phenomena, things, processes, various beings, etc.
The American Psychological Association (APA) defines attitude as "*a relatively stable and general evaluation of an object, person, group, issue, or concept on a dimension ranging from negative to positive.*" Attitudes provide summary evaluations of target objects and are often assumed to derive from specific beliefs, emotions, and past behaviors associated with those objects. (Anon., 2018)

A definition similar to APA is given by the authors Bohner and Wanke , an attitude "*is a summary evaluation of an object of thought. An object of attitude can be anything that a person discriminates or holds in mind." Attitudes include beliefs (cognition), emotional responses (affect) and behavioral tendencies (goals, motivations)* (Wanke, 2011)
Attitudes can be changed through persuasion, and an important area of research on attitude change focuses on responses to communication. Experimental research on factors that can influence the persuasiveness of a message includes:

a. Target characteristics such as intelligence, self-confidence, self-esteem (Rhodes&Wood, 1992)
b. Source characteristics: such as expertise, credibility, and interpersonal attraction or attractiveness. (Weiss, 1951)
c. Message characteristics: The nature of the message plays a role in persuasion (Petty&Cacioppo, 1984)

In the psychometric context it is important to know about the consistency of the variable. Regarding attitudes, information on the stability of attitudes depends on the consulted literature. In this context, in the classical definitions of the earliest dates, an attitude is stable, while in more contemporary conceptualizations, attitudes can change depending on situations, context or mood (Bohner&Wanke, 2011).

1.2.1.Measuring attitudes : A Likert scale assesses the degree of agreement or disagreement with a series of belief statements (Bohner & Wanke, 2011). The Guttman scale focuses on items that differ in their degree of psychological difficulty. The semantic differential uses bipolar adjectives to measure meaning associated with attitude objects. The three scales in question can often be combined or supplemented with indirect indicators such as standard non-imposing, physiological or neuroscientific measures (Krosnick, 2005). Following the explicit-implicit bipolar categorization, attitudes can are examined through direct and indirect measures.

a. Explicit or direct. Explicit indicators rely on self-reports or easily observed behaviors and typically include bipolar scales (eg, good-bad, agree-disagree, etc.) (Olson & Zanna, 1993). Explicit attitudes are formed through mental associations during socialization through the accumulation of early experiences. Once formed, these associations are very strong and resistant to change, as well as stable both across contexts and over time. Therefore, in the psychometric context, the influence of "contextual influences", can produce an ambiguous assessment of a person's "true" and stable evaluative disposition, as well as limit the capacity to predict subsequent behavior (Buhrmester, 2011),
b. Implicit. Implicit attitudes are automatic and not consciously directed, which makes them more valid and reliable indicators than explicit attitudes. For example, people are motivated to develop attitudes that in a social context are desirable by that society itself. An example of this is that people may hold implicit prejudiced attitudes but express explicit attitudes that report little prejudice. Implicit attitudes help evaluate these situations and report on attitudes that a person may not be aware of or wish to share (Whitley, 2010). Therefore, implicit indicators usually rely on an indirect measure of attitude eg the Implicit Associations Test (IAT). Over the past few decades, scientists have developed new measures to identify these unconscious biases (Sekaquaptewa, 2003)

1.3. Measuring AI: To develop the scale items, we drew heavily on recent literature on the topic of AI perception and attitude. The literature review enabled us to identify key themes and previous attempts to create similar scales. It was found that experts, the public and the media all expressed positive and negative views of AI ((Fast & Horvitz, 2017); (Cave, et al., 2019). Large-scale surveys confirmed these mixed perspectives and reflected similar major themes

(Zhang & Dafoe, 2019). Negative attitudes towards AI included concerns about potential job losses (Chui, et al., 2016); Fray & Osborne, 2017), ethical issues (Morley, et al., 2020) and non-transparent decision-making, while positive attitudes focused on the potential of AI to improve efficiency, economy as well as to provide innovative solutions in different fields.
Although there are instruments that assess people's acceptance of technology (eg, The Technology Acceptance construct, developed by Davis (1989), most of them do not specifically address AI. The scale in question (Davis, 1989) and similar (The Technology Readiness Index - TRI, developed by (Parasuraman & Colby, 2015) primarily emphasize a user's readiness to adopt technology through consumer choice. Other existing instruments tend to be lengthy, context-specific, or lack empirical validation. Furthermore, most questionnaires designed to assess technology attitudes and acceptance (Rosen, et al., 2013) have not been specifically developed and validated. considering modern consumer-oriented AI systems such as OpenAI, ChatGPT or text-to-image AI services.
The recently reviewed literature (after 2020) ensures that few scales have been developed specifically with the aim of assessing attitudes towards AI. Schepman and Rodway (2020) presented the General Attitudes Toward Artificial Intelligence Scale (GAISS), a 20-item scale with a two-factor structure (positive and negative attitudes toward AI: opportunities, benefits, and positive emotions toward AI, and this last worries and negative emotions about AI). Sindermann et al. (2021) proposed a concise 5-item scale, the Artificial Intelligence Attitude Scale (ATAI), which presents a two-factor structure (acceptance and fear). The Threat of Artificial Intelligent Scale TAI; (Kieslich, et al., 2021) was developed to specifically assess fear of AI technology. However, the scales in question are associated with challenges regarding their practicality and potential use in the context of assessing general attitudes towards AI.

2. Methodology

2.1 The purpose and tasks of the research: The purpose of the research is to develop questionnaires. In the realization of the purpose of the research, several tasks were set, including that of:

1. To develop a scale on the attitude and perception of Artificial Intelligence.
2. To determine the preliminary metric characteristics of the newly formed scale.
3. To explore and observe the importance of Artificial Intelligence as an innovative research field in psychology by defining the importance of AI as a growing and common "artificial-practical" construct for developing societies.

2.2 Sample: The sample consisted of 474 subjects from North Macedonia and Kosovo, all students of social sciences. The study was conducted in November 2023. Statistical significance testing was conducted at the 99% and 95% levels of confidence. All comparative claims made in this report are statistically significant. Demographic sub-groups of adults are defined below: Gender: Male (n=93); Female (n=381), Cultural subsamples n=474 (missing 19 subjects): North Macedonia (n=170) Kosovo (n=304).

2.3 Instrument- Preparation of Test Questions: In the development phase of the terms, a wide range of divergent terms was developed, reflecting the manifestations of perception towards artificial intelligence. It was important that the statements refer to the perception of AI in general terms, avoiding as much as possible the naming of specific applications. During the generation of events, we were guided on the basis of:

a. Valence, generating positive and negative statements about artificial intelligence, creating 30 positive items (applicability of artificial intelligence, benefits...) and 12 negative items (risks of using AI, negative perception, negative emotions).
b. Structural. The starting point of the authors was that the statements refer to three components of the attitude towards IA and that the same will be confirmed in the factor analysis. The starting point generated -items which refer to the cognitive, emotional and behavioral component.

All items were formulated as suitable for responses on a five-point Likert scale, where 1 is completely disagree and 5 is completely agree. In the SPAI scale, reverse coding was required for 10 items

3. Results

Data analysis of this research was done through SPSS (statistical package). Below are presented the tables with the relevant analyses derived to prove the research tasks.
The study was conducted in three phases. Phase I of the study ended with the process of generating data, while Phases II and III consisted of exploratory factor analysis.

Table 1. Preliminary analysis of the exploratory factor analysis of the SPAI questionnaire in the Albanian-speaking student population (N=474)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.776
Bartlett's Test of Sphericity	Approx. Chi-Square	7348.088
	df	780
	Sig.	.000

Before performing the factor analysis, its preconditions were tested. The Kaiser-Meyer-Olkin measure of sample fit was quite high (KMO = 0.776), and Bartlett's test of sphericity was found to be significant ($\chi 2 = 7348.01$; $p < 0.01$). The mentioned results justify the application of factorial analysis (Fulgosi, 1984).

3.1. Factor extraction: Principal components factor analysis produced the rotated distribution. Factor analysis was run on the empirically developed items to achieve the theoretical structure of the scale.
The 40-item scale was subjected to principal component analysis (PCA), using the Varimax Rotation method to increase the interpretability and orthogonality of the factors. Based on the given criteria, the structure of the scale was revised: (a) a simple structure with distinctive factors with factorial density of items in a single factor; (b) an eginvalue ≥1; (c) a factor loading of at least 0.30; and (d) the importance of factors in relation to the underlying construct as suggested by Field (2009). Significant or interpretable factors were extracted with the help of the criterion given by Kaiser (1974) and the explicit percentage from the total explained variance. This process ensures the extraction of 12 factors which together explain a significant amount of variance of 65.89%. Similarly, the component transformation matrix indicates that the orthogonal rotation method was appropriate for this study because most factors have low intercorrelations.

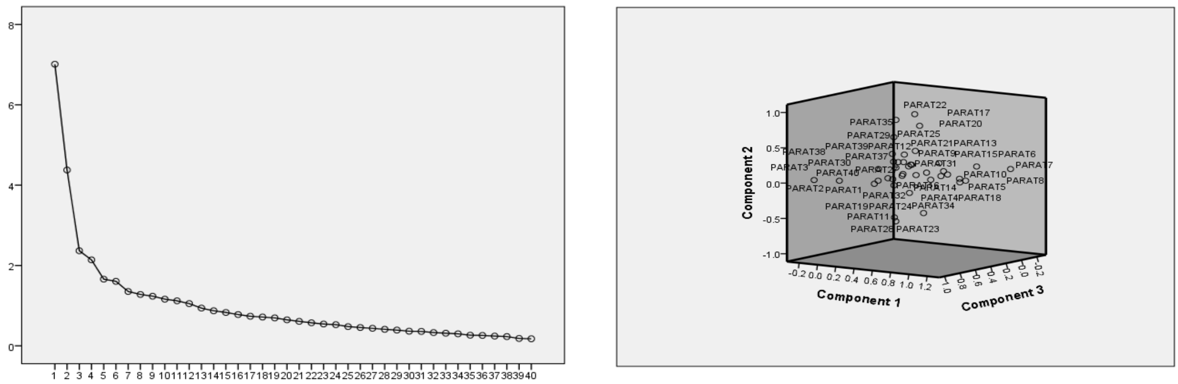

Figure 1. Scree full and Component full in the rotated sphere of the SPAI scale in the Albanian-speaking student population (N=474)

Scree plots were used as a criterion for factor selection based on eigenvalues (Cattell, 1966). Additionally, Chart 1 shows the full factor extraction scree. The break and bend clearly shows that the number of factors that explain the largest percentage of variance is between the 11th and 12th factor in the full scree. Therefore, 12 factors are relied upon to form the SPAI scale.

Table 2 shows that the eigenvalue of 7.01 was obtained for the first factor, 4.38 for the second factor, while 2.37 and 2.14 are the eigenvalues for the third and fourth factors, respectively. Similarly, eigenvalues were found for the other factors as well. In total, 17.52% of the variance was explained by Factor 1, while the variance explained by the second, third, fourth and fifth factors was 10.94%, 5.92%, 5.35% and 4.15%, respectively. However, the variance between 4.01% and nl 2.63% was explained by the remaining factors. Table 2 shows the eigenvalues and percentages of variance explained by each factor.

Table 2. Exploratory factor analysis of the SPAI scale in the Albanian-speaking student population (N=474)

	Initial Eigenvalues			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total
1	7.011	17.527	17.527	5.673
2	4.376	10.941	28.468	4.061
3	2.367	5.916	34.384	3.250
4	2.139	5.348	39.732	2.985
5	1.659	4.147	43.879	2.966
6	1.605	4.012	47.890	2.058
7	1.352	3.380	51.271	2.869
8	1.279	3.198	54.468	2.283
9	1.236	3.089	57.557	2.307
10	1.161	2.904	60.461	2.332
11	1.120	2.800	63.261	1.612
12	1.050	2.625	65.886	1.584
13	.938	2.346	68.232	

Extraction Method: Principal Component Analysis

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance

Table 2 includes eigenvalues and percentages of variance of the 40-item SPAI explained by 12 factors. Factor selection was developed through principal component analysis (N = 474). The

12 factors extracted together explain about 65.89% of the total variance accounted for by the scale.

Table 3. Presentation of the individual parts of the SPAI scale on the 12 components obtained from the principal component analysis in the student population (N=474)

	Component											
Ajtemet	1	2	3	4	5	6	7	8	9	10	11	12
6.	.733		.261							.314		
10.	.704		.395		.410	.286						
13.	.694	.278	.408				.280			.350		
07.	.676											
05.	.630					.254	.374		.461	.406		
18.	.599			.266	.379		.409			.424	.338	
16.	.521			.267		.342						
08.	.489				.313							
22.		.764						.267				
23.		-.720										
28.		-.711			.255						.435	
35.		.709		-.264								
20.		.661				.296	.270					
34.		-.614				-.278		-.426				-.378
02.			.829									
03.	.288		.789		.274					.282		
11.	.547		.643		.298		.310					
30.				.791	.256							
36.				.774								
04.	.536			.563			.439	-.309			-.273	
32.	.336		.364		.702	.265						
17.	.314			.269	.668			-.264	.276	.273	.300	
12.	.493				.560					.280		
39.	.291					.756						
09.	.512	.290	.351			.536	.262			.276		-.274
29.		.354					.680		.367	.332		.317
25.							.643					
21.	.405					-.312	.567		.335			-.281
24.		.290						.743				
14.		.507			.267			.573				
19.		.436						.554			-.271	
37.				.520					.720			
01.	.315			.318	.267		.259		.617			
06.				.429	.383				.469		.411	
10.			.262							.757		
13.	.369		.280	.425	.474	-.250	.437			.488		
07.			.418					.313		.464		
05.	.327			.281							.641	
18.	.317						-.267	.303			-.378	-.352
16.												.782

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

From the authors of the scale, the factorial density of 0.30 or higher was defined as the most preferable criterion for selecting items in a single scale, while the value of the item density which is <0.30 should be removed from the scale. As a result of the factor analysis, a 5-factor scale was finalized keeping in mind all the previously discussed assumptions. In addition, each factor was observed based on the theoretical importance of the items and their content. Although six items resulted with satisfactory factorial density, their content analysis was unstable within the 5 factors or in terms of the other separate factor. Therefore, we decided to drop the 6 items from the final scale.
So, it was decided that six items, namely items 39, 25, 24, 5, 18 and 16, would be eliminated from the final scale. The six items in question, despite the fact that they have a latent factorial density above 0.30, are still eliminated because the structural analysis did not result in having any meaningful structure and were not theoretically important to each other. The remaining 34 systems had high factorial densities (ranging from 0.31 to 0.74) based on the five factors that formed the SPAI.

Table 4. Component Score Covariance Matrix analysis of the SPAI questionnaire in the Albanian-speaking student population (N=474)

Component	1	2	3	4	5	6	7	8	9	10	11	12
1	2.787	.676	3.141	1.939	.676	2.270	3.685	.353	2.068	3.325	.943	1.746
2		1.203	1.177	.575	2.183	.671	.774	.434	1.925	.924	1.198	1.085
3			4.192	2.094	2.356	2.884	4.458	1.022	3.040	3.468	1.679	3.646
4				2.272	.933	1.530	2.557	.144	2.933	2.640	.850	1.299
5					4.659	1.161	.392	.746	3.698	.867	3.618	1.328
6						4.352	2.460	.716	2.462	3.892	2.057	.753
7							3.958	.339	1.574	1.807	.650	2.424
8								1.439	.855	.002	1.605	1.508
9									6.517	2.536	1.278	2.112
10										3.983	.502	1.183
11											4.435	1.382
12												5.053

From the tabular presentation, it results that the highest covariance between factors of 4.46 is found between the third and seventh factors, while the lowest is 0.00 between factors 8 and 10.

3.2. Internal consistency of the AI Attitude and Perception Scale: To measure the internal consistency of the 40-item **AI Attitude and Perception Scale**, Cronbah's alpha coefficient was calculated. A significant value was obtained, however the value was expected to decrease after eliminating 6 items from the final scale. Cronbach's Alpha reliability of the 40-item **AI Attitude and Perception Scale** was found to be 0.82 as given in Table 5 and is considered high enough for the test.

Table 5. Crombach alpha coefficient of the Scale for the assessment of AI attitude and perception.

	Cronbach's Alpha	N of Items
SPAI	.822	40
SPAI	.783	34
Faktori 1	.831	10
Faktori 2	.789	9
Faktori 3	.673	7
Faktori 4	.690	5
Faktori 5	.689	4

3.3. Construct validation Scale on attitudes and perception of IA: Construct validation was carried out in the context of the study on the development and validation of the scale. The convergent validity of the Scale on the perception of AI was determined in the second part of the study. The Scale Measuring Student Attitudes Toward Artificial Intelligence (SAAIQ; Suh&Ahn, 2022) was used to determine convergent validity.

Table 6. Convergent validity of the 40-item IA Attitude and Perception Scale (n=474).

	Scale Measuring Student Attitudes Toward AI
Scale Measuring attitudes and perception of AI	r=.665; p<0.01

Correlative analysis produced a correlation coefficient value of r=0.67; p<0.01 which is statistically significant

3.4. Correlations of SPAI subscales with SPAI totalscore: To determine the intercorrelations of the five factors with the SPAI totalscore, the total scores of the subscales and the overall SPAI scale were calculated. Correlational analysis confirmed the existence of significant positive intercorrelations between the general attitude and perception of AI and the five subcomponents of attitude and perception of AI. Correlation with the AI pragmatism subscale r=0.84; p<0.01 is considered the highest. The extent of intercorrelations between subscales shows that the correlations are weak or relatively moderate, while high correlations are evident with the total score in the SPAI. Intercorrelations among the five factors are presented in Table 7.

Table 7. Intercorrelations between the subscales of the scale on students' attitudes and perceptions towards AI (SPAI) and correlations with the items of the total scale.

	The pragmatism of AI	AI as a threat	Assessment of AI	Curiosity and information about AI	AI as an advanced perspective
Attitude and perception of AI	r=0.839; p<0.01	r=0..521; p<0.01	r=0..607; p<0.01	r=0..717; p<0.01	r=0..755; p<0.01
The pragmatism of AI	1	r=0..280; p<0.01	r=0..379; p<0.01	r=0..577; p<0.01	r=0..563; p<0.01
AI as a threat		1	r=0..080; p>0.05	r=0..212; p<0.01	r=0..366; p<0.01
Assessment of AI			1	r=0..269; p<0.01	r=0..401; p<0.01
Curiosity and information about AI				1	r=0..541; p<0.01

4. Discussion

The purpose of the research was to develop a Scale on the assessment of attitude and perception of Artificial Intelligence as well as to determine the preliminary metric characteristics of the newly formed scale. The goals were met thanks to three studies, but in this paper only the results from the first study in a sample of 474 subjects, all students, are presented.

In the development phase of the terms, a wide range of divergent terms was developed, reflecting the manifestations of perception towards artificial intelligence. It was important that the statements refer to the perception of AI in general terms, avoiding as much as possible the naming of specific applications. All items were worded as appropriate for responses on a five-point Likert scale.

The developed items were subjected to an analysis and evaluation by the authors of the scale, also in terms of content validity, suitability in accordance with artificial intelligence and the developmental context to which the subjects belong, clarity of statements and suitability for a wider population.

The factorial analysis of the 40-item SPAI, through Varrimax rotation and engainvalues, resulted in the extraction of 12 factors which together explain about 65.89% of the total variance derived from the scale. The extraction of items within the 12 factors was developed on the basis of a combined statistical analysis (latent factorial density) and analysis on the content and theoretical importance of the items. The combined analysis suggested the need to eliminate six items (39, 25, 24, 5, 18 and 16) from the final scale, despite the fact that they have latent factorial densities above 0.30. The 34-item SPAI scale was once again subjected to principal component analysis to obtain the final factor structure. However, a supplementary analysis of the principal components will not be presented here.

The analysis on the internal consistency proved that the SPAI with both 40 and 34 items enjoys a consistent homogeneous structure. Alpha Cronbach reliability with 40 items turned out to be 0.82 and with 34 items 0.78 and is considered high for a test. The value of Cronbach's alpha suggests that the items were homogeneously stable as theoretically expected during the construction of the SPAI**.**

Construct validation was performed using the Scale Measuring Student Attitudes Toward Artificial Intelligence (SAAIQ; Suh&Ahn, 2022). In the process of establishing construct validity, the scores of a newly developed scale are correlated with the scores of predetermined scales that assess similar constructs (Friedenberg, 1995). Correlative analysis produced a correlation coefficient value of $r=0.67$; $p<0.01$ which is statistically significant which indicates that the SPAI measures the same construct that the SAAIQ also measures.

The values of intercorrelations, between the general attitude and perception of AI and the five subcomponents of attitude and perception of AI, confirm that the five subscales characterize theoretically distinct dimensions. Therefore, it is concluded that all five subscales contribute significantly to the total score, which recommends that the 34-item SPAI assesses students' attitudes and perceptions toward AI, which includes five dimensions. The correlations of the five factors are presented in Table 7.

The following limitations need to be addressed in future studies despite the fact that the SPAI is a valid and reliable assessment instrument. First, although the sample size for the factor analysis was adequate, however, it was not sufficient for the generalizability of the results because social science majors were included. Therefore, it is suggested that in the future samples be collected from the faculties of night sciences, medicine, technology, humanities, etc. Second, an equal number of participants should be obtained for age groups, years of study, and gender, which may also affect research findings. Despite the limitations discussed earlier, the generated scale appears to have good reliability and adequate convergent validity. For the assessment of attitudes and perceptions towards AI for the student population, this scale will be useful.

5. Conclusion

In conclusion, the AAPAI offers a valuable tool for researchers and practitioners to assess attitudes toward AI technology. The scale can be used to explore factors influencing AI acceptance and adoption, evaluate development of the perception of the AI while the technology and contribute to a more comprehensive understanding of the complex interplay between AI technology and society.

References

[1]. Andreas, K., Haenlein, M. (2019) Siri, Siri in my hand, who's the fairest in the land? On the interpretations, illustrations and implications of artificial intelligence, Business Horizons, 62 (1).

[2]. Ahuja, 2023. Emotional AI and Human-AI Interactions in Social Networking. Elsevier.

[3]. APA Dictionary of Psychology. American Psychological Association. 2018-04-19. Retrieved 2024-01-04. https://dictionary.apa.org/attitude

[4]. Buhrmester, Michael D.; Blanton, Hart; William, B. Swann Jr (2011). "Implicit self-esteem: nature, measurement, and a new way forward". Journal of Personality and Social Psychology. 100 (2): 365–385.

[5]. Bohner, Gerd; Wanke, Michaela (2011). Attitudes and Attitude Change. Frontiers of Social Psychology (1 ed.). London: Taylor and Francis

[6]. Chui, M., Manyika, J., and Miremadi, M. (2016). Where machines could replace humans-and where they can't (yet). Available at: www.mckinsey.com

[7]. Cave, S., Coughlan, K., and Dihal, K. (2019). "Scary robots" examining public responses to AI. in Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society. Honolulu, HI, USA, 331–337

[8]. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13, 319–340. doi: 10.2307/249008

[9]. Fast, E., and Horvitz, E. (2017). "Long-term trends in the public perception of artificial intelligence" in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 31. San Francisco, California, USA.

[10]. Frey, C. B., and Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Chang. 114, 254–280. doi: 10.1016/j.techfore.2016.08.019

[11]. Morley, J., Machado, C. C., Burr, C., Cowls, J., Joshi, I., Taddeo, M., et al. (2020). The ethics of AI in health care: a mapping review. Soc. Sci. Med. 260:113172. doi: 10.1016/j.socscimed.2020.113172

[12]. Hovland, Carl I.; Weiss, Walter (1951). "The Influence of Source Credibility on Communication Effectiveness". Public Opinion Quarterly. Oxford University Press (OUP). 15 (4): 635–650.

[13]. Krosnick, J. A.; Judd, C. M.; Wittenbrink, B. (2005). "The Measurement of Attitudes". In Albarracín, Delores; Johnson, Blair T.; Zanna, Mark P. (eds.). The Handbook of Attitudes. Mahwah, NJ: Lawrence Erlbaum Associates. pp. 21–76.. Retrieved 2024-01-04.

[14]. Kieslich, K., Lünich, M., and Marcinkowski, F. (2021). The threats of artificial intelligence scale (TAI) development, measurement and test over three application domains. Int. J. Soc. Robot. 13, 1563–1577. doi: 10.1007/s12369-020-00734-w

[15]. Olson, James M.; Zanna, Mark P. (1993). "Attitudes and Attitude Change". Annual Review of Psychology. 44: 117–54.

[16]. Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined Technology Readiness Index: TRI 2.0. Journal of Service Research, 18(1), 59–74. https://doi.org/10.1177/1094670514539730

[17]. Petty, R.E.; Cacioppo, J.T. (1984). "The effects of involvement on responses to argument quantity and quality: Central and peripheral routes to persuasion". Journal of Personality and Social Psychology. 46: 69–81.

[18]. Rosen, L. D., Whaling, K., Carrier, L. M., Cheever, N. A., and Rokkum, J. (2013). The media and technology usage and attitudes scale: an empirical investigation. Comput. Hum. Behav. 29, 2501–2511. doi: 10.1016/j.chb.2013.06.006

[19]. Rhodes, Nancy; Wood, Wendy (1992). "Self-esteem and intelligence affect influenceability: The mediating role of message reception". Psychological Bulletin. 111 (1): 156–171.

[20]. Schepman, A., and Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. Comp. Hum. Behav. Rep. 1:100014

[21]. Sindermann, C., Sha, P., Zhou, M., Wernicke, J., Schmitt, H. S., Li, M., et al. (2021). Assessing the attitude towards artificial intelligence: introduction of a short measure in German, Chinese, and English language. KI-Künstliche Intelligenz 35, 109–118. doi: 10.1007/s13218-020-00689-0

[22]. Sekaquaptewa, D., Espinoza, P., Thompson, M., Vargas, P., & von Hippel, W. (2003). Stereotypic explanatory bias: Implicit stereotyping as a predictor of discrimination. Journal of Experimental Social Psychology, 39, 75-82

[23]. Whitley, B. E. (2010). The Psychology of Prejudice & Discrimination. United States: Wadsworth Engage Learning.

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