Determinants on the Learning Satisfaction of Art and Design Major Undergraduates in Traditional Craft Courses Based on AIGC

Chaochu Xiang

Visual Communication Design Department, Academy of Fine Arts and Design, Chengdu University, Chengdu, Sichuan, China
Email: xiangchaochu@cdu.edu.cn

Manuscript received July 7, 2025; accepted August 3, 2025; published September 10, 2025.

***Abstract*—Artificial Intelligence Generated Content (AIGC) technology has produced an essential impact in the field of higher education, and is a vital breakthrough point to open a new educational track and develop educational advantages in China. Currently, art design majors in multiple universities of Sichuan have begun to apply AIGC technology in the professional course instruction and curriculum achievement evaluation, while the academic circles have conducted relatively few quantitative research theoretical results on it. In order to analyze target students' learning satisfaction with AIGC, this study established six determinants, including Information Quality, System Quality, Interaction Learning Quality, Perceived Ease of Use, Perceived Usefulness, and AI-Assisted Design, constructed corresponding scale items, and collected empirical data. Finally, descriptive data analysis, Confirmatory Factor Analysis (CFA), and Structural Equation Model (SEM) were conducted on 546 valid samples by JAMOVI, SPSS, and AMOS statistical analysis software. It is statistically verified that all independent and mediator variables have positive and significant effects on the dependent variables, among which AI-Assisted Design has the greatest effect on Learning Satisfaction. It is suggested that the corresponding instruction units and relevant frontline teachers could evaluate and adjust the corresponding teaching of the current AIGC, to obtain the ideal teaching effect.**

***Keywords*—Artificial Intelligence Generated Content (AIGC), satisfaction, technology acceptance model, information system success model, structural equation model**

I. Introduction

With the rapid proliferation of Artificial Intelligence Generated Content (AIGC) technology in 2023, its transformative impact on the education sector has become increasingly pronounced [1]. A comprehensive review of existing scholarship reveals a consensus among researchers regarding the substantial positive implications of AIGC systems for higher education. Panigrahi and Joshi [2] asserted that artificial intelligence harbors considerable educational potential, presenting unprecedented opportunities for personalized learning implementation. Nie [3] maintained that AI will catalyze paradigm shifts in art and design disciplines, necessitating corresponding pedagogical innovations. Wang [4] argued that the exponential advancement of AIGC in image generation will precipitate a fundamental restructuring of art and design practices, transform conventional creative frameworks, and usher in novel models of professional education.

Leveraging the robust image and video processing capabilities of AIGC, along with the functionalities of open-source models, significant pedagogical transformations have been introduced for students and educators in art and design disciplines. Currently, AIGC systems such as Midjourney, Stable Diffusion, and Ernie Bot have emerged as highly specialized and widely adopted instruments in digital art education, demonstrating increasing applicability across various subfields, including Visual Communication Design, Environmental Art Design, Industrial and Production Design, Digital Media Design, and Animation Design. However, theoretical research remains relatively scarce in China, predominantly limited to qualitative studies, with a notable absence of empirical analyses or objective evaluations concerning the actual adoption and learning outcomes of AIGC in art and design education. As AI technology and educational paradigms continue to evolve, the effective mastery of AIGC-related competencies has become imperative to address the diverse needs of art and design students and to construct more efficient learning ecosystems.

Satisfaction serves as a pivotal metric for assessing the efficacy of educational delivery and constitutes a core dependent variable within the Information Systems Success Model [5]. Grounded in the Technology Acceptance Model (TAM), the Information Systems Success Model (ISSM), and prior quantitative research findings, this study establishes a comprehensive quantitative research framework. The investigation focuses on Chengdu University, one of the prominent institutions in Sichuan Province, recognized for its influential art and design programs. By analyzing the determinants influencing undergraduate students' AIGC-related learning satisfaction, this study elucidates the interaction mechanisms among latent variables and proposes actionable strategies to enhance learning satisfaction outcomes.

II. Theoretical Foundation and Conceptual Framework

A. Theoretical Foundation

The analytical framework of this study primarily draws upon the Technology Acceptance Model (TAM) and the Information System Success Model (ISSM).

The TAM represents one of the predominant theoretical frameworks in technology acceptance research and is widely recognized as a dominant model for explaining behavioral intentions in quantitative studies [6]. The model's originator, Davis, posited that assessing users' behavioral intentions toward specific technological systems through TAM would effectively promote their actual usage [7]. TAM has been extensively applied in educational quantitative research, typically employed to measure students' cognition and

doi: 10.18178/ijssh.2025.15.5.1258

acceptance levels of specific educational technology systems [8]. Some scholars contend that TAM is particularly suitable for elucidating users' psychological perceptions and logical behaviors regarding specific information systems [9].

TAM innovatively introduces two core latent variables: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Perceived ease of use is defined as the degree to which users assess the difficulty of operating a specific technological system, which subsequently influences perceived usefulness, attitudes, satisfaction, and behavioral intentions [7]. Numerous prior studies in educational technology have demonstrated that perceived ease of use serves as a critical determinant in students' acceptance and effective adoption of instructional technologies [10, 11]; students exhibit greater willingness to engage with and consistently utilize technological tools they perceive as user-friendly [12, 13]. Conversely, perceived usefulness refers to learners' subjective evaluation of the learning efficacy derived from using a particular technological system [8]. In this context, university students' assessment of whether AIGC enhances their learning efficiency constitutes a manifestation of perceived usefulness [14, 15]. Students are more inclined to adopt and continue using AIGC systems they deem instrumental in achieving their learning objectives [13, 16]. This empirical research's operationalization of perceived ease of use and perceived usefulness aligns with existing literature, emphasizing their pivotal role in measuring art and design students' engagement with AIGC systems, and accordingly positions them as mediating variables in the research model.

The ISSM represents a significant theoretical framework in information systems research, designed to identify, evaluate, and predict user satisfaction and behavioral intentions toward specific technological applications [17]. The ISSM theory has been applied in thousands of quantitative studies and is regarded as one of the most influential theories in information systems research [18].

Information Quality (INQ) and System Quality (SYQ) constitute two core latent variables within the ISSM framework. Information quality measures the quality of information stored and generated by a specific technological system, while system quality evaluates users' perceptions of the system's functional performance [17, 19]. Substantial empirical evidence confirms that both information quality and system quality exert direct and indirect significant effects on students' learning satisfaction and behavioral intentions when using specific systems [20–22]. Consistent with prior research, this study conceptualizes information quality and system quality as independent variables, acknowledging their critical role in assessing art and design students' utilization of AIGC systems.

B. Conceptual Framework

In the quantitative research which analyzed undergraduate students' satisfaction with using AIGC systems for assisted learning, Almulla [23] examined the mechanisms and effects of information quality, perceived ease of use, perceived usefulness, interaction learning quality, and AI-assisted learning on learning satisfaction. Interaction Learning Quality (ILQ) was specifically defined as: The effective learning outcomes students achieve when interactively utilizing AIGC for assisted learning [20]. The findings revealed that all specified exogenous variables exerted significant effects on their corresponding endogenous variables among these latent constructs [20]. Furthermore, Rezvani *et al.* [24] empirically validated that system quality significantly influences both perceived ease of use and perceived usefulness.

Within this framework, AI-assisted design emerges as the direct determinant of learning satisfaction, while information quality, system quality, interaction learning quality, perceived ease of use, and perceived usefulness operate as indirect antecedents. Consequently, this study suggested the conceptual framework, which was demonstrated in Fig. 1, delineating the learning satisfaction dynamics of art design undergraduates in AIGC-mediated learning environments. The model explicitly articulates the structural interconnections among the essential determinants and learning satisfaction, thereby establishing the clear pathway for subsequent Confirmatory Factor Analysis (CFA), Structural Equation Modeling (SEM), and practical strategy development.

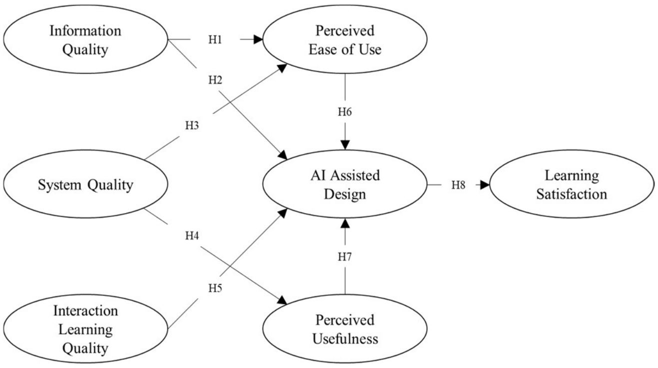

Fig. 1. Conceptual framework.

III. Research Methodology

A. The Design and Evaluation of Research Instruments

The research instruments employed in this empirical study were derived from three prior quantitative studies, encompassing 29 observed variables across seven latent constructs, as detailed in Table 1. All observed variables were assessed using a five-point Likert scale, with quantitative data collected through the 1–5 equidistant scoring system.

Table 1. Research instrument grid

Code	Indicator	Source
INQ1	The information provided by the AIGC system in the process of assisting design is accurate and reliable.	Almulla [23]
INQ2	The AIGC system in the process of assisting design offers high-quality information related to my learning goals.	
INQ3	I believe that the information provided by the AIGC system in the process of assisting my learning project is trustworthy.	
INQ4	The AIGC system in the process of assisting design has improved the overall information quality of my learning.	
INQ5	The information obtained from the AGCI-assisted design system is of great help to the information quality of my learning outcomes.	
SYQ1	In the process of assisting design, the completion steps of the design tasks in the AIGC system follow a reasonable logical sequence.	Chang [25]

SYQ2	In the process of assisting design, the operations executed by the AIGC system always produce the results I expect.	
SYQ3	In the process of assisting design, the functional components displayed by the AIGC system are organized in an orderly manner.	
SYQ4	In the process of assisting design, the problems that arise are relatively controllable.	
SYQ5	During the peak usage period, the AIGC system can still respond quickly to my operational needs.	
ILQ1	Interacting with the AIGC system in the aspect of assisting design can effectively enhance my positive learning experience.	Almulla [23]
ILQ2	The AIGC system in the field of assisting design makes my learning activities more interactive and participatory.	
ILQ3	I found that the interaction with the AIGC system has strengthened my understanding of the corresponding concepts and methods in design.	
ILQ4	The AIGC system has a positive helping effect on my mastery of complex design ideas.	
ILQ5	The interactivity with the AIGC system has improved my overall satisfaction in the learning of corresponding professional courses.	
PEOU1	The interaction with the AIGC system doesn't require too much effort or brainpower.	Nagy [5]
PEOU2	For the people who are important to me, they think I should use the AIGC to assist my art design practice.	
PEOU3	I find the operation of the AIGC system very flexible and convenient.	
PU1	The AIGC system can assist me in effective learning and design.	Nagy [5]
PU2	The AIGC system can provide me with crucial learning resources and enable me to complete high-quality design tasks.	
PU3	The AIGC system can effectively enhance my learning efficiency.	
AAD1	I will actively and proactively use the AIGC system to assist my design assignments.	Almulla [23]
AAD2	The AIGC system is an integral part of my daily learning.	
AAD3	In all aspects of my design assignments, I have consistently used the AIGC system.	
AAD4	The AIGC system is a significant and important technical tool in my learning.	
AAD5	The AIGC system is a core technical support in my design assignments.	
LSAT1	I am very satisfied with the assistance provided by the AIGC system for my design works.	Chang [25]
LSAT2	For me, using AIGC to assist in designing works was a very wise decision.	
LSAT3	I will recommend the use of AIGC for assisting in design work to the people around me.	

Source: Demonstrated by the author.

Following scale items development, the researchers first conducted content validity verification via Item Objective Congruence (IOC) analysis [26]. The IOC protocol mandated that at least three PhD-qualified domain experts evaluate each observed variable, with acceptable scores requiring a minimum threshold of 0.5 [27]. To ensure rigorous validation, five experts participated in the evaluation: all holding doctoral degrees and full professorship titles, with over seven years of experience in educational quantitative research. The IOC results demonstrated exceptional validity: 16 observed variables scored 1.0, nine achieved 0.8, and four attained 0.6, all surpassing the 0.5 benchmark, thus confirming robust content validity.

Following the content validity assessment, the researchers conducted a pilot test by sampling 40 undergraduate students majoring in art and design at Chengdu University to evaluate the scale's internal consistency reliability. A total of 40 valid questionnaires were obtained from this preliminary study. Subsequent analysis using JAMOVI statistical software revealed that all latent variables demonstrated Cronbach's Alpha (CA) coefficients exceeding 0.7, indicating excellent internal consistency reliability of the measurement scale. These psychometric properties confirm the instrument's suitability for subsequent large-scale data collection and statistical analysis. The detailed information was summarized in Table 2.

Table 2. Internal consistency reliability evaluation (n = 40)

Construct	Scale Items No.	Cronbach's Alpha
Information Quality	5	0.802
System Quality	5	0.873
Interaction Learning Quality	5	0.845
Perceived Ease of Use	3	0.778
Perceived Usefulness	3	0.812
AI-Assisted Design	5	0.853
Learning Satisfaction	3	0.872

Source: Demonstrated by the author.

B. Research Methodology

The Structural Equation Model (SEM) is a multivariate statistical analysis method widely employed in quantitative educational research, which integrates factor analysis and path analysis to evaluate complex interaction mechanisms among variables. Compared to regression analysis, SEM not only imposes more stringent requirements on data quality but also provides more precise measurements of indirect effects among multiple variables. Structural Equation Modeling is categorized into measurement models and structural models [28]. The measurement model, also referred to as Confirmatory Factor Analysis (CFA), is utilized to examine the consistency between the research model and empirically collected data, rigorously assessing the convergent validity and discriminant validity of the scales. Upon confirming data validity through CFA, the structural model is subsequently employed to test hypotheses and conduct path analysis. Given the technical characteristics of SEM, this research method demonstrates strong applicability to the targeted issues of the present study.

The SEM framework in this quantitative research is constructed based on the research model, primarily designed to analyze the interaction mechanisms among three independent variables: information quality, system quality, and interactive learning quality; three mediating variables: perceived ease of use, perceived usefulness, and AI-assisted design; as well as their collective direct and indirect effects on the dependent variable learning satisfaction. Data collection for this study was conducted via an online questionnaire, with the survey period spanning from April to June in 2025. The survey population comprised all undergraduate students majoring in art and design at Chengdu University. A total of 600 samples were selected using stratified random sampling, with 546 valid responses ultimately collected.

In the statistical analysis, this study first employed JAMOVI to perform descriptive analysis, comparing the means of latent variables to elucidate the target students' evaluation status regarding AIGC learning satisfaction. Subsequently, CFA and SEM validation were conducted using AMOS software to delineate the interaction mechanisms and influence efficacy among latent variables. Finally, the corresponding model was rationally interpreted, and scientifically grounded pedagogical optimization strategies were formulated.

IV. Result and Discussion

A. Demographic Information

Among the 546 valid questionnaires collected in this study, the demographic statistics were as follows: 67.2% were female students, while 32.8% were male students. In terms of academic year distribution, 20.9% were freshmen, 25.7% were sophomores, 28.9% were juniors, and 24.5% were seniors. From the disciplinary perspective, 32.5% majored in Visual Communication Design, 29.8% in Industrial and Production Design, 18.3% in Environmental Art Design, and 19.4% in Fine Arts. The overall sample distribution across these dimensions was relatively balanced and reasonable, ensuring the suitability of the quantitative data for further statistical analysis.

B. Fundamental Validity and Reliability Evaluation

The researcher conducted an internal consistency reliability test on the complete dataset using JAMOVI. The Cronbach's Alpha coefficients for all latent variables exhibited a slight overall decline, yet all values remained above 0.7, confirming that the data possessed satisfactory internal consistency reliability. The detailed information was summarized in Table 3.

Table 3. Internal consistency reliability evaluation (n = 546)

Construct	Scale Items No.	Cronbach's Alpha
Information Quality	5	0.892
System Quality	5	0.899
Interaction Learning Quality	5	0.856
Perceived Ease of Use	3	0.879
Perceived Usefulness	3	0.773
AI-Assisted Design	5	0.909
Learning Satisfaction	3	0.775

Source: Demonstrated by the author.

Table 4. KMO and Bartlett's test of sphericity

Indicators for the Measurements		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.838
Bartlett's Test of Sphericity	Approx Chi-Square	9252.979
	DF	406
	Sig	0.000

Source: Demonstrated by the author.

The specific details are presented in Table 4. Furthermore, the KMO and Bartlett's sphericity tests, performed via SPSS, yielded a KMO value of 0.838 and a Bartlett's test significance level of 0.000, both have matched the required thresholds. These results indicate that the variables demonstrated both desirable correlation and independence, thereby affirming the appropriateness of conducting subsequent factor analysis.

C. Confirmatory Factor Analysis

In accordance with the aforementioned research design, the researcher employed AMOS software to construct a Confirmatory Factor Analysis (CFA) model and further examined the consistency between the research model and the empirical data.

The CFA assessment initially requires evaluating the Goodness-of-FIT (GOF) between the data and the measurement model. This quantitative research primarily examined nine GOF indices across three dimensions: absolute fit, incremental fit, and parsimonious fit. With reference to the critical thresholds for GOF proposed by Hair *et al.* [28], the CFA was subjected to a comprehensive goodness-of-fit test. Detailed information is presented in Table 5. After the original CFA model was adapted to the data, the fitting value of RMSEA was 0.057, which did not match the standard; after the adjustment of the CFA model, all the fit indices matched the acceptable adaptation state.

Table 5. Goodness-of-Fit for CFA

Index	Criterion	Before Adjusted	After Adjusted
CIMIN/DF	< 3	2.798	2.286
GFI	≥ 0.90	0.882	0.909
AGFI	≥ 0.80	0.856	0.888
RMSEA	< 0.05	0.057	0.049
CFI	≥ 0.90	0.929	0.950
NFI	≥ 0.90	0.894	0.914
TLI	≥ 0.90	0.919	0.942
PGFI	≥ 0.50	0.784	0.783
PNFI	≥ 0.50	0.815	0.795

Source: Demonstrated by the author.

Following the GOF estimate, the core evaluation criteria for CFA consist of convergent validity and discriminant validity. Convergent validity is jointly determined by Factor Loading (FL), Composite Reliability (CR), and Average Variance Extracted (AVE). Based on Brown's research findings, the following thresholds must be met in CFA convergent validity testing: factor loadings should exceed 0.5, composite reliability should surpass 0.7, average variance extracted should be greater than 0.5, with all observed variables demonstrating t-values above 1.98 and p-values below 0.05 [29].

The validation results demonstrated that all variables matched these criteria: the minimum factor loading was 0.653, the minimum composite reliability was 0.773, and the minimum average variance extracted was 0.532. Additionally, the minimum t-value reached 13.141, with all p-values below 0.001. These metrics collectively confirm that the data exhibit strong convergent validity with the research model. Detailed information is presented in Table 6.

Table 6. Convergent validity evaluation for CFA

Construct	Code	Factor Loading	S.E.	t-Value	*p*-Value	CR	AVE
Information Quality	INQ1	0.763	–	–	–	0.884	0.606
	INQ2	0.813	0.055	18.804	***		
	INQ3	0.701	0.061	15.859	***		
	INQ4	0.768	0.057	17.755	***		
	INQ5	0.839	0.061	19.399	***		
System Quality	SYQ1	0.957	–	–	–	0.896	0.639
	SYQ2	0.940	0.023	41.450	***		
	SYQ3	0.693	0.036	20.681	***		
	SYQ4	0.700	0.035	21.087	***		
	SYQ5	0.653	0.042	18.751	***		
Interaction Learning Quality	ILQ1	0.719	–	–	–	0.857	0.546
	ILQ2	0.713	0.071	15.289	***		
	ILQ3	0.750	0.071	16.031	***		
	ILQ4	0.688	0.066	14.779	***		
	ILQ5	0.818	0.067	17.257	***		
Perceived Ease of Use	PEOU1	0.846	–	–	–	0.880	0.709
	PEOU2	0.819	0.046	21.528	***		
	PEOU3	0.860	0.043	22.458	***		
Perceived Usefulness	PU1	0.703	–	–	–	0.773	0.532
	PU2	0.764	0.086	13.141	***		
	PU3	0.720	0.084	12.020	***		
AI-Assisted Design	AAD1	0.725	–	–	–	0.901	0.650
	AAD2	0.954	0.059	22.286	***		
	AAD3	0.702	0.062	16.321	***		
	AAD4	0.678	0.062	15.736	***		
	AAD5	0.928	0.059	21.836	***		
Learning Satisfaction	LSAT1	0.723	–	–	–	0.777	0.538
	LSAT2	0.744	0.081	13.673	***		
	LSAT3	0.732	0.084	13.595	***		

Note: *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$.
Source: Demonstrated by the author.

In accordance with Brown's research findings, the assessment of discriminant validity in CFA requires that the correlation coefficient between any two latent variables should be lower than the square root of their respective AVE values [30]. The discriminant validity evaluation results for this quantitative research are detailed in Table 7: The diagonal elements represent the square roots of AVE for each latent variable, while the off-diagonal values indicate the correlation coefficients between latent variables. The highest correlation coefficient observed was 0.427, whereas the lowest square root of AVE was 0.729. All data met the established criteria, demonstrating satisfactory discriminant validity between the data and the model.

Table 7. Discriminant validity evaluation for CFA

Construct	INQ	SYQ	ILQ	PEOU	PU	AAD	LSAT
INQ	0.797						
SYQ	0.235	0.792					
ILQ	0.162	0.112	0.815				
PEOU	0.172	0.392	0.101	0.773			
PU	0.048	0.274	0.010	0.085	0.729		
AAD	0.220	0.130	0.395	0.168	0.128	0.764	
LSAT	0.074	0.088	0.174	0.118	0.069	0.427	0.764

Source: Demonstrated by the author.

Based on the empirical analysis, the CFA validation confirmed that the research data exhibit both ideal convergent validity and discriminant validity with the proposed model. These results indicate a strong consistency between the collected data and the research model, thereby justifying the subsequent SEM hypothesis testing and path analysis.

D. Structural Equation Model

Identical to CFA, SEM should initially conduct the GOF estimation, with the evaluation criteria remaining consistent with those indicators of CFA [30]. After verification, when the original SEM model was adapted to the data, the GFI was 0.873, RMSEA was 0.059, and NFI was 0.886, all of which did not match the standards. Identically, after modifying the model structure of SEM, all the fit indices reached the acceptable adaptation state. The detailed GOF information of the SEM is detailed in Table 8.

Table 8. Goodness-of-Fit for SEM

Index	Criterion	Before Adjusted	After Adjusted
CIMIN/DF	< 3	2.926	2.290
GFI	$\geq$ 0.90	0.873	0.906
AGFI	$\geq$ 0.80	0.851	0.888
RMSEA	< 0.05	0.059	0.049
CFI	$\geq$ 0.90	0.921	0.948
NFI	$\geq$ 0.90	0.886	0.912
TLI	$\geq$ 0.90	0.913	0.942
PGFI	$\geq$ 0.50	0.741	0.758
PNFI	$\geq$ 0.50	0.805	0.817

Source: Demonstrated by the author.

The entire hypotheses which suggested in this quantitative research were all verified to have t-values greater than 1.98

and all p-values lower than 0.05. Therefore, all the hypotheses were found to be valid. Among them, H1, H3, H5, H6, and H8 were significant at the 0.001 level, H4 and H7 were significant at the 0.01 level, and H2 was significant at the 0.05 level. Detailed information is shown in Table 9.

Among them, AI-assisted design had the strongest significant impact on learning satisfaction, with its standardized path coefficient (β) being 0.467. Perceived ease of use had a positive significant impact on AI-assisted design, with its standardized path coefficient (β) being 0.263. System quality had the third strongest significant impact on perceived ease of use, with its standardized path coefficient (β) being 0.259. Information quality had the fourth strongest significant impact on perceived ease of use, with its standardized path coefficient (β) being 0.196. Interaction learning quality had the fifth strongest significant impact on AI-assisted design, with its standardized path coefficient (β) being 0.181. Information quality had the sixth strongest significant impact on AI-assisted design, with its standardized path coefficient (β) being 0.153. System quality had the seventh strongest significant impact on perceived usefulness, with its standardized path coefficient (β) being 0.133. Perceived usefulness had the weakest significant impact on AI-assisted design, with its standardized path coefficient (β) being 0.131.

Table 9. Hypotheses examination

Hypothesis	Path			Standardized Path Coefficient (β)	S.E.	t-Value	*p*-Value	Test Results
H1	PEOU	←	INQ	0.196	0.038	4.130	***	Supported
H2	ADD	←	INQ	0.153	0.040	2.225	*	Supported
H3	PEOU	←	SYQ	0.259	0.039	5.716	***	Supported
H4	PU	←	SYQ	0.133	0.046	2.675	**	Supported
H5	AAD	←	ILQ	0.181	0.030	3.953	***	Supported
H6	AAD	←	PEOU	0.263	0.045	5.581	***	Supported
H8	AAD	←	PU	0.131	0.040	2.738	**	Supported
H8	LAST	←	AAD	0.467	0.049	8.661	***	Supported

Note: *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$.
Source: Demonstrated by the author.

Table 10. The path diagram analysis

MV & DV	IV & DV						
	Effects	ILQ	SYQ	INQ	PU	PEOU	ADD
PU	Direct Effect	–	0.133	–	–	–	–
	Indirect Effect	–	–	–	–	–	–
	Total Effect	–	0.133	–	–	–	–
	R^2	0.018					
PEOU	Direct Effect	–	0.259	0.196	–	–	–
	Indirect Effect	–	–	–	–	–	–
	Total Effect	–	0.259	0.196	–	–	–
	R^2	0.105					
AAD	Direct Effect	0.181	–	0.101	0.131	0.263	–
	Indirect Effect	–	0.085	0.052	–	–	–
	Total Effect	0.181	0.085	0.153	0.131	0.263	–
	R^2	0.142					
LSAT	Direct Effect	–	–	–	–	–	0.467
	Indirect Effect	0.085	0.040	0.071	0.061	0.123	–
	Total Effect	0.085	0.040	0.071	0.061	0.123	0.467
	R^2	0.218					

Source: Demonstrated by the author.

For the path diagram analysis of this study, the three mediator variables: perceived ease of use, perceived usefulness, and AI-assisted design, as well as a unique dependent variable learning satisfaction. The detailed results of the path diagram analysis are presented in Table 10.

Initially, for perceived usefulness, the R^2 value is 0.018, indicating that 1.8% of the variance of this mediating variable is directly and significantly influenced by system quality, which the path coefficient is 0.133.

For perceived ease of use, the R^2 value is 0.105, indicating that 10.5% of the variance of this mediator variable was determined by the joint influence of system quality and information quality. System quality and information quality generated a direct and significant influence on perceived ease of use. The path coefficient of system quality is 0.259, and that of information quality is 0.196.

For AI-assisted design, the R^2 value is 0.142, indicating that 14.2% of the variance of this mediator variable is determined by the combined influence of interaction learning quality, system quality, information quality, perceived ease of use, and perceived usefulness. Among them, interaction learning quality, perceived ease of use, and perceived usefulness have only generated direct and positive significant on AI-assisted design, with path coefficients of 0.181, 0.263, and 0.131, respectively. System quality generated the indirect positive influence on AI-assisted design, with the path coefficient of 0.085. While information quality generated both the direct and indirect significant influence on AI-assisted design, with direct influence path coefficients of 0.101, indirect influence of 0.052, and total influence of 0.153.

Eventually, for the learning satisfaction, the R^2 value is 0.218, indicating that 21.8% of the variance of this dependent variable is determined by all the independent variables and mediator variables. Among them, AI-assisted design generated the direct significant influence on learning satisfaction, with the path coefficient of 0.467; interaction learning quality, system quality, information quality, perceived ease of use, and perceived usefulness generated the indirect significant influences on learning satisfaction, with path coefficients of 0.085, 0.040, 0.071, 0.123, and 0.061, respectively.

V. Conclusion, Discussion, and Recommendations

A. Conclusion and Discussion

This quantitative research aimed to explore and analyze the significant influencing determinants of the learning satisfaction of undergraduate students majoring in art design at Chengdu University regarding AIGC. Through verification, the entire hypotheses in the research framework have been supported. All independent and mediator variables have had direct or indirect significant effects on the dependent variable.

Initially, regarding the correlation between information quality and perceived ease of use, the analysis demonstrated that information quality exerted a direct and significant influence on perceived ease of use, with its standardized path coefficient ranked fourth among all the hypothesized interconnections (β at 0.196). This finding indicates that the target student population perceived that in the instructional design of AIGC systems, the provision of sufficiently comprehensive key information could, to a certain extent, reduce the learning difficulty associated with these systems.

Furthermore, according to the associations among system quality, perceived ease of use, and perceived usefulness, the analysis confirmed that system quality exerted a direct and significant influence on both perceived ease of use and perceived usefulness. Moreover, the impact of system quality on perceived ease of use was substantially stronger than its effect on perceived usefulness, with standardized path coefficients ranking third (β at 0.259) and seventh (β at 0.133), respectively, among all hypothesized relationships in this study. This suggested that the target student cohort perceived that an AIGC system with high stability, robust functionality, or course designs that fully leveraged the system's capabilities could significantly reduce the perceived learning difficulty associated with the AIGC system while also markedly enhancing their assessment of its learning effectiveness.

Moreover, concerning the correlations among information quality, interaction learning quality, perceived ease of use, perceived usefulness, and AI-assisted design, the analysis revealed that all four latent variables exerted a direct and significant influence on AI-assisted design. Based on the standardized path coefficients, the total effects on AI-assisted design were ranked as follows: perceived ease of use (β at 0.263) > interaction learning quality (β at 0.181) > information quality (β at 0.153) > perceived usefulness (β at 0.131). This indicated in the context of AI-assisted design in art education, perceived ease of use had the strongest relative impact, implying that students believed that greater perceived ease in operating the AIGC system would enhance their learning outcomes in AI-assisted design skills. Interaction learning quality followed, which suggests that well-structured interactive learning methods could significantly improve students' mastery of AI-assisted design competencies. Information quality ranked next, as AIGC instructional designs with higher information quality effectively facilitated students' acquisition of AI-assisted design skills. Lastly, perceived usefulness indicated that when students held strong expectations of the system's utility, their subjective motivation to learn AI-assisted design skills increased.

Finally, for the correlation between AI-assisted design and learning satisfaction, the analysis demonstrated that AI-assisted design exerted the greatest direct and significant influence on learning satisfaction in this study, with the highest standardized path coefficient (β at 0.467) among all hypothesized relationships. This signified that AI-assisted design integrated the combined significant effects of information quality, system quality, interaction learning quality, perceived ease of use, and perceived usefulness, collectively influencing learning satisfaction. Second, the target students exhibited a relatively positive attitude toward the learning outcomes of AI-assisted design in their current specialized coursework. When they perceived that they had effectively acquired AI-assisted design skills, their learning satisfaction was substantially enhanced.

B. Recommendation for Practice

Based on the aforementioned analysis in this quantitative survey, this research suggests the following five practical recommendations for the practice according to the statistical analysis:

1) Obtain high-quality AIGC information resources

Leading AIGC technology companies such as OpenAI (GPT-4o), Midjourney, Stable Diffusion, Microsoft Azure, and ERNIE Bot periodically release iterative updates to their image-generation large language models, with newer versions typically featuring significant functional breakthroughs. Consequently, in developing instructional designs for AIGC-assisted design, educators should first promptly acquire information resources regarding these iterative model updates while simultaneously consulting authoritative official documentation to obtain accurate, high-quality technical information about AIGC systems.

Furthermore, reviewing authoritative academic papers that examine AIGC technological principles, algorithmic improvements, and operational characteristics, as well as studying research findings disseminated through influential AIGC social media platforms, constitutes another crucial approach to ensuring the information quality of AIGC instructional designs remains high. When evaluating information sources, educators should prioritize research outputs from AIGC domain experts, researchers affiliated with relevant institutions, and seasoned industry professionals to access specialized information characterized by both high value and credibility.

Given the rapid iteration pace of AIGC technologies, priority should be given to professional research outputs published within the past year. Additionally, educators should integrate multi-source information by cross-validating AIGC-related professional knowledge from different origins, thereby further guaranteeing that their instructional designs maintain superior information quality.

2) Enhancing AIGC system quality through university-enterprise collaboration

Although current image-generation AIGC systems possess relatively comprehensive functionalities, their practical application in assisting design across various sub-disciplines of art and design still presents certain challenges, with system quality remaining unsatisfactory. Therefore, relevant educational institutions should establish feedback channels with AIGC technology companies to enable timely identification of issues encountered by educators and students during practical implementation. This would facilitate targeted system quality improvements.

Educational institutions should provide technology providers with precise discipline-specific and pedagogical requirements for AIGC systems, including but not limited to: characteristics and specific instructional objectives of various design sub-disciplines, distinctive features and stylistic preferences of different artistic media, and core production specifications from relevant art and design industries. Such information would assist technology providers in implementing effective enhancements, including optimized encoding and organization of artistic datasets, adjustments and innovations in AI algorithms, and more rational personalized interface modifications – thereby achieving substantive improvements in AIGC system quality.

Concurrently, it is recommended that technology providers conduct periodic evaluations of AIGC systems, assessing multiple dimensions such as the accuracy of art and design knowledge outputs and the effectiveness of generated design works, to ensure continuous refinement of system quality.

3) Enhancing interactive learning quality through blended instruction methodology

AIGC systems demonstrate strong compatibility with online resources, and well-structured blended teaching models combining online and offline components can significantly improve interactive learning quality in AIGC applications. Regarding online instructional design, educators may refer to exemplary courses available on platforms such as XuetangX, Coursera, Udemy, and edX to ensure their online course designs incorporate robust theoretical foundations and practical demonstration cases.

Additionally, establishing dedicated online communication platforms through WeChat groups or Discord servers can facilitate free exchange of AIGC learning experiences and design insights among students. Regular online activities, including expert lectures, live demonstrations, and Q&A sessions via video conferencing tools, can further enhance interactive learning engagement. Educators may also leverage learning management systems like Chaoxing Learning to develop and distribute personalized AIGC-assisted design study plans for students.

For offline teaching components, academic institutions are advised to establish dedicated AIGC art and design laboratories and practical workshops, where enhanced software and hardware environments can elevate students' interactive learning experiences. Organizing students into project-based collaboration teams to work on practical AIGC design projects can effectively develop their communication and teamwork competencies. Incorporating structured peer-review sessions and group presentations among teams can foster mutual learning and healthy competition, thereby further improving interactive learning outcomes.

Educators should pay particular attention to creating effective synergies between online and offline learning modalities. Theoretical components, such as AIGC algorithm principles, can be delivered online, while corresponding practical applications in artistic design can be conducted in physical classrooms. Furthermore, establishing data-sharing mechanisms between online and offline environments – such as uploading physical classroom design works to online AIGC communities – can provide students with broader professional feedback and design analysis from peer networks.

4) Multidimensional approaches to mitigating perceived difficulty

To alleviate students' apprehension toward AIGC systems, instructors should first comprehensively demonstrate the technological advantages of these systems, highlighting their efficiency and convenience in generating high-quality design drafts. This enables students to clearly recognize the superior usability of AIGC-assisted design compared to traditional methods.

Subsequently, educators may initially introduce more accessible AIGC systems, such as ERNIE Bot and Midjourney. Once students achieve proficiency with these platforms and develop foundational AIGC creative thinking, instructors can then progress to teaching more complex systems like Stable Diffusion. This phased approach effectively minimizes beginners' anxiety.

Furthermore, instructors should employ strategically designed course materials that emphasize key concepts and challenging aspects, supplemented with video tutorials and functional manuals. These resources enable students to rapidly master core AIGC-assisted design skills, thereby objectively reducing their unfamiliarity and aimless exploration of the systems while simultaneously enhancing perceived ease of use.

Additionally, through comparative analysis of different AIGC systems' functional characteristics, educators should encourage students to select tools that best align with their individual needs, thereby optimizing artistic design efficiency. Educators must also promote practical application of acquired AIGC skills through real-world projects and case studies. As practice serves as the optimal method for evaluating learning outcomes, the results of practical assignments constitute an effective means of improving perceived ease of use regarding AIGC systems.

5) Multifaceted motivation strategies for raising prospective usefulness

To cultivate students' positive perceptions regarding the usefulness of AIGC-assisted design learning, instructors should primarily demonstrate the extensive application scope and effectiveness of AIGC technology. This includes illustrating its practical utility in various design disciplines such as visual communication design, environmental art design, product design, digital media design, and animation design, along with showcasing corresponding design outcomes.

Subsequently, educators should stimulate students' learning interest by effectively highlighting both the convenience and engaging aspects of AIGC content generation models. Concurrently, students should be guided to conduct self-assessments of their existing artistic design competencies to identify strengths and weaknesses in AIGC-related domains, thereby facilitating the development of targeted learning plans.

The implementation of a "learning-through-competition, competition-motivated-learning" approach represents an effective strategy to enhance perceived usefulness. Educators may organize student participation in prestigious disciplinary competitions such as Future Designer Awards and Milan Design Week using course projects, while leveraging award-winning works to create positive reinforcement for subsequent student cohorts, ultimately establishing a virtuous cycle of motivation.

When substantial improvements are achieved across multiple dimensions – including information quality, system quality, interactive learning quality, perceived ease of use, and perceived usefulness – students will inevitably develop favorable psychological expectations toward AIGC-assisted design. This comprehensive enhancement will consequently lead to significant improvements in learning satisfaction.

C. Limitation and Subsequent Research

The current study has several limitations that warrant acknowledgment. First, the research model incorporated only selected latent variables from the TAM and ISSM, excluding relevant constructs from other quantitative theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and Expectation-Confirmation Model (ECM). Future research should consider incorporating additional variables to enhance the model's comprehensiveness and diversity.

Second, due to objective research constraints, the sample was limited to undergraduate students majoring in art and design from one public university in Sichuan Province. To obtain more generalizable statistical results, subsequent studies should expand the sample to include a broader geographical and institutional representation.

Conflict of Interest

The author declares no conflict of interest.

Funding

This empirical research was funded by: Determinants of Instructional Satisfaction and Behavioral Intention for Traditional Craft Courses from the Perspective of Design Major, A Project Supported by Traditional Crafts Institute, the Key Research Institute Academic Center of Chinese Culture for Sichuan Province, grant number CTGY24YB03.

References

[1] U. A. Khan and A. Alamäki, "Harnessing AI to boost metacognitive learning in education," *eSignals Pro.*, pp. 1–7, 2023

[2] A. Panigrahi and V. Joshi. "Use of artificial intelligence in education," *The Management Accountant Journal*, vol. 55, pp. 64–67, 2020.

[3] Y. Nie, "Research on the environmental art design industry and education in the AI era," *Art Design Research*, vol. 5, pp. 120–128, 2024.

[4] M. Wang, "The foreground of art and design education: The application and consideration of generative AI," *Journal of Zhejiang Industry & Trade Vocational College*, vol. 24, no. 2, pp. 76–83, 2024.

[5] J. Nagy, "Evaluation of online video usage and learning satisfaction: An extension of the technology acceptance mode," *International Review of Research in Open and Distributed Learning*, ED-19, pp. 160–185, 2018.

[6] K. Mathieson, "Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior," *Information Systems Research*, vol. 2, pp. 173–191, 1991.

[7] F. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.

[8] C. Wang and X. Gu, "The promotion of OMO education: Breaking through the predicament of online teaching by taking primary and secondary school students' participation willingness of online learning as penetration point – Empirical research based on technology acceptance," *Modern Educational Technology*, vol. 32, no. 2, pp. 72–80, 2022.

[9] E. Fokides, "Greek pre-service teachers' intentions to use computers as in-service teachers," *Contemporary Educational Technology*, vol. 8, no. 1, 56–75, 2017.

[10] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003.

[11] M. A. Almaiah, M. A. Jalil, and M. Man, "Extending the TAM to examine the effects of quality features on mobile learning acceptance," *Journal of Computers in Education*, vol. 5, no. 3, pp. 453–485, 2016.

[12] N. A. Dahri, N. Yahaya, W. M. Al-Rahmi, *et al.*, "Extended TAM based acceptance of AI-powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study," *Heliyon*, vol. 10, no. 8, e29317, 2024.

[13] I. Baroni, G. R. Calegari, D. Scandolari, and I. Celino, "AI-TAM: A model to investigate user acceptance and collaborative intention in human-in-the-loop AI applications," *Human Computation*, vol. 9, no. 1, pp. 1–21, 2022.

[14] W. M. Al-Rahmi, N. Yahaya, A. A. Aldraiweesh, *et al.*, "Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use e-learning systems," *IEEE Access*, vol. 7, pp. 26797–26809, 2019.

[15] W. M. Al-Rahmi, N. Yahaya, M. M. Alamri, *et al.*, "Integrating innovation diffusion theory with technology acceptance model: Supporting students' attitude towards using a Massive Open Online Courses (MOOCs) systems," *Interact Learning Environments*, vol. 29, no. 8, pp. 1380–1392, 2021.

[16] J. M. Romero-Rodríguez, M. S. Ramírez-Montoya, M. Buenestado-Fernández, and F. Lara-Lara, "Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness," *Journal of New Approaches in Educational Research*, vol. 12, pp. 323–339, 2023.

[17] W. H. DeLone and E. R. McLean, "The DeLone and McLean model of information systems success: A ten-year update," *Journal of Management Information Systems*, vol. 19, no. 4, pp. 9–30, 2003.

[18] L. Yang, "Determinants for the satisfaction and behavioral intention of the Huidao education system for the senior high school students – An empirical research in Panzhihua region of China," Assumption University of Thailand, 2023.

[19] A. Al-Azawei, A. Abdullah, M. Mohammed, and Z. Abod, "Predicting online learning success based on learners' perceptions: The integration of the information system success model and the security triangle framework," *International Review of Research in Open and Distributed Learning*, vol. 24, no. 2, pp. 72–95, 2023.

[20] Ö. E. Kurt, "Examining an e-learning system through the lens of the information systems success model: Empirical evidence from Italy," *Education and Information Technologies*, vol. 24, pp. 1173–1184, 2019

[21] G. Chopra, P. Madan, and P. Jaisingh, "Effectiveness of e-learning portal from students' perspective: A Structural Equation Model (SEM) approach," *Interactive Technology and Smart Education*, vol. 16, no. 2, pp. 94–116, 2019.

[22] S. Rughoobur-Seetah and Z. A. Hosanoo, "An evaluation of the impact of confinement on the quality of e-learning in higher education institutions," *Quality Assurance in Education*, vol. 29, no. 4, pp. 422–444, 2021.

[23] M. A. Almulla, "Investigating influencing factors of learning satisfaction in AI ChatGpt for research: University students perspective," *Heliyon*, vol. 10, e32220, 2024.

[24] S. Rezvani, S. Heidari, N. Roustapisheh, and S. Dokhanian, "The effectiveness of system quality, habit, and effort expectation on library application use intention: The mediating role of perceived usefulness, perceived ease of use, and user satisfaction," *International Journal of Business Information System*, vol. 1, no. 1, pp. 1–18, 2022.

[25] C. Chang, "Exploring the determinants of e-learning systems continuance intention in academic libraries," *Library Management*, vol. 34, no. 1/2, pp. 40–55, 2012.
[26] J. Rovinelli and K. Hambleron, "On the use of content specialists in assessment of criterion referenced test item validity," *Duch Journal of Education Research*, pp. 49–60, 1997.
[27] Z. Shen and D. Wu, "An investigation into the factors affecting the effectiveness and satisfaction of online learning among college students: An empirical study based on structural equation modeling," *Research in Educational Development*, vol. 40, no. 11, pp. 25–36+59, 2020.
[28] J. F. Hair, R. E. Anderson, R. L. Tatham, and W. C. Black, *Multivariate Data Analysis*, Upper Saddle River, NJ: Prentice Hall, 2010.
[29] T. A. Brown, *Confirmatory Factor Analysis for Applied Research*, The Guilford Press, 2006.
[30] J. F. Hair, T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Least Suares Structural Equation Modeling*, Saga Publications Inc, 2021.