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Constructing and testing the psychometrics of an instrument to measure the attitudes, benefits, and threats associated with the use of Artificial Intelligence tools in higher education

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Abstract

Under the acceleration in the body of information regarding AI technology and the paucity of instruments that assess the views and reactions of consumers, we have constructed this instrument to measure the attitudes, benefits, and threats (ABT) toward using Artificial Intelligence (AI) tools in higher education. Google Form was used in August of 2023 to collect data from students and teachers at higher education institutions in 11 Asian and African countries. After the ABT instrument obtained a sufficient score in content validity, additional statistical analyses were done. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were performed. This study included 503 participants who are familiar with AI tools. Over 56% have Bachelor's degrees and 35% have Master's or Doctoral degrees. The most popular AI tool was ChatGPT. One model out of six models created for the factor structure of the 35 items that measure attitudes, benefits, and threats was chosen. The selected model provides the highest explained variance (55.6%). The CFA, using AMOS software, demonstrated that the fit indices were satisfactory for the adopted model. Attitude (15), benefits (6), and threats (14 items) are the three factors of the model. The CFA supports the EFA with the ABT three-factor structure model. The high factor loadings and communalities suggest that the factors are reliable and valid measures of the attitude, benefits, and threats toward AI tools among highly educated personnel.

Introduction

In recent years, Artificial intelligence (AI) has made tremendous advances, resulting in a vast collection of tools and applications (Ismail et al., 2023; Soori et al., 2023). The field of AI-based education and research has entered a brand-new phase of rapid development (Yagi et al., 2023). The enhancement of research and educational efficiency and precision is one of the main advantages (Makeleni et al., 2023). However, few instruments test how individuals perceive, react, and comprehend the new technologies that are continuously growing.

Early identification of a good attitude can assist in establishing the conditions for a successful implementation (Jones et al., 2022). Positive attitudes are usually associated with increased adoption rates (Munianday et al., 2022). A positive mindset can promote the quicker and more effective application of AI tools (Jones et al., 2022). If consumers have a negative attitude, these insights can help designers and developers make the necessary modifications (Lin & Shi, 2022). Analysing attitudes makes it easier to identify ethical difficulties, which is essential for developing AI responsibly. However, the gathering of attitude data may involve sensitive information that could be exploited if not appropriately safeguarded (Almaghrabi & Bugis, 2022). Quantitative threat assessments assist companies in minimising dangers and optimising returns by determining which risks to address first and allocating resources effectively (Żebrowski et al., 2022).

To fully exploit the economic and societal advantages of AI technologies, it is vital to comprehend and quantify their benefits. By understanding the specific benefits, businesses may better align AI projects with their strategic objectives and improve their long-term planning (Allioui & Mourdi, 2023). In a digital world that is always getting bigger, knowing AI strengths could give the person an edge over competitors from all over the world (Duong et al., 2022; Perifanis & Kitsios, 2023). Furthermore, the analysis of AI's positive consequences, such as health gains and environmental benefits, may influence public opinion and legislation (Littman et al., 2022). Having a firm understanding of the benefits and threats enables a more comprehensive approach to threats assessment (Tepylo et al., 2023). If companies know how people feel about their AI products, they can market them better (Haleem et al., 2022). Geographical and cultural differences might be considered when customising AI solutions for various markets (Salo-Pöntinen & Saariluoma, 2022).

In the literature, there are few articles discussing the attitudes toward AI tools. One article, for instance, proposes the development and validation of the AI Attitude Scale (AIAS), a brief self-report instrument designed to assess public perceptions of AI technology (Grassini, 2023). Many reasons necessitate the development of an instrument to assess attitudes toward AI in higher education. First, it can assist educators in comprehending students' attitudes toward AI to create appropriate curricula and educational materials (Moldt et al., 2023). Second, it can assist researchers in analysing the impact of AI on higher education and identifying areas in need of improvement (Escotet, 2023). In our study, we have focused on students at the higher education level and the faculty members as well.

AI tools can analyse student performance and behaviour, identify knowledge gaps, and provide individualised support and feedback to enhance learning outcomes (Alqahtani et al., 2023). Thus, it is necessary to measure the benefits of AI tools in higher education to comprehend their impact on students' learning outcomes and identify improvement areas.

There are numerous articles discussing the threats of AI tools. Two articles, for instance, discuss the threats of using AI for cybersecurity, such as the need for substantial investments in computing power, memory, and data (Hassoulas et al., 2023; Saeed et al., 2023). Other articles discuss the disadvantages of artificial intelligence, such as ethical concerns regarding bias and privacy, security risks posed by hacking, and a lack of human-like creativity and empathy (Huang et al., 2023; Wach et al., 2023). However, finding the threats associated with using AI tools from the viewpoints of students and faculty members is essential in higher education. Therefore, we used a systematic strategy to explore the literature in order to develop an instrument that measures the attitudes, benefits, and threats related to the use of AI tools in higher education among students and teachers.

This study's purposes were to: 1) construct an instrument to measure attitudes, benefits and threats (ATB); 2) examine the factor structure of the ATB instrument using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Methods

Participants and settings

Data were collected from 503 students and staff members at higher education institutions in Asia and Africa using Google Forms during August 2023. Participants came from 11 different countries, including two from Africa (Egypt and Sudan) and nine from Asia (Jordan, Palestine, Lebanon, Saudi Arabia, Iraq, Thailand, India, Philippines, and Kuwait). The eligibility criteria were being a graduate or undergraduate student or a faculty member at a university. Participants were required to be able to read English because the instrument was written in English.

Ethical considerations

The study was authorised by the Institutional Review Board (IRB) at the School of Nursing/University of Jordan. The first page of the questionnaire contains information regarding the research purpose, methodology, participants' right to decline participation, and assurance of confidentiality. An email address was provided for members of the study team to receive and respond to inquiries from anticipated participants. Informed consent was gained by selecting "yes" in response to the question "Are you willing to participate in this study?" The data were saved on the desktop of the principal investigator (PI), and only approved members of the study team had access to them.

Instrument

The research instrument has two components—first, the sociodemographic and personal characteristics. Participants' age, gender, level of education, frequency of AI tool use, and nationality were collected. The second component consists of three subscales evaluating attitudes, benefits and threats of using AI tools. The research team developed the instrument to measure the ABT associated with teachers' and students' use of AI tools in higher education settings. The research team did a comprehensive evaluation of the literature, and then each member of the team extracted and categorised essential features under the titles' attitudes, benefits, and threats. The three proposed drafts were combined, and redundant text was removed. Following this, psychometric tests were conducted.

Data analysis

For descriptive statistics and EFA, IBM SPSS 29.01 was used (IBM, 2023b). IBM AMOS 26.0 was used to develop the CFA using structural equation modeling (IBM, 2023a). Data are visualised in tables and figures.

Psychometrics of the instrument

Seven items assessed the benefits of AI technologies, 16 items assessed the threat, and 17 items assessed the attitudes. Three professionals in higher education were consulted to obtain the content validity index (CVI): one in computer technology and artificial intelligence, one is a professor in nursing with a subspecialty in health informatics, and one is a professor in medical education. The panel of experts assessed the applicability of each item on the instrument. The CVI is then calculated using the average of the expert assessments. Five items were eliminated from the study because their CVI scores were below 0.70 or they were irrelevant. The remaining 35 items were reviewed by five specialists, including three from the initial panel and two from the physics and sociology departments. Each item's minimum score was 0.85, and the overall CVI score for the scale was 0.95. Each item was scored using a 5-point Likert scale ranging from strongly disagree (0) to strongly agree (4).

Exploratory factor analysis (EFA) and CFA were used to test the construct validity of the study scale. The 35 items were divided into three subscales: Attitudes (15 items), benefits (6 items), and threats (14 items). The overall explained variance for this study was 55.6%. The Cronbach's alpha coefficient was calculated for each of the three subscales and for the overall scale. The benefits subscale score was 0.82, the threat subscale score was 0.91, and the attitudes subscale score was 0.90. In addition, the scale's overall reliability was 0.93.

Results

Participants in this study were highly educated and came from 11 different countries in Asia and Africa, with the majority coming from the Middle East. There were a total of 503 participants. About 56% of them have a Bachelor's degree, and over 35% have a Master's or Doctoral degree. Women constituted almost 58% of the sample. Almost a quarter of the sample reported using AI technologies on a daily or weekly basis. The participants' ages ranged from 18 to 69 years (Table 1).

Table 1: Descriptive statistics for the study sample (N=503).

Characteristics	Frequency	%
Age (Mean=30.9 , SD=11.3)		
Gender		
Male	246	48.9
Female	257	51.1
Education		
Diploma	37	7.4
Bachelor	266	52.9
Master	108	21.5
PhD	92	18.3
Frequency of using AI tools		
Daily	35	7.4
Weekly	88	17.5
Monthly	62	12.3
Rarely	316	62.8
Country		
Egypt	30	6.0
India	17	3.4
Iraq	53	10.5
Jordan	136	27.0
Kuwait	63	12.5
Lebanon	100	19.9
Palestine	67	13.3
Philippine	5	1.0
Saudi Arabia	15	3.0
Sudan	17	3.4

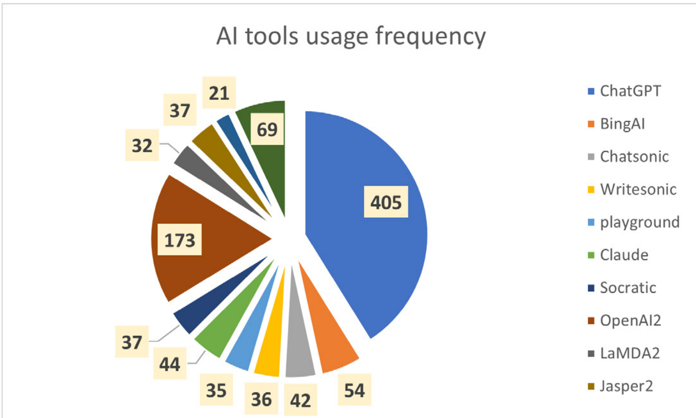

Figure 1: The 12 AI tools frequency usage among the study sample.

Exploratory factor analysis

Exploratory Factor Analysis (EFA) is a statistical technique similar to Principal Component Analysis (PCA) that is used to reduce data from numerous variables to fewer dimensions (Vitoratou et al., 2023). Both are utilised for dimensionality reduction, but their approaches and interpretations are fundamentally distinct (Schreiber, 2021). Principal Component Analysis aims to maximise variance and does not concern itself with explaining the data. It transforms the original variables into a new set of uncorrelated variables (principal components). Furthermore, Principal Axis Factoring (PAF) seeks to uncover latent links ('factors' or latent variables) between observed variables. In contrast to PCA, it is intended to model the underlying structure, and is typically used to identify a theory or construct (Schreiber, 2021).

The Principal Component Analysis (PCA) and Principal Axis Factoring (PAF) were utilised with various rotation settings, in addition to using Eigenvalues greater than 1 and limiting the number of output factors to three (Table 2). Most factors with high item loadings, clean loading (difference between two loadings on the same factor should be greater than 0.20), and good overall model fit constitute the best EFA model (Liao et al., 2023).

Therefore, in this study, we have chosen model six in Table 2. Model six was conducted through PCA with Oblimin rotation and Kaiser Normalisation. The model has 55.6% of the total variance explained. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy was .93. The Bartlett's Test of Sphericity had a Chi-Square = 8169 ($p<.001$). A significant Bartlett's test of sphericity (p-value < 0.05) indicates that the correlation matrix is not an identity matrix. The two items with unclean loading were allocated to the suitable factor based on theoretical reasoning (Dautle & Farrell, 2023). Thus, one was allocated under the threats factor and the other under the attitudes factor.

Table 2: Descriptive statistics for the 6 models in EFA.

Model	Extraction and Rotation	Extraction Either Eigenvalue or fixed number of factors	Number of factors	Total variance explained	Number of items with un-clean loading^
1	PCA, No Rotation	Eigenvalue>1	6	54.3%	20
2	PCA, No Rotation	Fixed number=3	3	47.8%	7
2	PCA, Varimax with Kaiser Normalisation	Eigenvalue>1	6	55.3%	8
3	PCA, Varimax with Kaiser Normalisation	Fixed number=3	3	47.1%	3
4	PCA, Equamax with Kaiser Normalisation	Fixed number=3	3	47.1%	9
5	Principal Axis Factoring, Equamax with Kaiser Normalisation	Fixed number=3	3	42.3%	10
6	PCA, Oblimin with Kaiser Normalisation	Fixed number=3	3	55.6%	2

^Unclean loading means the difference in loading between the same items is less than .20

Table 3 presents the means and standard deviations for all the study items. The range of means for each of the 35 items could range from 0 to 4.

Table 4 presents the loading of items on the three factors of the instrument. The analysis was conducted through PCA with Oblimin rotation and Kaiser Normalisation. The three factors are labelled as attitudes (15 items), benefits (6 items), and threats (14 items). The loadings for the three factors were significant. The commonalities for all factors were also high, suggesting that the factors explained a significant amount of the variance in the observed variables.

Table 3: The means and standards deviation for the 35 items in the instrument.

Items*	Mean	SD
B1 Easy to use	2.78	.914
B2 Save time	2.97	.906
B3 Accessible with low cost	2.69	.961
B4 Help students to ask questions and interact with the material at their own pace	2.67	.956
B5 AI tools are user-friendly	2.59	.842
B6 I know that AI tools are used in education and research	2.80	.986
T1 Lack of human interaction	2.76	1.045
T2 Legal issue (e.g. copyright issues, authorship)	2.63	1.044
T3 Decrease creativity and critical thinking	2.82	1.059
T4 AI tools does not replace practical training	2.80	.982
T5 Security concerns	2.59	1.025
T6 Technical issue	2.51	.994
T7 Over-reliance on technology	2.71	1.028
T8 Ethical dilemma/concerns such as plagiarism	2.58	.951
T9 Threats of AI tools: Need Internet all the time	2.87	.994
T10 Difficulty in handling complex task in research	2.50	.961
T11 Threats of AI tools: Inaccurate/incorrect or biased information	2.41	.940
T12 Over-detailed, redundant, excessive content	2.34	.967
T13 Using AI tools will reduce skills and abilities of person who use it (e.g., writing skills, critical thinking …..etc)	2.67	.991
T14 I see AI tools as a threat to human ethics	2.34	1.019
A1 AI tools content can be used if properly cited and documented	2.71	.875
A2 Authors should have proper knowledge on how to use AI tools	2.70	.895
A3 I recommend AI tools to a friend or colleague		
A4 I'm interested in using of a premium version of AI tools with advanced features	2.43	.977
A5 AI tools has a positive impact on my education/learning	2.51	.888
A6 There is a need for specific training on how to use AI tools in order for them to be useful.	2.63	.964
A7 I suggest providing adequate information on establishing ethical guidelines for the use of AI tools.	2.68	.920
A8 I think AI tools should be included in the study curricula	2.41	1.003
A9 To improve AI applications in the real world, it is essential to encourage researchers to be honest and transparent about their methods.	2.76	.886
A10 I review and edit the response that generated by AI tools before using them in my work	2.71	.869
A11 AI tools can be listed as an author based on its significant contribution	2.45	.958
A12 I feel comfort with ethical and responsible use of AI-generated content from AI tools.	2.34	.965
A13 AI tools could enhance research (e.g., assisting the researchers in framing the sentences, improving the content drafted by the authors.	2.63	.902
A14 I think the responses generated by AI tools are overall easy and coherent	2.68	.988
A15 I trust the information that I read and see on AI tools?	2.21	.916

*B=Benefits, T=Threats, A=Attitude; SD=Standard deviation.

Table 4: Pattern matrix and items loading on the three factors.

Items*	Attitudes	Threats	Benefits
A8	.701		
A1	.696		
A4	.694		
A5	.686		
A3	.676		
A11	.623		
A2	.607		
A6	.604		
A12	.591		
A7	.566		
A15	.551		
A9	.518		
A10	.476		
A13	.451		
A14	.402		
T1		-.755	
T2		-.748	
T6		-.733	
T5		-.707	
T3		-.688	
T4		-.666	
T11		-.659	
T7		-.655	
T12		-.635	
T10		-.627	
T8		-.556	
T14		-.507	

T9	-.507		
T13	-.497		
B1		-.782	
B2		-.724	
B3		-.697	
B6		-.626	
B4		-.477	
B5		-.402	

*The letter and number correspond to the same items in Table 3.

Confirmatory Factor Analysis

The CFA was conducted using AMOS 26.0 (IBM, 2023a). The fit indices were all within acceptable ranges, suggesting that the model fit the data. The fit indices for the study instrument are presented in Table 5.

Table 5: Fitting indices for the 3-factor model.

Fitting index	Index Value	Thresholds
Chi-squared test of model fit (**CMIN**)	2053.557*	
CMIN/DF	3.687*	< 2 to < 5
Root mean square error of approximation (RMSEA)	.07	< 0.05 (good), 0.05–0.08 (acceptable) < 0.10 (poor but sometimes acceptable)
Goodness-of-fit index (GFI)	.92	> 0.90 (acceptable) > 0.95 (good)
Adjusted goodness-of-fit index (AGFI)	.91	> 0.80 (acceptable) > 0.90 (good)
Comparative fit index (CFI)	.90	> 0.90 (acceptable) > 0.95 (good)
Tucker-Lewis index (TLI)	.90	> 0.90 (acceptable) > 0.95 (good)

*p<.001

With confirmatory factor analysis, one can determine the efficiency of the construct. It is a crucial phase and analysis in structural equation modelling (SEM). Standardised Confirmatory Factor Analysis for the three factors with a 35-item structure model is depicted in Figure 2.

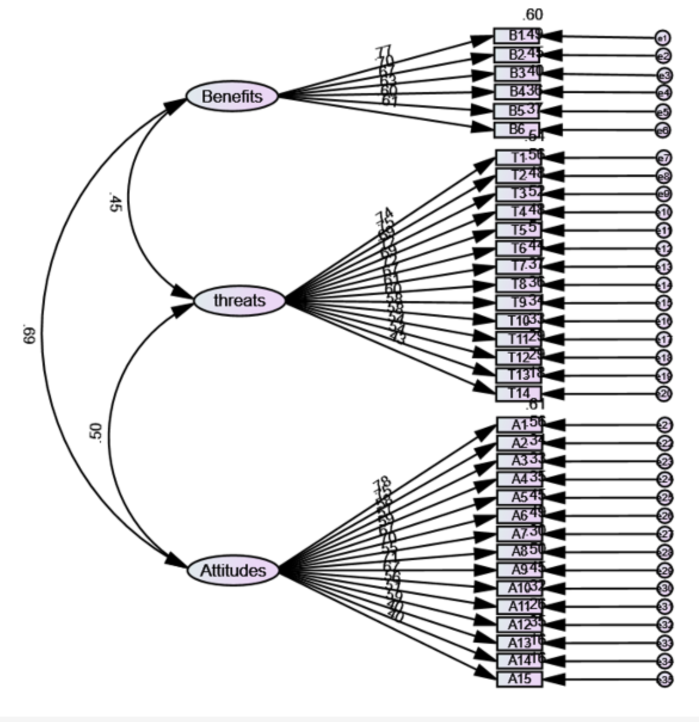

Figure 2: Standardised Confirmatory Factor Analysis for the three factors 35-item structure model.

Discussion

In this study, we have constructed the ABT instrument and examined its psychometric properties across a large, heterogeneous sample of university students and faculty members from 11 Asian and African nations. It is projected that the use of AI tools will continue to grow worldwide. Better customer experiences can be offered through the deployment of AI technologies that can be personalised to give each client the information and services they require (Chaturvedi & Verma, 2023), which may increase customer satisfaction (Chaka, 2023; Cui & van Esch, 2023).

The existing literature is lacking in providing measuring instruments for the perceptions of university students and academic staff toward AI technologies (Mantello et al., 2023). Thus, it was necessary to develop the ABT instrument to contribute to the body of knowledge in this rapidly developing field.

Using standard EFA approaches, a preliminary investigation of the measurement properties of the scale was done. This method is suitable for the first phases of empirical research when exploration is the major objective, and there are no theoretical models available (Mantello et al., 2023). Consequently, it produces more precise data on the acceptability of the specified instrument. However, exploratory factor models do not generate explicit test statistics for assessing convergent and discriminant validity like CFA does (Ahmad et al., 2018). Therefore, the CFA methodology of structural equation modelling was used for measuring unobserved (latent) variables (Dhaene & Rosseel, 2023; Navandar et al., 2023).

The three-factor model of this study has explained more than half of the variance (55.6%), the highest proportion among the six models under EFA. Additionally, the items with clean loading were superior to the other models. The CFA has supported the ABT structural model examined in this study. Moreover, the internal consistency coefficients for the three subscales and the entire instrument were high. Therefore, the authors of this study recommend administering the ABT to students and teachers in higher education to gauge their attitudes, benefits, and threats toward AI tools.

Conclusion

The ABT instrument structure was examined using both EFA and CFA methodologies. It was determined that the 35-item scale with the three-factor model is concise, valid, and empirically verified. The findings of this study can be used to assess the attitudes, benefits, and threats toward AI tools among students and faculty members at high education levels, and possibly other sectors in the community.

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Appendix

Attitudes, benefits, and threats associated with the use of Artificial Intelligence tools in higher education

Please answer each of the following questions about what you know, how you feel, and what you do with AI tools. (Please note that there is no best answer; we just want to know your opinion about each item.)

	Attitudes (15 items)	**Strongly disagree 0**	**Disagree 1**	**Neutral 2**	**Agree 3**	**Strongly agree 4**
A1	AI tools content can be used if properly cited and documented					
A2	Authors should have proper knowledge on how to use AI tools					
A3	I recommend AI tools to a friend or colleague					
A4	I'm interested in using of a premium version of AI tools with advanced features					
A5	AI tools has a positive impact on my education/learning					
A6	There is a need for specific training on how to use AI tools in order for them to be useful.					
A7	I suggest providing adequate information on establishing ethical guidelines for the use of AI tools.					
A8	I think AI tools should be included in the study curricula					
A9	To improve AI applications in the real world, it is essential to encourage researchers to be honest and transparent about their methods.					
A10	I review and edit the response that generated by AI tools before using them in my work					
A11	AI tools can be listed as an author based on its significant contribution					
A12	I feel comfort with ethical and responsible use of AI-generated content from AI tools.					
A13	AI tools could enhance research (e.g., assisting the researchers in framing the sentences, improving the content drafted by the authors.					
A14	I think the responses generated by AI tools are overall easy and coherent					
A15	I trust the information that I read and see on AI tools?					
	Benefits (6 items)	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
B1	Easy to use					
B2	Save time					
B3	Accessible with low cost					
B4	Help students to ask questions and interact with the material at their own pace					
B5	AI tools are user-friendly					
B6	I know that AI tools are used in education and research					

	Threats (14 items)	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
T1	Lack of human interaction					
T2	Legal issue (e.g. copyright issues, authorship)					
T3	Decrease creativity and critical thinking					
T4	AI tools does not replace practical training					
T5	Security concerns					
T6	Technical issue					
T7	Over-reliance on technology					
T8	Ethical dilemma/concerns such as plagiarism					
T9	Need Internet all the time					
T10	Difficulty in handling complex task in research					
T11	Inaccurate/incorrect or biased information					
T12	Over-detailed, redundant, excessive content					
T13	Using AI tools will reduce skills and abilities of person who use it (e.g., writing skills, critical thinking ….etc)					
T14	I see AI tools as a threat to human ethics					