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Artificial Intelligence Attitude Scale

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SUMMARY

The aim of this study is to develop a reliable and valid scale to determine individuals' attitudes toward artificial intelligence. The study was conducted during the spring semester of 2024 with the participation of pre-service teachers studying at the Faculty of Education at Muğla Sıtkı Koçman University in Turkey. A total of 410 pre-service teachers participated in the exploratory factor analysis, and 201 pre-service teachers participated in the confirmatory factor analysis. The scale was found to have a three-factor structure consisting of 13 items. The reliability test results indicated that the scale is reliable both at the overall scale level and within its subdimensions. The confirmatory factor analysis also demonstrated that the goodness-of-fit indices were at an acceptable level. The scale consists of three subdimensions: "Benefits of Artificial Intelligence," "Risks of Artificial Intelligence," and "Use of Artificial Intelligence." The scale explains 53.86% of the variance.

Keywords: Artificial intelligence attitudes, scale development, reliability and validity analysis

INTRODUCTION

In today's world, technological developments are radically changing the way of life of humanity and progressing rapidly. In this process of rapid change and transformation, advances in areas such as digitalization, artificial intelligence, biotechnology and renewable energy affect and direct not only the technology industry but also the whole world. In this context, developments in the field of artificial intelligence (AI) are also rapidly increasing. These developments affect many areas such as economy, education and industry (Suh & Ahn, 2022). Although people are not very aware of it, they often use artificial intelligence-based technological tools and applications in their daily lives (Kaya et al., 2024; Persson et al., 2021). In other words, the penetration and use of artificial intelligence in every aspect of our lives is happening very quickly (Nikolenko & Astapenko, 2023). There are many different definitions of the concept of AI, which was first put forward by John McCarthy in the USA in 1956 (Coşkun & Gülleroğlu, 2021). For example, Milosheska (2019) defined AI as machines that improve themselves within the scope of machine learning, reasoning and regulation, imitating human intelligence. Arslan (2020) defined AI as a computer's ability to use skills specific to human intelligence. Coppin (2004) discussed artificial intelligence more comprehensively and defined it as the ability of machines to adapt to new situations, solve emerging problems, answer questions, make plans, and perform various other functions. When all these definitions are examined, it can be said that AI is a simulation of human intelligence. Therefore, artificial intelligence, from medicine to engineering; It is effective in every field of human intelligence, covering every discipline from biology to psychology.

Education (Aktay et al., 2023; Aygün, 2019; Kim & Han, 2021; Kim & Park, 2017; Ottenbreit-Leftwich et al., 2021; Ryu & Han, 2017; Shin, 2020; Shin & Shin, 2020; Son, 2020), health (Fenech et al., 2018; Vayena et al., 2018), transportation (Sindermann et al., 2021) and digital marketing (Milosheska, 2019) are used in the fields from AI. In addition, humanoid robots, referred to as social robots (Erica, Atlas, Pepper, etc.), personal assistants such as Siri, Alexa (Sindermann et al., 2021; Lim et al., 2022) and generative AI such as ChatGPT, Google Bard, Bing AI and SORA can also be listed as different areas of use of artificial intelligence. Artificial intelligence has many useful uses such as diagnosing diseases, protecting natural resources, predicting natural disasters, improving education and reducing risks in the workplace (Brooks, 2019, cited in Kaya et al., 2024). Despite all these positive effects of artificial intelligence, it is also stated that developments within the scope of artificial intelligence have disadvantages and dangers. Studies conducted in this context show that individuals have some concerns. Chief among these concerns are concerns about job loss (Frey & Osborne, 2017). Granulo et al. (2019) underlined that every year people are replaced by machines, so many people are laid off. However, concerns about data privacy (Gillespie et al., 2021; Nikolenko & Astapenko, 2023) and ethical concerns (Choi et al., 2024) are also frequently expressed. The EU (European Union) Commission proposes global standards to address ethical concerns for AI-based technology companies and users and encourages all member states to adopt a common approach. Therefore, the EU Commission (2019) has determined ethical rules that must be followed for reliable AI. From another perspective, individuals are also negatively affected by the fact that leading figures in the field, such as Stephen Hawking and Elon Musk, state that progress in artificial intelligence research has the potential to end humanity (Sindermann et al., 2021).

The positive and negative aspects of artificial intelligence are also reflected in the studies conducted in this context. For example, in a study conducted by Ghotbi et al. (2022) with university students, it was revealed that the students had a positive attitude towards artificial intelligence. Again, as a result of the study conducted by Scantamburlo et al. (2023) with 4006 European citizens (Spain, France, Italy, Poland, Germany, Sweden, Netherlands and Romania), it was seen that the participants had positive attitudes towards artificial intelligence. However, in Sit et al.'s (2020) study with a total of 484 medical students from 19 universities, the participants stated that AI may have an important role in healthcare, but may lead to job loss. Similarly, another study conducted in five different countries with 6054 participants revealed that trust in artificial intelligence is at a very low level (Gillespie et al., 2021). When studies on artificial intelligence are examined, it is seen that people's approaches to artificial intelligence differ considerably. Individuals especially emphasize the positive and negative aspects of artificial intelligence (Cave et al., 2019; Edelman, 2019; Fast & Horvitz, 2017). In other words, while some people support the advantages of artificial intelligence-based products in daily life, some people seem skeptical and even worried about artificial intelligence-based products (Sindermann et al., 2021). The transformative effect of artificial intelligence makes it difficult to evaluate its positive and negative effects in every field. In this context, it is emphasized that as artificial intelligence continues to advance and becomes more complex, challenges as well as opportunities may arise in areas such as employment, security, medicine, defense industry and transportation (Ghotbi et al., 2022). The positive or negative attitudes of individuals in studies on artificial intelligence also coincide with the nature of the concept of attitude. In this context, it is seen that attitude is defined as "a psychological tendency expressed by evaluating a certain entity positively or negatively" (Eagly & Chaiken, 1993, cited in Gawronski, 2007). Acceptance of artificial intelligence is thought to be related to attitudes towards it (Kaya et al., 2024). Attitudes towards artificial intelligence may also be an important element in the success or failure of artificial intelligence education (Suh & Ahn, 2022). Because our knowledge about a specific subject or phenomenon forms the basis of our beliefs, and our beliefs form the basis of our attitudes (Ajzen & Cote, 2008).

Based on all these, it can be seen that many attitude scales towards artificial intelligence have been developed. Developing an attitude scale towards artificial intelligence can contribute to the development of public awareness studies in this context by revealing concerns and misunderstandings about artificial intelligence (Grassini, 2023), as well as providing important information about how individuals perceive artificial intelligence and to what extent they accept it (Persson et al., 2021). Moreover, knowing individuals' views on the field can play an important role in the integration of rule mechanisms regarding the use and development of AI into society. In short, it is thought that individuals' general attitudes towards artificial intelligence play a major role in their acceptance and widespread use of this technology (Schepman & Rodway, 2020).

When international studies conducted in this context are examined, it is seen that many attitude scales towards artificial intelligence have been developed. At this point, Schepman and Rodway's (2020) 20-item scale with a two-factor structure (positive and negative attitudes), Sindermann et al.'s (2021) 5-item attitude scale with two factors (acceptance and fear), and Grassini's (2023) The 4-item scale can be given as an example. A 26-item scale developed in the context of three basic components of attitude (cognitive, emotional and behavioral) is also noteworthy (Suh & Ahn, 2022). Although there are scales such as the Artificial Intelligence Anxiety Scale (Akkaya et al., 2021), Artificial Intelligence Anxiety Scale (Kolcu et al., 2021), Artificial Intelligence Literacy Scale (Çelebi et al., 2023) developed in Turkish, the general studies on artificial intelligence are among the studies reached, there is no attitude scale. In only one study (Kaya et al., 2024), Schepman and Rodway's (2020) general attitude scale towards artificial intelligence was adapted. Based on this, the aim of this study is to develop a reliable and valid scale that can determine attitudes towards artificial intelligence.

METHOD

Exploratory factor analysis study group

The study group of this research consists of two different populations for exploratory factor analysis and confirmatory factor analysis. The exploratory factor analysis part of the study consisted of 410 pre-service teachers studying at Muğla Sıtkı Koçman University Faculty of Education in the spring semester of the 2023-2024 academic year. The personal characteristics of the pre-service teachers were enriched by including different classes and departments of the faculty of education in the study group. The characteristics of the study group are summarized in Table 1.

Table 1. The Characteristics of The Exploratory Factor Analysis Study Group

Exploratory factor analysis study group	**f**	**%**
Departments		
Classroom teaching	82	20
Social studies education	49	12

Preschool education	46	11.2
Science education	26	6.3
Mathematics education	41	10
Turkish education	25	6.1
English language teaching	2	0.5
German language teaching	27	6.6
Music teaching	17	4.1
Guidance and Psychological Counseling	78	19
Special education	17	4.1
Gender		
Female	295	72.5
Male	112	27.5
Grade Level		
1st year	50	12.4
2nd year	167	41.4
3rd year	169	41.9
4th year	17	4.2
Total	**410**	**100.0**

As seen in Table 1, the study group consisted of 410 students from eleven different teaching fields studying at the Faculty of Education. While the participants were mostly in classroom teaching and guidance and psychological counseling teaching, they differed in other departments. In addition, it is seen that the pre-service teachers in the study group are mostly female. When the grade levels are analyzed, it is seen that mostly second and third grade pre-service teachers are involved.

Confirmatory factor analysis study group

The confirmatory factor analysis of the study was conducted with the participation of 201 pre-service teachers studying at Muğla Sıtkı Koçman University Faculty of Education in the spring semester of the 2023-2024 academic year. The characteristics of the pre-service teachers who participated in the confirmatory factor analysis are given in the table below.

Table 2. The Characteristics of The Confirmatory Factor Analysis Study Group

Confirmatory factor analysis study group	f	%
Departments		
Classroom teaching	02	1.0
Social studies education	63	31.3
Preschool education	36	17.9
Mathematics education	34	16.9
Guidance and psychological counseling	66	32.8
Gender		
Female	142	70.6
Male	59	26.4
Grade Level		
1st year	140	69.7
2nd year	5	2.5
3rd year	54	26.9
4th year	02	1.0
Total	**201**	**100.0**

As seen in the table above, pre-service teachers from 5 different departments participated in the confirmatory factor analysis. While 70 percent of the pre-service teachers were female, most of them were in the first grade. There were 201 pre-service teachers in total and this number was sufficient for confirmatory factor analysis.

Scale development process

In the process of developing the scale, firstly, a literature review was conducted and scans related to artificial intelligence were conducted. After the scans, a general framework about attitudes towards artificial intelligence was created in the light of the information obtained from the literature. Then, an item pool of 31 items was created by utilizing the information obtained from the literature and experts in the field. In order to determine the competency levels in the items, five-grade options were placed. These options were organized as "strongly disagree", "disagree", "undecided", "agree" and "strongly agree" respectively.

The draft items were examined by experts in the field in terms of both language and grammar usage and content validity, and expert opinion was obtained in the context of the scale. In line with the criticisms and suggestions, the number of items was reduced to 27 and necessary corrections were made on the items. Then, the draft scale was applied to 40 4th grade pre-service teachers from Muğla Sıtkı Koçman University Faculty of Education for a preliminary test. After the pre-test, the items that were not understood by the pre-service teachers were corrected or removed. Finally, the draft scale consisting of 23 items was applied to 410 pre-service teachers in Muğla Sıtkı Koçman University Faculty of Education. The collected data were entered into the SPSS program to statistically analyze the validity and reliability of the scale and were subjected to statistical procedures.

After the exploratory factor analysis tests were performed, 13 items remained in the scale. It was revealed that the scale had a three-factor structure. Confirmatory factor analysis was then conducted for the final version of the scale. The analyses followed during the development of the scale and the findings related to these analyses are presented in the following section.

FINDINGS

In this section, the development process of the scale and the statistical tests conducted on the scale are presented.

Construct validity

In order to test the construct validity of the scale, Kaiser-Meyer-Oklin (KMO) and Bartlett test analyses were performed on the data and the KMO=.883 and Bartlett test value was determined as x2= 2636.220; df=231 (p=.000). The KMO value should be 0.60 or above and the p value of Bartlett's test should be .05 or below (Pallant, 2020). Based on these values, it was understood that factor analysis could be performed on the 23-item draft scale. Factor analysis is used to reveal whether the items in a scale are divided into fewer factors that exclude each other (Balcı, 2009).

The next step was to determine the number of factors representing the items of the scale. Factor analysis aims to reveal the factors and number of factors that best represent the scale. In this context, it is important to obtain as few factors as possible and to explain as much variance as possible. The most important techniques that determine the number of factors in factor analysis are principal components analysis, which is the most commonly used approach, and Kaiser criterion and scree plot graph as support for this analysis (Pallant, 2020).

In the literature, the factor loading value should be above .45. However, in conditions where the number of items is low, the factor loading value can be reduced to .30 (Büyüköztürk, 2007). In this study, it was preferred that the factor loading of the items of the scale should be at least .50. After the eliminated items were discarded, the KMO value of the scale was determined as .835 and Bartlett's test value was determined as x2= 1272,013; df=78 (p=.000). The factor loadings of the remaining 13 items in the scale were found to be between 0.585 and 0.818. The Scree plot graph of the scale is shown in Figure 1.

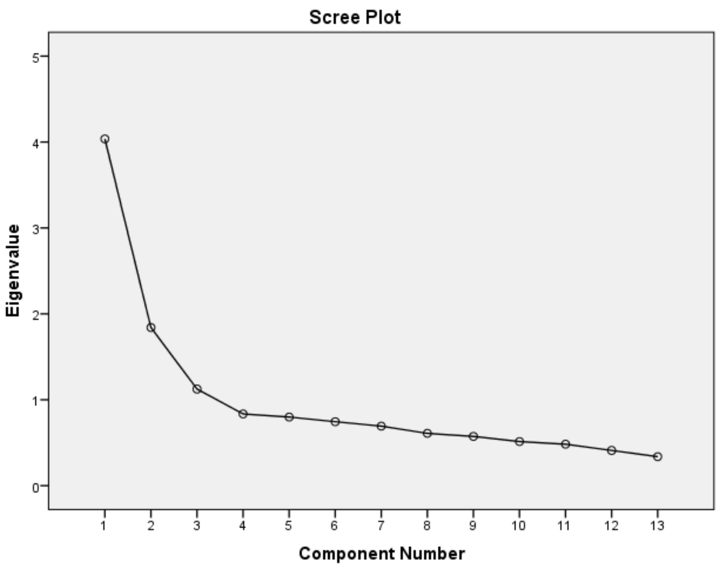

Figure 1. Scree Plot

As can be seen in the figure above, it is observed that after the first three factors, the acceleration continues in a decreasing and horizontal manner. Therefore, the contributions of the factors after the three factors to the variance are close to each other. Eigenvalues, variance percentages and total variance percentages for the remaining 13 items in the scale are given in the table below.

Table 3. Eigenvalues

Factor	Eigenvalue	Variance Percentage	Total Variance Percentage
1	4.036	31.049	31.049
2	1.841	14.161	45.210
3	1.124	8.650	53.860

As seen in the table above, the variance percentages of the three factors in the scale vary between 31 percent and 8.6 percent. It is also seen that the total variance is 53.86%. This rate is above the acceptable rate of 41% (Kline, 1994). The factors in the scale and the items under these factors are given in the table below.

Table 4. Factor Loadings

Factor 1		**Factor 2**		**Factor 3**	
Item	Factor Loading	Item	Factor Loading	Item	Factor Loading
i19	.719	i8	.818	i10	.747
i7	.714	i11	.755	i16	.709
i12	.712	i2	.717	i4	.694
i14	.621			i21	.665
i20	.604				
i6	.585				

As seen in the table above, there are 6 items in the first factor, 3 items in the second factor and 4 items in the third factor. When the items in the factors in the scale are analyzed, it is seen that the first factor is related to the contributions of artificial intelligence to humanity. When the second factor is examined, it is found that the second factor is related to the perception of risks and threats related to artificial intelligence. Finally, the third factor is related to the production possibilities of artificial intelligence.

Item distinctiveness

In this section, the item-total correlation of the scale was examined and the degree of correlation of the scale items with the score obtained from the whole scale was analyzed. The correlation between the score of the scale item and the score obtained from the whole scale is an indicator of how well that item measures the phenomenon to be measured. An item-total score correlation above .30 is an indication that the items have good discrimination (Büyüköztürk, 2007). The correlation data between item-total score are shown in the table below.

Table 5. Item-Total Correlation

Factor 1		**Factor 2**		**Factor 3**	
Item	Item-Total Correlation	Item	Item-Total Correlation	Item	Item-Total Correlation
i19	.522	i8	.420	i10	.302
i7	.561	i11	.526	i16	.356
i12	.562	i2	.387	i4	.392
i14	.366			i21	.337
i20	.542				
i6	.449				

As seen in the table above, the item-total item correlations of the items in the scale ranged between .302 and .562. Therefore, it was seen that all of the scale items were above .30, which is accepted as the limit that does not require correction.

In addition, for criterion validity, after dividing the extremes into upper group and lower group based on the scale scores, it was tested by item analysis whether the difference between the averages of these two groups was significant. In this context, the scores of the upper group of 27% and the lower group of 27%, which were formed according to the scale mean scores of the participants, were subjected to independent samples t-test for each item and also as a factor, and the difference between the item mean scores of the groups was tested. As a result of the analysis, all items and the general factor were found significant at (p<.001) level.

Reliability of the scale

Reliability analysis of the scale consisting of 13 items and three factors was conducted. In this context, the reliability of both the overall scale and the sub-dimensions was calculated using Cronbach's alpha analysis. Reliability analysis data for the scale are shown in the table below.

Table 6. Reliability of The Scale

Reliability test	Overall scale	Factor 1	Factor 2	Factor 3
Cronbach's alpha	.802	.781	.732	.679

As seen in the table above, the Cronbach's alpha reliability value of the whole scale was found to be .802. In addition, the Cronbach's alpha reliability values of the sub-dimensions of the scale ranged between .679 and .781. Considering the results of the Cronbach's alpha reliability test, it can be said that the overall scale and its sub-dimensions are reliable (Büyüköztürk, 2010).

Findings related to confirmatory factor analysis

As a result of the exploratory factor analysis, it was found that the scale had a three-factor structure. Confirmatory factor analysis (CFA) was conducted using the Lisrel program to reveal the structural validity of the factors obtained. Confirmatory factor analysis is a form of analysis in which it is tested whether a previously established and constructed structure is confirmed through a model.

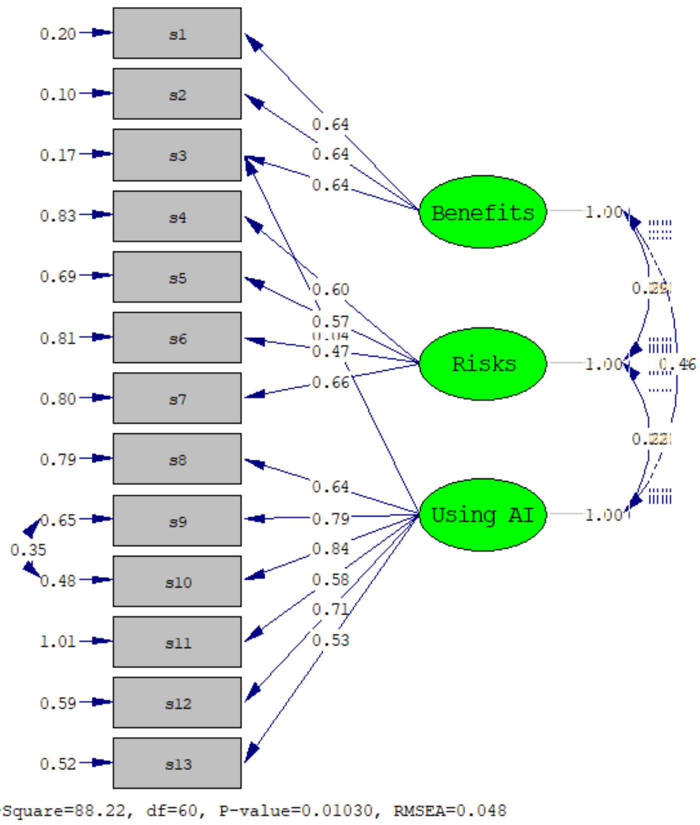

Figure 2. CFA Results

With CFA, the fit indices of the model consisting of 13 items were examined. As a result of CFA, SRMR=0.058, RMSEA=0.048, RMR=0.060, AGFI=0.90, GFI=0.94, NFI=0.93, NNFI=0.96, CFI=0.97, IFI=0.97 fit indices were found. Although the significance of the chi-square test does not fully support the fit of the model, this data is sensitive to the sample size. Since the SRMR value is less than 0.08, it provides a good fit. The RMR value of 0.060 indicates that the errors of the model are low and represent the data in an acceptable way. Since GFI and AGFI values are above 0.90, it can be said that the scale shows a good fit. The RMR value being less than 05 indicates that the model-data fit is at a good level. NFI, NNFI, CFI and IFI values also indicate a very good fit. In addition, since the RMSEA value is between 0.00-0.05, it can be said that the scale shows high fit (Kline, 2005; Hooper et al., 2008; Blunch, 2008; Kenny, 2024). As a result, the scale shows a strong fit in terms of both general fit criteria and comparative fit criteria (Schermelleh-Engel et al., 2003; Schumacker & Lomax, 2004; Tabachnick & Fidell, 2001).

CONCLUSION AND DISCUSSION

As a result of the exploratory factor analysis conducted on the data obtained, it was seen that the scale had a three-factor structure consisting of 13 items. The scale consists of "Benefits of artificial intelligence", "Risks of artificial intelligence" and "Use of artificial intelligence" sub-dimensions. The scale explains 53.86% of the variance. The Cronbach's alpha reliability value of the scale was found to be reliable both in the context of the overall scale and in the context of the sub-dimensions. As a result of the validity and reliability analyses, it was found that the "Artificial Intelligence Attitude Scale" is a valid and reliable scale.

The lowest score that can be obtained from the scale is 13 and the highest score is 65. A high score from the scale can be considered as a high level of artificial intelligence attitude. It is thought that the results obtained within the scope of determining the attitudes of individuals towards artificial intelligence with the developed scale will contribute to the literature.

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YAPAY ZEKA TUTUM ÖLÇEĞİ

	Kesinlikle katılmıyorum	Katılmıyorum	Kararsızım	Katılıyorum	Kesinlikle katılıyorum
1. Yapay zekanın önemli bir gelişme olduğunu düşünüyorum.					
2. Yapay zekanın insanların yaşamını kolaylaştırdığını düşünüyorum.					
3. Yapay zekanın insanlığa önemli katkılar sağlayacağına inanıyorum.					
4. Yapay zekayı bir tehdit olarak görüyorum.					
5. Yapay zekanın insanlar arası iletişimi azalttığını düşünüyorum.					
6. Yapay zekanın insan gücünün yerini alacağından endişe ediyorum.					
7. Yapay zekanın yaratıcılığı yok ettiğini düşünüyorum.					
8. Metinsel içerik üretmek için yapay zekayı kullanmayı seviyorum.					
9. Yapay zeka konusundaki gelişmeleri takip etmekten hoşlanıyorum.					
10. Yapay zeka ile ilgili konularda konuşmaktan hoşlanıyorum.					
11. Yapay zeka ile sohbet etmek isterim.					
12. Yapay zeka ile yaratıcı görsel ürünler oluşturmayı seviyorum.					
13. Eğlence amaçlı olarak yapay zeka araçlarını kullanmak isterim.					

Birinci faktör (Yapay zekanın faydaları): 1, 2 ve 3. Madde
İkinci faktör (Yapay zekanın riskleri): 4, 5, 6 ve 7. Madde
Üçüncü faktör (Yapay zeka kullanımı): 8-13. Madde
4, 5, 6 ve 7. Maddeler olumsuz ifadelerdir.

ARTIFICIAL INTELLIGENCE ATTITUDE SCALE

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. I think artificial intelligence is an important advancement.					
2. I believe artificial intelligence makes life easier for people.					
3. I believe artificial intelligence will provide significant contributions to humanity.					
4. I see artificial intelligence as a threat.					
5. I think artificial intelligence reduces human-to-human communication.					
6. I am concerned that artificial intelligence will replace human labor.					
7. I believe artificial intelligence destroys creativity.					
8. I enjoy using artificial intelligence to produce textual content.					
9. I like keeping up with developments in artificial intelligence.					
10. I enjoy talking about topics related to artificial intelligence.					
11. I would like to chat with artificial intelligence.					
12. I enjoy creating visual products using artificial intelligence.					
13. I would like to use artificial intelligence tools for entertainment purposes.					

First Factor (Benefits of Artificial Intelligence): Questions 1, 2, and 3
Second Factor (Risks of Artificial Intelligence): Questions 4, 5, 6, and 7
Third Factor (Use of Artificial Intelligence): Questions 8–13
Items 4, 5, 6, and 7 are negatively worded statements.