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Research Scale of College Students' Attitude towards Learning under the Influence of Artificial Intelligence

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Abstract: Intelligence and information are important elements in the current development of education, where research on the application of artificial intelligence has been a hot topic in recent years. The assessment using a scale is an important method to explore the learning situation of learners. The article combines three dimensions of artificial intelligence, college students' learning status, and ability development to design the scale, and obtains samples through actual surveys to test the scale. The results show that the scale has good reliability and validity, good internal consistency among the items, a good fit to the scale structure, and meets the index requirements of the scale design. The scale is suitable for investigating the influence of artificial intelligence on college students through information-based university teaching, can provide a basis for the application and development of artificial intelligence in colleges and universities, and can provide scientific help for college students to better use artificial intelligence.

1. Introduction

In recent years, with the rapid development of information technology and the increasing maturity of artificial intelligence, education technology has become an important way to promote the modernization of education. In this context, college students, as an important force in the future of society, are facing new educational challenges and opportunities. As a hot topic in today's technology field, the application of artificial intelligence in the field of education is also getting more and more attention. Traditional education methods and approaches are facing challenges. With the continuous changes in learning contents, modern college students have put forward higher requirements on education, hoping to acquire knowledge, cultivate innovative thinking, and develop practical ability more conveniently through advanced technological means. And the powerful ability of artificial intelligence as an emerging technology provides new opportunities for education informatization, such as intelligent assisted learning, performance assessment, personalized learning, and other aspects that provide students with richer and more diverse learning resources and learning methods. Therefore, the research content between AI and college students is of great practical significance to explore the positive effects of AI on college students' education and other possible impacts under the background of education informatization, to clarify the principles and methods of reasonable application of AI technology, to promote the integration and development of college students' education and AI, and to provide a strong theoretical and practical reference for college education.

The research in this paper centers on the scale of development, and the research is conducted in response to two questions: First, from which dimensions should we explore the impact of AI on college students? The second is how to properly design a scientifically valid scale. The AI referred to in the study are AI products defined in terms of breadth, such as ChatGPT, newbiing, baidu-yiyan, etc.

2. Status of Research

Currently, AI in education has been increasingly researched and has made remarkable progress from the initial stage of knowledge presented to intelligent-assisted teaching and adaptive learning, and then to the stage of learning analysis and intelligent education ecology. By developing smart education tools, building smart education platforms, and mining learning data, researchers have continued to explore how AI can better assist teaching and improve learning and have promoted the development of smart education both inside and outside the classroom, at the educational management and policy levels. From the perspective of student engagement, some scholars have found that student-centeredness is still at the core of contemporary education, and even with the powerful help of AI technology, student engagement is the most important core part of the personalized learning model, and increasing student initiative is considered to be the key to it [1-3]. Some scholars' studies affirm the role of AI, arguing that with the right implementation, AI is effective and does some aspects better than humans. They argue that giving most of the human responsibility to AI does not solve many educational problems, but it does not yet refute the effectiveness of AI [4-6]. Some scholars have found that AI will not replace the traditional education system, but it will provide more effective learning opportunities for students and can help teachers and students in many ways, including curriculum implementation, assignment evaluation, and academic testing. This will improve learning productivity in and out of the classroom, and students can enhance their interests with the help of AI [7-10].

The results of this series of studies are showing that, in reality, AI does play a very big role in the educational process. But no research content specifically shows the way AI influences the college student population. Yet student motivation is an important way to improve learning, and active learning is a key component that has been advocated in pedagogy and is a core element of constructivist theory. Therefore, this study examines the impact of AI influence on student motivation and initiative and the research on the development of students' learning abilities. Because the college student population is the group with the highest level of information technology education among all student groups and can be more effectively exposed to AI, this study targets the college student population.

3. Scale Design

The scale developed in this study is oriented to common 21st-century learning frameworks and China's Education Informatization 2.0 and was scientifically and systematically designed by combining common methods of scale creation [11-13]. The purpose of the in-depth study was achieved by taking into account the present-day topicality and the perspective of the university students themselves. The scale has three primary dimensions: "active learning attitude", "artificial intelligence support and assistance", and "learning facilitation and competence enhancement", which cover the real attitudes of university students toward learning through primary and secondary dimensions. The real attitudes of university students toward learning are in line with the current international understanding of educational development (Table 1). The understanding of motivation and initiative is guided by the theoretical content of constructivism and is based on the international recognition of constructivism as a learning initiative [14,15]. The scale was initially designed with 27 questions and 2 validation questions, using a Likert 5-point scale, with a score of 1 indicating the lowest fit to the topic and 5 indicating the highest fit to the topic. The questionnaires were then distributed via the Internet, and a total of 211 responses were collected from students in different universities in Thailand and China, among which 190 valid questionnaires were removed from those that did not pass the validation questions, had too little time to respond, and had the same answer options, with an effective rate of 90%.

Table 1: Two-level dimensional scale.

<table>
<tr><th>Level 1 Dimension</th><th>Level 2 Dimension</th><th>Reference</th></tr>
<tr><td rowspan="3">Proactive learning attitude</td><td>A positive mindset in life every day</td><td rowspan="8">Maud Chassignol(2018); Keith Willey(2020); Martin L. Hoffman(1977); Alexia Gillen(2014); Saskia Brand-Gruwel(2013);</td></tr>
<tr><td>Self-awareness and adaptation</td></tr>
<tr><td>Reasonable combination of work and rest</td></tr>
<tr><td rowspan="2">Artificial intelligence support help</td><td>Level of mastery and application of AI</td></tr>
<tr><td>Use of AI in learning</td></tr>
<tr><td rowspan="3">Learning Promotion and Ability Enhancement</td><td>Knowledge learning and efficiency improvement</td></tr>
<tr><td>Acquire additional skills and competencies</td></tr>
<tr><td>Increase interest and focus level</td></tr>
</table>

4. Scale Test

The statistical software used for the study was IBM SPSS 23 and IBM AMOS 26.

4.1. Expert Validity Test

After the initial design of the scale was completed, the scale questions corresponded to the first-level dimensions, and the appropriateness was evaluated using a four-level scale, with no score for the first and second levels and one score for the third and fourth levels. Eight experts serving in universities, including four professors (associate professors) and four lecturers, were invited to the study. Two main aspects were evaluated: first, whether the language expression of the question item itself is reasonable; second, whether the question item can fit the content of the first level dimension. The question items were evaluated by dividing the score by the total number of experts, with 0.7 or more being good and 0.9 or more being excellent. The evaluation results showed that one of the items was good and the rest were excellent. This indicates that the scale's questions are well-designed and that there is no need for censoring or adjustment at the level of expert validity testing.

4.2. Analysis Based on CR Values

Using the critical ratio method for item analysis, individual samples of all data were summed and then ranked, and the first 27% and the last 27% of the ranking after calculating the total score were used as the critical points for high and low groupings, with the first 27% (52) of the total score being the high grouping and the last 27% (52) of the total score being the low grouping. A one-sample K-S analysis was first conducted on the samples of high and low subgroups, and the results showed normal distribution. The independent sample t-tests were conducted on the high and low subgroups to calculate the significant differences between the high and low subgroups, and the results are shown in (Table 2). Based on the analyzed data, it can be seen that the sig values of all question items are less than 0.05 and the CR values are greater than 3, indicating a significant difference between the question items. Correlation analysis was also performed, and the results showed that the Pearson correlation coefficient for all question items reached 0.01 (two-tailed) significant correlation, and the correlation coefficient with the total score exceeded 0.5, indicating a significant correlation between each question item and the total score.

Table 2: CR Values.

No.	t	Sig	No.	t	Sig	No.	t	Sig
A1	9.562	0.000	B10	10.478	0.000	C19	15.317	0.000
A2	10.791	0.000	B11	13.129	0.000	C20	13.813	0.000
A3	11.846	0.000	B12	13.019	0.000	C21	13.553	0.000
A4	11.072	0.000	B13	10.062	0.000	C22	11.843	0.000
A5	11.794	0.000	B14	15.108	0.000	C23	11.867	0.000
A6	7.678	0.000	B15	16.119	0.000	C24	15.150	0.000
A7	12.922	0.000	B16	14.604	0.000	C25	14.867	0.000
A8	9.307	0.000	B17	14.930	0.000	C26	14.523	0.000
A9	10.889	0.000	B18	16.626	0.000	C27	14.778	0.000

4.3. Exploratory Factor analysis

KMO and Bartlett's tests were performed on the scale, and the results showed that KMO = 0.951>0.9 and the significance was >0.001, which indicated that the correlation between the items of the scale was significant and suitable for EFA factor analysis. Then, principal component analysis was performed on all question items, and the results of the analysis are shown in (Table 3). Factors were selected based on eigenvalues greater than 1. As a result, three principal components were extracted, and the cumulative variance contribution explained 77.5% of the variance. It can also be seen from the gravel plot that the eigenvalue of the first factor is relatively large and has the largest contribution to the explanation of the original variables, and the curve flattens out after the fourth factor, which has a smaller eigenvalue and does not show much performance on the original variables. Combined with the practical significance of the scale, the three principal components and the three dimensions of the scale are consistent in number, and there is no need to censor the scale-level dimensions.

Table 3: KMO and Bartlett.

Component	Initial Eigenvalue			Extract load			Rotating load
	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %	Total
1	15.576	57.688	57.688	15.576	57.688	57.688	9.364
2	3.897	14.434	72.122	3.897	14.434	72.122	7.113
3	1.440	5.335	77.457	1.440	5.335	77.457	4.437

The maximum variance method of orthogonal rotation was used in the process of principal component analysis, which converged after 6 iterations. The analysis was performed by the factor loading matrix after the rotation, and the values in the matrix are the loadings of the question items in the principal component factors, and the larger the value indicates the greater correlation with the principal component factors. The factor loading matrix is shown in (Table 4). From the analysis results, most of the correlations between the question items and the principal component factors were consistent with the meaning of the scale design, but the factor loadings of the question items B15.B16.B17.B18 showed deviations and were consistent with similarity (Difference less than 0.1) on several factors, so these question items were removed. The 23 retained items were then subjected to a second exploratory analysis, and the results showed that all items had relatively high loadings on the corresponding factors, consistent with the design implications of the scale.

Table 4: Factor Loading.

	Components				Components				Components		
	1	2	3		1	2	3		1	2	3
A1	.161	.824	.181	B10	.247	.384	.714	C19	.834	.276	.235
A2	.198	.809	.221	B11	.401	.242	.785	C20	.886	.199	.190
A3	.193	.848	.220	B12	.444	.259	.694	C21	.828	.143	.298
A4	.256	.862	.090	B13	.330	.287	.742	C22	.794	.298	.179
A5	.211	.856	.145	B14	.525	.198	.708	C23	.767	.178	.366
A6	.221	.672	.159	B15	.635	.236	.541	C24	.884	.206	.180
A7	.236	.830	.212	B16	.663	.164	.525	C25	.778	.325	.227
A8	.172	.866	.084	B17	.724	.174	.445	C26	.827	.277	.200
A9	.160	.792	.275	B18	.769	.197	.424	C27	.880	.198	.220

4.4. Reliability Test

The reliability test used for the scale is the commonly used Cronbach's alpha coefficient method, and the results of the analysis of the scale questions are shown in (Table 5). The alpha value of the scale as a whole is 0.965, and the alpha value of each dimension is greater than 0.9, indicating that the scale has good internal consistency.

Table 5: Cronbach's alpha.

Factor	Cronbach's alpha	Item Number
Proactive learning attitude	0.957	9
Artificial intelligence support help	0.926	5
Learning Promotion and Ability Enhancement	0.971	9
Total	0.965	23

4.5. Validity Testing

Table 6: Validity Testing.

Category	Indicators	Standard	Fit index	Results
Absolute Fit Statistics	CMIN/DF	1-3	2.769	Yes
	RMSEA	<0.1	0.097	Yes
Value-Added Fit Statistics	IFI	>0.9	0.918	Yes
	TLI	>0.9	0.908	Yes
	CFI	>0.9	0.918	Yes
Parsimony fit index	PNFI	>0.5	0.787	Yes
	PGFI	>0.5	0.643	Yes

The validity test used for the scale was validated using the validated factor analysis (CFA) method, and the AMOS tool was used to test the scale structure for fit. The model was first set up through the meaning of the scale design and previous studies, with the three dimensions of the scale as latent variables of the common factor and the question items in each dimension as observed variables. The items on the scale were designed with a reflective perspective, so they conformed to the reflective structure characteristics in the CFA model. Using the maximum likelihood method for testing, the structural fit of the scale was obtained (Table 6). Because of the design significance of this scale, the degrees of freedom are relatively small and the sample size is not large, so the criterion of RMSEA is taken to be less than 0.1 [15]. All values of the fitted data are in the acceptable range, indicating that the structure of this scale is a good fit [14].

5. Conclusion

Based on the current situation of the rapid development of artificial intelligence, this study investigated the influence of artificial intelligence on college students and designed a scale with three dimensions that can explore the influence of artificial intelligence, a positive learning attitude, and the development of learning abilities in college students. The research method of this scale is similar to that of conventional scales, but the content of this scale is sufficiently relevant to the actual situation, which provides some practical help for the current research on the development of artificial intelligence in college students.

Due to the limitations, the sample of this study is relatively small, and there is still room for improvement in terms of sample size, regional distribution, student population, etc. The scope and depth of the scale can be expanded, and the contents of the scale can be applied to the empirical project to further verify the reliability and validity of this scale.

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