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ANALYSIS ON THE ACCEPTANCE OF AIGC TECHNOLOGY BY ART AND DESIGN STUDENTS IN UNIVERSITIES IN CHINA

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Abstract

This study investigates the factors influencing the attitudes, behaviors and intentions toward the adoption of Artificial Intelligence Generated Content (AIGC) technology, among art and design students at Chinese universities. The conceptual framework is grounded in the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and economic consumption theory. Data were collected from 434 art and design students with AIGC experience at a university in Henan, China. Partial least squares structural equation modeling (PLS-SEM) was utilized for analysis. The findings show that Perceived Benefit, Perceived Usefulness, and Social Influence, are necessary conditions, positively affecting students' attitudes towards AIGC. Perceived Benefit, Attitude, Social Influence, Hedonic Motivation, and Facilitating Conditions, were found to be necessary conditions for behavioral intentions, positively influencing students' behavioral intentions to adopt AIGC. Social Influence showed significance, but the necessity was not strong. Perceived Risk held neither significance nor necessity. Therefore, promoting AIGC adoption in Chinese art and design programs should focus on resource allocation and perception creation.

Keywords: TAM, Artificial Intelligence Generated Content (AIGC), UTAUT2, PLS-SEM, Behavioral Intentions

1. INTRODUCTION

Artificial Intelligence Generated Content (AIGC) pertains to Generative AI, that caters to users' personalized needs in content production domains such as videos, images, audio, and text (J. Wu et al., 2024). The unique advantages of AIGC in content generation are highly consistent with creativity in the realm of art and design. In the creative stage, AIGC can be used to assist in the divergence of creative concepts and rapid iteration (Lanzi & Loiacono, 2023). In the content generation stage, Generative Adversarial Network (GAN) is used to generate works that meet creative needs and aesthetic standards (Zhao et al., 2021; Lee et al., 2022).

As China, which holds the largest scale of higher education in the world, is at an advanced level in the realm of artificial intelligence (AI) (Zhao et al., 2021), how to apply AIGC technology to higher education to enhance the quality and level of higher education is also a very challenging and urgent research issue (Knox, 2020). As the birthplace of traditional

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Chinese art and culture, Henan Province is also the province with the largest number of college entrance examinations, at 1.36 million candidates in China (Des Forges, 2003).

The application of AIGC has brought profound and drastic changes to the traditional art and design creation process (F. Wu et al., 2024; Lou, 2023). In China, AIGC technology has appeared in the realm of art creativity and design production and has ushered in a great improvement in creative production efficiency (Verganti et al., 2020; Huang et al., 2024). Understanding students' acceptance and behavioral intentions toward AIGC can assist institutions, educators, and developers, in better formulating teaching strategies and adjusting course content to adapt to future technological transformations.

2. LITERATURE REVIEW

2.1 Theoretical Background

The concept of AIGC refers to content customized by Artificial Intelligence to meet users' personalized needs, such as text, images, videos, and audio (J. Wu et al., 2024). AIGC possesses both content and technical characteristics, encompassing content automatically generated by AI based on deep learning architectures, as well as the production method where AI searches through existing data patterns to generate content. Additionally, it includes a set of technologies for automatic content generation (Li et al., 2023). In 2023, significant advancements in AI technology blurred the boundaries between human-created and machine-generated content (Park et al., 2023), marking a shift in AI from perception and understanding to generation and creation. Regarding the disruptive impact of AIGC technology on traditional creative methods in art and design, people hold polarized attitudes (Nussberger et al., 2022). Proponents believe that AIGC is no longer just a tool, as it has completely transformed the creative process (Hwang, 2022), turning creativity into a matter of choice, and that creative professionals should embrace it. Opponents, however, argue that AIGC technology leads to job loss for creators (Boyd & Holton, 2018) and raises copyright issues. The debate surrounding whether AIGC is a "Stochastic Parrot" has thus emerged (Bender et al., 2021).

Many studies on AIGC focus on its production and application in art and design. For example, F. Wu et al. (2024) attempted to use AIGC technology for product color matching design, while Davoodi et al. (2020), Wei et al. (2024), Lou (2023), Huang et al. (2024), and Ma and Huo (2024) explored the application of AIGC in fields such as game design, architecture, advertising, industrial design, and painting. Research on the educational applications of AIGC is relatively scarce and tends to focus on experimental classroom applications.

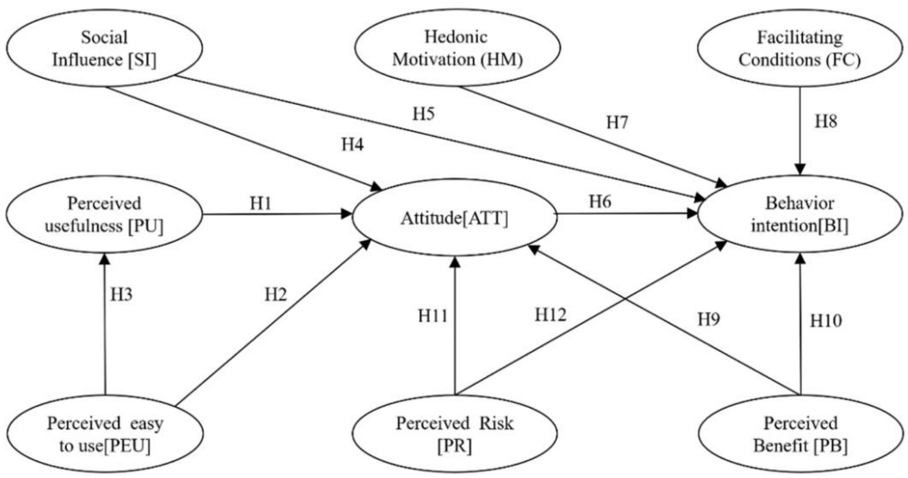
The Technology Acceptance Model (TAM) is a model employed to examine the degree of acceptance and adoption of new technologies by users (Albayati, 2024; Davis, 1989). The UTAUT2 model is a technology acceptance model developed based on UTAUT to make it suitable for broader application environments (Venkatesh et al., 2012). Perceived risk (PR) and perceived benefit (PB) are important factors affecting customer consumption and are a pair of opposite variables (Tingchi Liu et al., 2013; Lin, 2008). This study, based on these theoretical frameworks, extracts key components from these models as a foundation. Perceived Usefulness (PU) and Perceived Ease of Use (PEU) were extracted from the TAM model. Perceived Usefulness (PU) plays a crucial role in the TAM model (Karahanna & Straub, 1999). Its concept pertains to the degree to which users believe that a technology can enhance the quality of their work and productivity (Autry et al., 2010). Perceived Ease of Use (PEU) is another core factor in TAM. It means that if users believe that the new technology can be easily mastered and requires a low learning cost, they are more inclined to accept and adopt the new technology (Venkatesh & Bala, 2008; Martins et al., 2014). Al-Sharafi et al. (2016) asserts that PEU played a very important role in TAM. Three key elements were extracted from the UTAUT and

UTAUT2 framework: Social Influence (SI), Hedonic Motivation (HM), and Facilitating Conditions (FC). Social influence (SI) can be construed as the degree to which an individual believes that significant others think he or she should adopt the new technology (Venkatesh et al., 2003; He et al., 2022). Venkatesh et al. (2012) discovered that Hedonic Motivation (HM) is the happiness that users obtain from using technology. In research, it has been found that HM directly affects Behavioral Intentions (Van der Heijden, 2004; Ma & Huo, 2023; Habibi et al., 2023). Facilitating Conditions (FC) is the availability of resources and the support of technical systems (Venkatesh, 2022). FC is an important variable factor in the UTAUT2 model (Shareef et al., 2024). Numerous studies relying on the UTAUT theory also show this. Perceived benefit refers to the belief in positive outcomes associated with behaviors that address real or perceived threats (Tingchi Liu et al., 2013). Perceived risk is negative and reflects consumers' views on the uncertainty of outcomes (Abramova & Böhme, 2016). Perceived risk will depend on the degree of subjective uncertainty of the outcome (Kesharwani & Singh Bisht, 2012). Finally, this study incorporated the theories of perceived risk and benefit, adding Perceived Benefit (PB) and Perceived Risk (PR) to the conceptual framework.

2.2 Conceptual Framework and Hypotheses

Based on the above models and theories, this research developed a conceptual framework as shown in Figure 1.

Figure 1 Conceptual Framework



The hypotheses related to the extracted elements are as follows:

H1. Perceived Usefulness has a significant impact on students' attitude toward using AIGC.

H2. Perceived Ease of Use has a significant impact on students' attitude toward using AIGC.

H3. Perceived Ease of Use has a significant impact on students' Perceived Usefulness of AIGC.

H4. Social Influence has a significant impact on students' attitude toward using AIGC.

H5. Social Influence has a significant impact on the students' Behavioral Intentions toward using AIGC.

H6. Attitude has a significant impact on students' Behavioral Intentions toward using AIGC.

H7. Hedonic Motivation has a significant impact on students' Behavioral Intentions toward using AIGC.

H8. Facilitating Conditions has a significant impact on students' Behavioral Intentions toward using AIGC.

H9. Perceived Benefit has a significant impact on students' attitude toward using AIGC.

H10. Perceived Benefit has a significant impact on students' Behavioral Intentions toward using AIGC.

H11: Perceived Risk has a significant impact on students' attitude towards use of AIGC.

H12: Perceived Risk has a significant impact on students' Behavioral Intentions towards use of AIGC.

3. RESEARH METHODOLOGY

3.1 Population and Sample

The population targeted by this study was students of art and design colleges in universities in Henan Province, China. The data sampling was approved by the Ethics Working Committee of the Henan Institute of Science and Technology. The respodents were sampled through simple random sampling (Etikan & Bala, 2017) and data collection was conducted using an online questionnaire. To obtain accurate sample data, the questionnaire used a screening question, "Have you used AIGC?" to filter out those who have not used AIGC technology. To better collect data with the aid of the social software, WeChat, this research distributed the questionnaire through the Tencent Questionnaire platform, and the distribution website was https://wj.qq.com/s2/15085061/9c10/. In total, 514 questionnaires were obtained, after filtering out 80 invalid questionnaires, the final sample of valid questionnaires obtained was 434.

3.2 Measurement and Questionnaire Design

The research was carried out by employing a questionnaire consisting of 5-point Likert scale items, with a total of 36 questions, divided among 3 sections, including 1 screening question, 5 demographic information questions, and 30 questions regarding the 9 variables providing information on the perception of AIGC. All measurement items were derived from previous literature, as shown in Table 1. In terms of the validity measurement of this questionnaire research tool, the CVI method was adopted, and 3 experts were consulted. The validity measurement was conducted by Item-level CVI with Agreement Among Raters. The CVI of all items was higher than 0.5, with a Mean CVI of 1. Therefore, the questionnaire passed validity testing. A pilot test was also conducted. A questionnaire sample of 31 people was collected through an online questionnaire, yielding a minimum Cronbach's alpha of 0.811, all Cronbach's alpha values were bigger than 0.7, as shown in Table 3 indicating that the questionnaire has good reliability.

3.3 Data Analysis

The method of verifying that the observed phenomenon conforms to the specified model through traditional factor-based methods is prone to overfitting bias (Subongkod & Hongsakul, 2024). This study employed PLS-SEM (Least Square Structural Equation Modeling) procedures for evaluating the measurement and structural models due to their flexibility in handling varying sample sizes and non-normal data (Becker et al., 2023; Rigdon et al., 2017). This is a common method suitable for analyzing complex frameworks with many latent variables and which can be used for examining the connections between variables in social science contexts (Habibi et al., 2023, Pongwat & Talawanich, 2024). By utilizing PLS-SEM analysis, the researchers gained deeper insights into how effectively the hybrid model based on the TAM framework in this study explains students' attitudes and behavioral intentions toward using AIGC. The presentation of results further clarifies the factors influencing students' adoption and use of AIGC technology (Albayati, 2024).

Table 1 Source of Measurement Items Used in the Questionnaire

Variables	Measurement Items	Source
Perceived Usefulness (PU)	Using AIGC would improve my work quality Using AIGC would enhance my work effectiveness Using AIGC would allow me to have more convenience at work	(Albayati, 2024)
Perceived Ease of Use (PEU)	Learning to operate AIGC would be easy for me I believe it would be easy to use AIGC to accomplish what I want to do It is easy for me to become skillful at using AIGC I believe AIGC is easy to use	(Albayati, 2024)
Social Influence (SI)	Individuals significant to me believe that I ought to adopt AIGC. Those who shape my actions feel that I should utilize AIGC. The people whose viewpoints I respect would rather I make use of AIGC.	(Albayati, 2024) (Habibi et al., 2023)
Attitude (ATT)	I am interested in using AIGC I use AIGC because of its attractiveness I feel my work overall will be better with AIGC	(Albayati, 2024) (Habibi et al., 2023)
Hedonic Motivation (HM)	Using the AIGC system is fun Using the AIGC system is enjoyable Using the AIGC system is very entertaining	(Habibi et al., 2023)
Facilitating Conditions (FC)	I possess the resources required to implement AIGC. I have the knowledge needed to operate AIGC. AIGC is compatible with the technology I currently use. I can seek assistance from others when I encounter challenges using AIGC.	(Habibi et al., 2023)
Perceived Benefit (PB)	AIGC can lower the threshold for painting and design AIGC can help me remove technological constraints better AIGC can help my design and painting to be more creative	(Ma & Huo, 2023) (Lu, 2024)
Perceived Risk (PR)	The use of AIGC will leak personal information The use of AIGC will pose a threat to information security The use of AIGC will bring hidden dangers to intellectual property rights The use of AIGC will bring about ethical issues	(Ma & Huo, 2023) (Lu, 2024)
Behavioral Intention (BI)	Given access to AIGC, I aim to utilize it. If AIGC is available to me, I would make use of it. I intend to start using AIGC in the coming months.	(Albayati, 2024)

Table 2 shows the demographic information of the respondents in this study. Among the respondents, a relatively high proportion were women (72.4%), the majority were aged between 20 and 25 years (50.2%), and most had been using AIGC technology for less than half a year (77.6%). Table 3 shows the descriptive statistics, including the mean, standard deviation (SD), skewness, and kurtosis, of each item. The mean values are concentrated between 3 and 4, and SD values are all less than 1, while Kurtosis and Skewness are both distributed between -2 and 2.

Table 2 Demographic Profile of the Respondents (n = 434)

Item	Values	Frequency	Percentage
Gender	Male	120	27.6%
	Female	314	72.4%
Age	15-20	214	49.3%
	20-25	218	50.2%
	25-30	2	0.5%
Major	Fine art	187	43.1%
	Design	247	56.9%
Duration of using	Less than half a year	337	77.6%
	Less than one year	51	11.8%
	More than one year	46	10.6%

Note. n = 434

Table 3 Mean, Standard Deviation, Kurtosis, and Skewness

Type	Antecedent	Measurement Items	Mean	S.D.	Kurtosis	Skewness
Component	PU	PU1	3.37	0.734	1.476	0.093
		PU2	3.59	0.756	0.938	-0.187
		PU3	3.64	0.775	1.249	-0.409
Component	PEU	PEU1	3.37	0.708	1.361	0.088
		PEU2	3.43	0.736	1.048	0.023
		PEU3	3.29	0.691	1.275	0.273
		PEU4	3.31	0.671	1.222	0.322
Component	SI	SI1	3.24	0.741	1.224	0.025
		SI2	3.24	0.703	1.833	-0.061
		SI3	3.26	0.701	1.613	0.067
Component	ATT	ATT1	3.42	0.738	1.170	-0.084
		ATT2	3.37	0.77	1.127	-0.064
		ATT3	3.38	0.77	1.137	-0.082
Component	HM	HM1	3.5	0.773	0.883	-0.136
		HM2	3.48	0.772	1.175	-0.210
		HM3	3.44	0.752	0.898	0.008
Component	FC	FC1	3.52	0.805	0.754	-0.194
		FC2	3.29	0.761	1.027	0.156
		FC3	3.42	0.75	1.115	0.088
		FC4	3.44	0.73	1.086	-0.033
Component	PB	PB1	3.23	0.843	0.371	-0.076
		PB2	3.33	0.741	0.999	0.078

Table 3 (Continued)

Type	Antecedent	Measurement Items	Mean	S.D.	Kurtosis	Skewness
		PB3	3.38	0.782	0.989	-0.116
Component	PR	PR1	3.17	0.69	1.338	0.406
		PR2	3.13	0.709	1.710	0.354
		PR3	3.38	0.805	0.364	0.365
		PR4	3.13	0.751	1.473	0.236
Component	BI	BI1	3.47	0.738	0.326	0.319
		BI2	3.49	0.733	0.316	0.280
		BI3	3.3	0.73	1.043	0.397

4. FINDINGS

4.1 Measurement Model Assessment

Hair Jr. et al. (2021) highlighted the significance of evaluating the reliability and validity of the measurement items for each variable. The loading for each item should be a minimum of 0.7 under consistent testing conditions. As shown in Table 4, all 30 measurement items across the 9 variables in this study have loadings between 0.7 and 0.9. Indicator reliability therefore exceeds the 0.5 threshold, confirming strong convergent validity. Table 3 demonstrates that the Composite Reliability for all items exceeds 0.7, ranging from 0.87 to 0.95, while the Cronbach's Alpha values range between 0.75 and 0.92, both surpassing the 0.7 threshold. The Average Variance Extracted (AVE) is also greater than 0.5, with values ranging from 0.69 to 0.86. These values confirm that both Cronbach's Alpha and Composite Reliability are above 0.7, while the AVE exceeds 0.5, thereby establishing the convergent validity of the constructs.

This study employs the Fornell–Larcker criterion and cross loadings to assess discriminant validity (Ab Hamid et al., 2017). The results shown in Table 5 demonstrate that the AVE of each construct exceeds the square of its correlation with other latent variables, confirming discriminant validity. According to Table 6, each indicator has a higher loading on its corresponding latent variable compared to its loadings on other variables, with differences exceeding 0.1. Thus, the model's discriminant validity is confirmed.

Table 4 Measurement Model Results

Latent Variable	Indicators	Convergent Validity (CV)			Internal Consistency Reliability (ICR)		Discriminant Validity?
		Loading	Indicators Reliability	AVE	Composite Reliability	Cronbach's Alpha	
Perceived usefulness	PU1	0.899	0.808	0.859	0.948	0.917	yes
	PU2	0.943	0.889				
	PU3	0.938	0.880				
Perceived Ease of Use	PEU1	0.85	0.723	0.717	0.91	0.87	yes
	PEU2	0.815	0.664				
	PEU3	0.87	0.757				
	PEU4	0.852	0.726				
Social influence	SI1	0.875	0.766	0.828	0.935	0.896	yes
	SI2	0.926	0.857				
	SI3	0.928	0.861				
Attitude	ATT1	0.919	0.845	0.819	0.931	0.89	yes
	ATT2	0.913	0.834				

Table 4 (Continued)

Latent Variable	Indicators	Convergent Validity (CV)			Internal Consistency Reliability (ICR)		Discriminant Validity?
		Loading	Indicators Reliability	AVE	Composite Reliability	Cronbach's Alpha	
	ATT3	0.882	0.778				
Hedonic Motivation	HM1	0.924	0.854	0.847	0.943	0.91	yes
	HM2	0.925	0.856				
	HM3	0.912	0.832				
Facilitating Conditions	FC1	0.883	0.780	0.785	0.936	0.908	yes
	FC2	0.87	0.757				
	FC3	0.919	0.845				
	FC4	0.871	0.759				
Perceived Benefit	PB1	0.7	0.490	0.693	0.87	0.779	yes
	PB2	0.914	0.835				
	PB3	0.868	0.753				
Perceived Risk	PR1	0.903	0.815	0.716	0.91	0.873	yes
	PR2	0.855	0.731				
	PR3	0.785	0.616				
	PR4	0.838	0.702				
Behavioral Intention	BI1	0.944	0.891	0.851	0.945	0.912	yes
	BI2	0.945	0.893				
	BI3	0.878	0.771				

Table 5 Fornell–Larcker Criterion Results

	ATT	BI	FC	HM	PB	PEU	PR	PU	SI
ATT	0.905								
BI	0.781	0.923							
FC	0.682	0.740	0.886						
HM	0.843	0.785	0.753	0.920					
PB	0.746	0.772	0.715	0.724	0.833				
PEU	0.658	0.659	0.749	0.707	0.655	0.847			
PR	0.147	0.168	0.212	0.129	0.159	0.262	0.846		
PU	0.734	0.755	0.651	0.726	0.679	0.735	0.132	0.927	
SI	0.779	0.727	0.683	0.727	0.672	0.692	0.192	0.712	0.910

4.2 Structural Model Assessment

The R-squared (R^2) value is a key metric in PLS-SEM, to assess the explanatory power of exogenous latent variables over endogenous ones. It indicates how much variance in one variable is explained by another (Hair Jr. et al., 2021). Additionally, the value helps to evaluate a model's predictive and explanatory abilities (Wong, 2013). In this study, Behavioral Intentions (BI) has an R^2 of 74%, a relatively high value, demonstrating that the factors considered significantly influence students' intentions to use AIGC technology. Attitude (ATT) has an R^2 of 72%, also high, indicating that the independent variables associated with ATT have a significant positive effect on students' attitudes toward using AIGC. Perceived Usefulness (PU) has an R^2 of 54%, meaning that the model explains 54% of students' perceptions regarding the usefulness of AIGC technology.

Table 6 Cross Loading Results

	Attitude (ATT)	Behavioral Intentions (BI)	Facilitating Conditions (FC)	Hedonic Motivation (HM)	Perceived Benefit (PB)	Perceived Ease of Use (PEU)	Perceived Risk (PR)	Perceived Usefulness (PU)	Social Influence (SI)
ATT1	0.919	0.729	0.629	0.764	0.66	0.61	0.183	0.672	0.733
ATT2	0.913	0.668	0.616	0.773	0.649	0.591	0.143	0.608	0.69
ATT3	0.882	0.721	0.604	0.753	0.715	0.585	0.074	0.708	0.69
BI1	0.731	0.944	0.675	0.739	0.694	0.6	0.143	0.718	0.668
BI2	0.735	0.945	0.699	0.74	0.711	0.608	0.154	0.72	0.665
BI3	0.695	0.878	0.675	0.693	0.731	0.614	0.167	0.651	0.678
FC1	0.581	0.626	0.883	0.674	0.596	0.617	0.152	0.578	0.55
FC2	0.572	0.624	0.87	0.605	0.621	0.675	0.222	0.506	0.629
FC3	0.576	0.655	0.919	0.633	0.634	0.658	0.229	0.562	0.58
FC4	0.677	0.71	0.871	0.745	0.677	0.7	0.151	0.65	0.655
HM1	0.799	0.73	0.694	0.924	0.659	0.655	0.105	0.653	0.657
HM2	0.785	0.764	0.688	0.925	0.689	0.652	0.097	0.722	0.72
HM3	0.741	0.668	0.698	0.912	0.649	0.646	0.158	0.625	0.624
PB1	0.419	0.449	0.481	0.438	0.7	0.42	0.246	0.367	0.386
PB2	0.679	0.728	0.668	0.653	0.914	0.632	0.182	0.628	0.643
PB3	0.714	0.703	0.619	0.68	0.868	0.558	0.019	0.648	0.608
PEU1	0.491	0.532	0.624	0.551	0.498	0.85	0.241	0.607	0.571
PEU2	0.679	0.676	0.668	0.717	0.694	0.815	0.179	0.76	0.634
PEU3	0.509	0.486	0.609	0.529	0.469	0.87	0.294	0.533	0.557
PEU4	0.499	0.483	0.616	0.547	0.496	0.852	0.183	0.525	0.554
PR1	0.178	0.182	0.22	0.162	0.202	0.267	0.903	0.162	0.214
PR2	0.072	0.065	0.088	0.053	0.049	0.174	0.855	0.011	0.095
PR3	0.073	0.093	0.165	0.093	0.055	0.178	0.785	0.063	0.064
PR4	0.116	0.162	0.187	0.082	0.142	0.22	0.838	0.129	0.195
PU1	0.689	0.719	0.622	0.653	0.668	0.678	0.098	0.899	0.693
PU2	0.66	0.687	0.602	0.671	0.607	0.686	0.145	0.943	0.637
PU3	0.69	0.692	0.584	0.695	0.61	0.679	0.125	0.938	0.647
SI1	0.649	0.632	0.615	0.628	0.625	0.669	0.117	0.664	0.875
SI2	0.694	0.629	0.595	0.636	0.564	0.602	0.22	0.616	0.926
SI3	0.775	0.716	0.652	0.715	0.644	0.622	0.186	0.663	0.928

Table 7 Hypothesis Testing Results

Direct influence				Path coefficient	P-value	2.5% Confidence Intervals	97.5% Confidence Intervals	T-value	Result	
H1	PU	→	ATT	0.229	0.000	0.136	0.332	4.553	Significant	Accept
H2	PEU	→	ATT	0.010	0.871	-0.107	0.128	0.162	Not Significant	Reject
H3	PEU	→	PU	0.735	0.000	0.676	0.791	24.634	Significant	Accept
H4	SI	→	ATT	0.397	0.000	0.261	0.520	5.952	Significant	Accept
H5	SI	→	BI	0.131	0.024	0.017	0.244	2.252	Significant	Accept
H6	ATT	→	BI	0.181	0.008	0.062	0.326	2.663	Significant	Accept
H7	HM	→	BI	0.208	0.005	0.056	0.345	2.802	Significant	Accept
H8	FC	→	BI	0.175	0.001	0.077	0.276	3.443	Significant	Accept
H9	PB	→	ATT	0.320	0.000	0.215	0.429	5.897	Significant	Accept
H10	PB	→	BI	0.271	0.000	0.157	0.382	4.758	Significant	Accept
H11	PR	→	ATT	-0.013	0.732	-0.086	0.064	0.342	Not Significant	Reject
H12	PR	→	BI	0.009	0.834	-0.068	0.098	0.210	Not Significant	Reject

Path coefficients are also a basic indicator for evaluating the structural model. The results of the hypothesis testing are shown in Figure 2. Three hypotheses were not statistically significant: PEU has no statistical significance on ATT (H2: β =.010, $t = 0.162$, $p > 0.01$); PR has no statistical significance on ATT (H11: $\beta = -0.013$, $t = 0.342$, $p > 0.01$) and PR has no statistical significance on BI (H12: β =.009, $t = 0.210$, $p > 0.01$). All the other hypotheses had statistical significance, showing that the variables in the model's structure have a positive impact on ATT and BI. In terms of ATT towards using AIGC, H1 (β =.229, $t = 4.553$, $p < 0.001$), H4 (β =.397, $t = 5.952$, $p < 0.001$), and H9 (β =.320, $t = 5.897$, $p < 0.001$) indicate that PU, SI, and PB have a strong impact on ATT. In terms of BI to use AIGC, H10 (β =.271, $t = 4.758$, $p < 0.001$), H7 (β =.208, $t = 2.802$, $p < 0.1$), H6 (β =.181, $t = 2.663$, $p < 0.1$), and H8 (β =.175, $t = 3.443$, $p < 0.001$), were accepted, indicating that PB and HM, FC, and ATT have a significant impact on BI, as illustrated in Table 7.

A necessary condition analysis (NCA) is utilized to determine the essential factors (Napontun et al., 2024), because NCA can effectively identify and predict the results of variables in a structural framework (Wattanawaraporn & Manosudhtikul, 2024), and analyze and reveal different conditions that have not been identified in the SEM analysis before (Pinthong et al., 2024). Based on the component-based SEM, each factor can be measured by analyzing whether it is necessary and sufficient (Rasmidatta, 2023). The results of Single Necessary Condition Analysis (NCA) as shown in Table 8, indicate that ATT, FC, HM, PU and PB are necessary conditions for students' BI to use AIGC technology, with a 95% confidence level. PB, PU, SI, and PEU are necessary conditions for improving students' ATT towards using AIGC technology, with a 95% confidence level. PEU is a necessary condition for PU, with a 95% confidence level. Analysis of the NCA values, for SI ($p = 0.006$, CR-FDH = 0.082), indicates that it is significant yet not necessary. For PR, it is neither significant nor necessary. Meanwhile PEU, was found to be non-significant but necessary. All other variables were both significant and necessary.

Figure 2 Final Model Investigating the Acceptance of AIGC among Chinese Art and Design Students

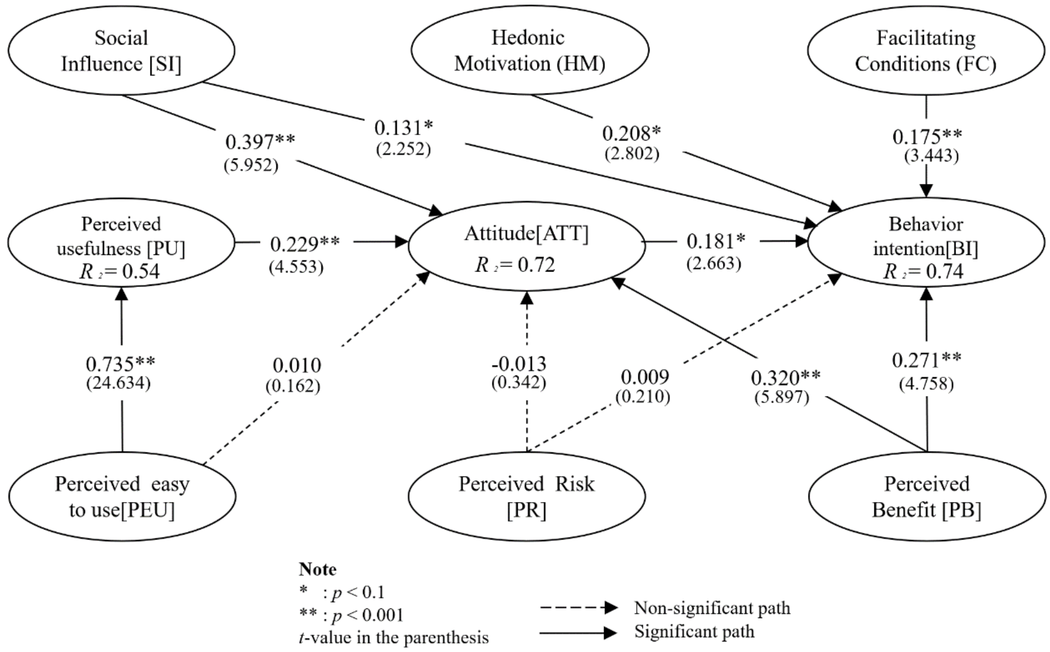


Table 8 Single Necessary Condition Analysis

Outcome BI	CR-FDH (d)	p-value	Necessary?
ATT	0.12	0.001	**In kind***
FC	0.173	0.000	**In kind***
HM	0.187	0.000	**In kind***
PB	0.266	0.000	**In kind***
PEU	0.1	0.064	In degree
PR	0.013	0.786	In degree
PU	0.104	0.002	**In kind***
SI	0.082	0.006	**In kind***
Outcome ATT	CR-FDH (d)	p-value	Necessary?
PU	0.323	0.000	**In kind***
PB	0.263	0.000	**In kind***
SI	0.187	0.000	**In kind***
PEU	0.141	0.000	**In kind***
PR	0.055	0.371	In degree
Outcome PU	CR-FDH (d)	p-value	Necessary?
PEU	0.207	0.000	**In kind***

Note. * = .05, CR-FDH=Ceiling Regression with Free Disposal Hull

5. DISCUSSION

The relationships for Hypothesis 2, Hypothesis 11, and Hypothesis 12 are not supported by the research findings. Regarding Hypothesis 2, PEU was not found to have an impact on

ATT. This shows that there is no significant correlation between students' perceived ease of use of AIGC and their attitude towards using this technology. This situation may be caused by the different software used by students for AIGC technology, as the perception differences in ease of use of different software vary. Hypothesis 11 and Hypothesis 12 are both related to the PR variable. No impact of PR on ATT and BI was detected. Specifically, students' perception of the risk of using AIGC is not related to their ATT and BI. In this case, it is necessary to consider the influence of mediating variable factors related to internet security awareness, such as age, personal social experience, and cultural background.

All other hypotheses have been confirmed by the research results. That is, there is a positive correlation between variables, the dependent variable has a positive and significant impact on the independent variable. Hypothesis 1: PE has a positive and significant impact on ATT, confirming the TAM model, and Hypothesis 3: PEU has a positive and significant impact on PU, were both supported, indicating that if students think AIGC technology is easy to use, they will find it more useful. This reminds us that when applying AIGC technology in the future, we should try to choose AIGC software with a relatively low difficulty threshold which is easy to master. Hypotheses 4 and 5: SI has a positive and significant impact on ATT and BI, were also supported, fully confirming the structure of the UTAUT2 model. Hypothesis 6 stands out as unique, as TAM theory suggests that the relationship between ATT and BI should be significantly stronger than any other in the model. However, the path data reveals a relatively low value, even lower than the path values from HM, FC, and PB to BI. This discrepancy warrants further investigation in future research. The support of Hypothesis 7: HM has a positive and significant impact on BI, proves that students attach great importance to the happy experience brought by this technology in the process of accepting AIGC. This suggests that when introducing AIGC technology into teaching courses, researchers should pay attention to the experience of fun and happiness. Hypothesis 8: FC has a positive and significant impact on BI, was supported. That is to say, students have a relatively good hardware environment for learning and using AIGC technology (such as laptops and networks), and have a suitable environment to solve technical problems in the process of learning AIGC, which greatly enhances their use of AIGC technology. Hypothesis 9 and Hypothesis 10, which both relate to the PB variable were also supported. Research results show PB is the biggest factor affecting students' BI to use AIGC, and that students realize that AIGC can bring benefits to themselves in enhancing creativity and reducing technical thresholds.

In addition, the majority of results from NCA are consistent with those of the PLS-SEM. Based on Napontun et al., (2024) who utilized NCA in his research, for this research, PR has neither significance nor necessity, indicating that students are not aware of the risks of information and privacy leakage when using AIGC. According to risk theory, risk is mainly categorized into six aspects: financial, performance, social, physical, privacy, and time loss. Perceived risk is a basic element for people who come into contact with new things and engage in business activities (Featherman & Pavlou, 2003). The dimensions of perceived risk differ depending on the product or technology being used (Lee, 2009). As a new computer application technology, AIGC's perceived risk is clearly necessary (Featherman & Pavlou, 2003), because all AIGC software and platforms require registration, login, and the submission of personal information. Despite the fact that large companies develop these AIGC software and systems, the risk of personal information and privacy breaches objectively exists. Additionally, AIGC technology is based on machine deep learning, including large language models for text, generative adversarial networks (GAN) and diffusion models for images, and algorithmic analysis (J. Wu et al., 2024). Any AIGC application platform requires the use of web crawling technology to collect a vast amount of existing data for training, which originates from other people, undoubtedly leading to ethical and intellectual property risks (Boyd & Holton, 2018). The best example of this is the "NO TO AI GENERATED IMAGES" movement initiated by visual artists worldwide on Artstation in December 2022 to protest against AIGC technology's infringement on their artwork. These objective facts highlight the necessity of perceived risk. The study results showing non necessity and significance suggest that users' perception is problematic. This situation is related to factors such as the sampled population's cultural background, awareness of internet security, internet usage habits, and age.

Interestingly, SI shows significance but is not strongly necessary, which is inconsistent with the SEM results. This suggests that at the current stage, university students pay attention to social influence factors when using AIGC, but this is not the most essential factor. It is necessary to discuss the necessity of SI here, as this is one of the potential limitations of this study. The focus was solely on traditional interpersonal influence, neglecting the significant changes in today's social and media environment. The growing social influence of social media and short videos is becoming more prominent, with "social apathy" and "hikikomori culture" emerging as new attitudes and choices for young people regarding social interactions, both of which are becoming increasingly mainstream.

5.1 Theoretical Contributions

First of all, the study explored introducing the perceived risk (PR) and perceived benefit theory (PB) in the field of commercial consumption into the technology acceptance model to explore and expand the framework of technology acceptance theory. Although the experimental data showed that there is no correlation between perceived risk PR and students' ATT and BI for using AIGC, it is necessary to consider mediating variable factors such as the age group and internet experience of the respondents. These explorations were very conducive to the development of technology acceptance models such as TAM and UTAUT.

Secondly, this study integrated the key elements of technology acceptance models, integrating SI from UTAUT and HM and FC from UTAUT2 into the basic framework of TAM and conducting model verification. Although the elements of PR and PEU experienced data verification failure and the original hypotheses were rejected, this was a beneficial exploration. Eventually, a technology acceptance model for AIGC was explored and formed.

Finally, by exploring the key core elements that affect students' acceptance of using AIGC technology and examining the relationship between various elements. The research integrated evaluation of objective environmental factors, hardware factors, and personal experience factors, making the factors for students' use of AIGC rich. Moreover, this study clarified how to control relevant core elements according to the intensity of variables, thereby enhancing students' positive attitudes and behavioral intentions in the process of accepting AIGC technology.

In conclusion, this study was an integrative research, combining the risk and benefit theories in the field of commercial consumption with the TAM and UTAUT models, making positive and important theoretical contributions to the application of AIGC technology in art and design education. It explored the core factors for students in accepting AIGC, enhancing the understanding and recognition of the educational application of AIGC technology, exploring AIGC teaching technology theory, and enriching the application theory of teaching technology.

5.2 Practical Implications

First of all, this research is of practical significance for promoting the use of artificial intelligence within higher education in China. In today's era of rapid digital development, AIGC technology holds significant promise in the art and design field and is expected to become an essential skill for art and design students in the future. This study provides research data and a theoretical framework for the application of AIGC technology in specific professional fields and determines that PB, SI, and HM are strong influencing factors in promoting students' acceptance of AIGC technology.

Secondly, this study helps colleges and universities to better introduce AIGC technology in teaching. By clarifying strong influencing factors such as PB (perceived benefit), SI (social influence), and HM (hedonic motivation), colleges and universities can adjust teaching strategies and resource allocation in a targeted manner. For example, strengthening the promotion of the advantages of AIGC technology and improving students' awareness of its perceived benefits; creating a positive social atmosphere and encouraging students to exchange and share experiences in using AIGC technology; stimulating students' hedonic motivation and allowing them to feel the improvement of fun and creativity in the process of using technology. This will inject new vitality into the intelligent development of higher education in China and improve teaching quality and students' comprehensive qualities.

Thirdly, for art and design majors in Henan, it provides a highly valuable alternative plan for professional reform. Through in-depth research, a large amount of feasibility data on students' acceptance of AIGC technology has been collected and analyzed. This data covers multiple aspects such as students' attitudes towards AIGC technology, usage intentions, and influencing factors. On this basis, core theoretical factors have been further explored and formed. These core theoretical factors will guide the direction of professional reform and help educators to better understand students' needs and responses to new technologies, to enable targeted adjustments in teaching content and methods, thereby helping art and design majors stay current and achieve innovative development.

Finally, this research offers a practical foundation for applying AIGC in art and design programs within higher education. Through in-depth research on students' acceptance of AIGC technology, the researchers have pinpointed the critical factors influencing students' acceptance of technology. This enables teachers to optimize teaching in a targeted manner and take corresponding measures for these factors. For example, by enhancing students' perceived benefits of AIGC technology, strengthening their confidence and interest in the technology; creating a positive social influence in the atmosphere, and by encouraging students to communicate and cooperate with each other and jointly explore the application of AIGC technology. Teachers can more actively integrate this technology into learning and creation, thereby improving teaching quality and students' professional qualities.

6. CONCLUSION

This study mixed perceived risk and perceived benefit with TAM and UTAUT, extracting key elements, and establishing a new theoretical model to explain students' acceptance of AIGC technology. The results showed that PB, PU, and SI are the most important factors affecting students' attitude towards accepting AIGC. The factor with the path coefficient of highest influence is PB. PEU has no effect on students' attitude towards accepting AIGC but has a strong influence on students' PU; SI, HM, FC, and PB, have a definite influence on students' BI to use AIGC. PB is also the variable factor with the strongest influence coefficient on BI. Therefore, PB is the most positive variable in the research structure for students' attitude and intentions to use AIGC technology. On the contrary, from the research data, PR has no influence on students' attitude and behavioral intentions to use AIGC technology, which was unexpected. This may be related to mediating variables such as the age, social experience, and safety awareness, of the sampled students. This study supports the research on AIGC acceptance and expands the TAM model by incorporating core elements such as PB and PR, as well as the social and personal perceptual elements of UTAUT. The research findings help us to identify the key factors influencing students' attitudes and intentions toward using AIGC technology, thereby facilitating its adoption in higher education.

This study may have the following limitations. First, the study was conducted in the early stage of AIGC application in education. Many AIGC technology software and platforms have great differences in usage experience, and the user experience is uneven, which will cause strong differences in users' subjective feelings. Secondly, the intervention of mediating variables such as age and safety awareness were required. Substantial differences in students' perceived benefits and risks were found by the study's results. Perceived benefits were strong influencing factors on attitude and behavioral intentions, but there were no influencing factors on perceived risks. The most likely reason is that the respondents were mainly undergraduates who have relatively little social experience and insufficient information on security awareness. Therefore, in future research structures, mediating variables such as age, information security awareness, and privacy awareness in UTAUT can be considered to enrich the research relationship and provide more comprehensive and accurate research. Third, since AIGC technology is relatively new, each sample student has different usage times for AIGC. In this study, many sampled students had relatively short usage times for AIGC. 77.6% of sampled users had usage experience of less than half a year. The relatively short usage time may affect the accuracy of their perception of AIGC technology. Finally, the examination of SI should include an assessment of the social interaction status of the sampled participants.

The discussions on future research mainly focus on the following aspects. First, pay attention to the reasons for the failure of PR. In later research, mediating variables such as age, gender, cultural background, safety awareness, and privacy awareness, should be added to verify the specific situation of the PR variable in the TAM extended model. Secondly, changes in the attitude factor and behavioral intentions of the traditional TAM model should be explored after adding personal perceptual factors. Finally, teachers are also a subject of educational technology application. Therefore, relevant data with teachers as the research object should be added in future to make the research more three-dimensional.

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