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An Empirical Study of Undergraduate Satisfaction and Adoption Intentions of Artificial Intelligence in Chengdu, China

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Abstract

Purpose: The research aimed to investigate the important factors impacting the satisfaction and intention to use Artificial Intelligence of Undergraduates in Chengdu, China. The conceptual framework presented cause-and-effect relationships between informational support, emotional support, perceived ease of use, perceived usefulness, satisfaction, attitude, and intention to use. **Research design, data, and methodology:** At Sichuan University of Media and Communications in Chengdu, China, undergraduate students were given a questionnaire by the researcher using a quantitative approach (n=500). Non-probability sampling included judgmental sampling to select four art majors of Sichuan University of Media and Communications, quota sampling to define the sample size, and convenience sampling to collect data and distribute the questionnaires online and offline. The researcher used structural equation modeling (SEM) and confirmatory factor analysis (CFA) to analyze the data **Results:** The results show that informational support, emotional support, perceived usefulness, and perceived ease of use have a significant effect on satisfaction, and satisfaction, as an intermediate variable, has a significant effect on the intention to use. Also, the attitude has a significant effect on the intention to use. **Conclusions:** To enhance the adoption of AI in higher education, it is essential to continuously address factors influencing student satisfaction and intention to use AI. Additionally, ongoing feedback should be provided to refine and adapt the AI implementation.

Keywords: Emotional Support, Perceived Ease of Use, Perceived Usefulness, Intention To Use, Artificial Intelligence

JEL Classification Code: E44, F31, F37, G15

1. Introduction

McCarthy (2007) argued that the science and engineering of creating intelligent devices, particularly clever computer programs, is known as Artificial Intelligence (AI). Tapalova and Zhiyenbayeva (2022) argued that creating tailored learning paths requires using artificial intelligence-based technology. According to Yang et al. (2021), artificial intelligence (AI) has the potential to be used in a variety of situations, including education, healthcare, and the production of food and drinks, as it becomes more and more commonplace in people's daily lives. Alam (2021) claims that artificial intelligence (AI) might help teachers by figuring out the training required for the job and helping with tedious classroom activities. According to Zhang and Aslan (2021), artificial intelligence (AI) opens new possibilities for educators by bridging the gap between technological breakthroughs and their use in the classroom. According to Gonzalez Calatayud et al. (2021), productive cooperation between artificial intelligence (AI) and education specialists is essential since educational technology cannot exist in a vacuum. There are links between the job market, communication in educational environments, and students who acquire professional skills and competencies.

According to Ermagan and Ermagan (2022), artificial intelligence can offer individualized learning environments and resources that support students' personal development. Artificial intelligence considers the distinct characteristics of the target individual or group to facilitate efficient self-learning. According to Aktay, S. (2022), there has been an increase in the use of artificial intelligence (AI) technology in classrooms during the past several years. Artificial

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intelligence (AI) makes teaching more productive and enables teachers to employ technology to personalize learning settings and provide student's feedback.

According to Kuleto et al. (2021), replacing antiquated technology and manual processes in higher education institutions with cutting-edge artificial intelligence technology is critical. This helps such institutions adapt to change and raise the standard of instruction. Studies already conducted on the advantages and disadvantages of AI suggest that college students may already access individualized learning environments.

According to Yang (2019), as the AI age progresses, higher education must train professionals who specialize in AI and help experts in other disciplines understand, use, and integrate AI. Higher education in China is generating multiskilled people who are deeply educated in AI theory, methods, techniques, products, and applications and knowledgeable about the use of AI in economics, sociology, management, law, and other areas.

Yang (2019) described China as considering several novel ways and plans for the education sector, focusing on basic education, higher education, and both short—and long-term goals in a new age of AI approaches. With artificial intelligence technology, learning may be more effectively tailored depending on a student's habits, interests, cognitive ability, and other characteristics. Major Chinese colleges are already incorporating artificial intelligence into their curricula.

This study examined the variables affecting Chengdu University art undergraduates' satisfaction and plans to use artificial intelligence (AI). Undergraduates studying art were chosen for the study because they represent a unique subset of the artificial intelligence (AI) user community. For the past 50 years, many scientists and artists have been researching how to create computer algorithms that can generate art, according to Mazzone and Elgammal (2019). According to Scheider et al. (2018), the most well-known early example of algorithmic art is Harold Cohen's software AARON (aaronshome.com).

American artist Lillian Schwartz, who pioneered computer graphics in art, also experimented with AI (Lillian.com). However, the development of GANs has spurred an explosion in algorithmic art in recent years, which uses artificial intelligence (AI) creatively to produce artistic creations. The phrase "art artificial intelligence" (AI) intervention, as defined by Mazzone and Elgammal (2019), refers to the integration of AI tools and technology into many aspects of the process of creating and appreciating art. Artificial Intelligence is used in the arts to generate new forms of expression, increase creative potential, and change the relationship between technology and artistic pursuits.

This study examined the variables impacting Chengdu, China, undergraduates' satisfaction with and intention to use artificial intelligence (AI). This study first examined variables that could impact art undergraduates' satisfaction with and intention to use artificial intelligence (AI) in higher education. These factors included Informational Support, Emotional Support, perceived ease of use, perceived usefulness, and attitude. Together with intention to use and satisfaction, these five factors formed the seven variables in this paper.

Therefore, the researcher believes AI is an important way to facilitate learning for art undergraduates. This study aimed to investigate the factors impacting undergraduate satisfaction and intention to use Artificial Intelligence in Chengdu, China, and to explore further creative talent development using AI.

2. Literature Review

2.1 Informational Support

Sarajärvi et al. (2006) assert that the primary goal of information support is to ensure accurate and relevant information is available when needed, thereby enhancing decision-making processes. Buis (2008) underscores that information support is essential for effective decision-making and problem-solving, providing a sense of relief and overall organizational effectiveness. Xing et al. (2018) elaborate that information support, a blend of technique, technology, and human understanding, transforms information into a powerful tool for problem-solving and goal attainment.

When consumers have trouble utilizing financial services, AI-powered M-banking can offer them individualized support and show care. Improving consumers' emotional assessment of M-banking can increase customer satisfaction (Tajvidi et al., 2020). One of the main benefits of IS and ES is user satisfaction, which also affects consumers' CI (Li et al., 2021). If m-banking customers are satisfied, they are more likely to continue (Sharma & Sharma, 2019).

According to Lee et al. (2022), artificial intelligence technology may provide users with emotional and informational support, collectively called social support. Consumer satisfaction with a system increases significantly if the information support provided by the system is useful, valuable, efficient, and accurate (Butcher et al., 2020). According to Song et al. (2021), customer satisfaction increases with the quality of informational support. According to Bugshan (2015), users depend on the informational support they provide and get inside the network to make the best judgments. Several studies have explored the relationship between information support and satisfaction and have proposed the hypothesis that information support has a significant effect on satisfaction,

as demonstrated in the following hypotheses.
H1: Informational support has a significant impact on satisfaction.

2.2 Emotional Support

The positive influence of emotional support on consistent utilization was highlighted by Lin and Lee (2022). Krause (2004) further emphasized that emotional support not only lessens negative feelings but also significantly improves mental health, providing a beacon of hope in navigating life's stressors and obstacles. Gual-Montolio et al. (2022) underscored the pivotal role of emotional support in the development of emotionally intelligent robots, the enhancement of human-computer interaction, and the provision of personalized recommendations and mental health services, instilling a sense of reassurance in the potential of AI technology.

According to Guo et al.'s (2018) investigation, participants in emotional support profit from giving and receiving support, and they view this advantage as a key determinant of users' engagement. During a social crisis, emotional assistance may be provided by sharing sorrow or expressing worry on the Government's social media accounts. According to Leong et al. (2020), social presence, emotional support, and informational assistance impact people's confidence in social commerce. According to Fan et al. (2019), interpersonal interactions that result in perceived emotional support can improve relationship quality and satisfaction. Empirical data suggests that social help, including emotional and informational support, can promote positive relationships.

Emotional support is the perceived utility resulting from a combination of different feelings, emotions, and states of reality while choosing substitute objects (Kashif et al., 2018). Researchers Gelbrich et al. (2021) and Zhu et al. (2016) found that in the context of technology-mediated services and online brand communities, emotional support directly impacted consumers' enjoyment. Based on the above literature, the following research hypotheses emerged from this paper.
H2: Emotional support has a significant impact on satisfaction.

2.3 Perceived Ease of Use

Lee et al. (2015) not only create an integrated app service model by integrating perceived usefulness and perceived ease of use but also incorporate perceived enjoyment and compatibility to examine the influence of attitude toward using an app service on customer satisfaction. Relative advantage is comparable to perceived usefulness, whereas complexity is akin to perceived usability. Lai and Li (2005) investigated how users' perceptions of ease of use affect their intents and attitudes. According to Davis et al. (1989), attitudes about usage are influenced directly by perceived ease of use and indirectly by perceived utility.

Perceived usefulness, perceived ease of use, and satisfaction with hotel self-service kiosks positively correlate with attitudes toward utilizing them (Kim & Qu, 2014). According to Ram and Sheth (1989), customers' perceived risk is associated with the risk barrier in TAM. In contrast, perceived utility and ease of use are connected to the value and use barriers.

The findings demonstrated that user satisfaction, which dictates whether or not a user wants to continue using, is influenced by perceived usability, perceived ease of use, and information quality (Legramante et al., 2023). Customers' views towards new technologies are greatly influenced by their perceived ease of use and usefulness, shaping their plans to utilize them (Davis, 1989). According to Venkatesh and Davis (1996), perceived usefulness and ease of use are the two main factors that influence IT acceptance, making them useful for forecasting or gauging end-user satisfaction with IT. Based on the above literature, the following research hypotheses emerged from this paper.
H3: Perceived ease of use has a significant impact on satisfaction.

2.4 Perceived Usefulness

Le (2022) looked at how the perceived utility of IS greatly impacts adoption. Studies that have previously been done indicate that perceived usefulness greatly impacts adoption intentions for ISs.It is a crucial part of the Technology Acceptance Model (TAM) and other acceptance models, stressing the importance of users' perceptions of the value and usefulness of a technology (Hess et al., 2014). Consumers' opinions on the value of technology influence whether or not they adopt and use it, according to Adams et al. (1992). Technology adoption and usage are more likely among users who think the technology will improve performance and provide real advantages.

Ashfaq et al. (2020) state that while information and service quality increase satisfaction, TAM antecedents (i.e., perceived usefulness and simplicity of use) encourage contentment and continued intention. Innovativeness, trust, and attitude drive use intention, according to Kasilingam (2020); on the other hand, innovativeness, ease of use, perceived usefulness, enjoyment, cost concerns, and perceived danger all significantly influence attitude. Le (2023) emphasized that ease of use refers to how simple users believe an information system (IS) to be to use, whereas perceived utility shows how users believe an IS may help them perform better.

Erkan and Evans (2016) contended that information credibility is a significant predictor of perceived usefulness in the context of the information acceptance paradigm. Shang et al. (2021) developed a conceptual model of information sharing and discovered that information processing (i.e., argument quality and information credibility) promotes perceived usefulness. Based on the above literature, the following research hypotheses emerged from this paper.

H4: Perceived usefulness has a significant impact on satisfaction.

2.5 Satisfaction

Kumari and Biswas (2023) discovered that it stresses the antecedents of user satisfaction with M-payment, which may increase M-payment long-term usage intention and user retention. Furthermore, the study seeks to quantify the influence of dual moderators, namely perceived utility and perceived severity of security concerns, to understand better the link between user satisfaction with M-payment and the desire to continue using the service. According to Churchill and Surprenant (1982), it comprises subjective assessments of how well AI systems meet needs, live up to expectations, and provide value in various businesses. User satisfaction with AI technologies is critical to their acceptance, adoption, and effective integration into various applications.

Recommendation algorithms are essential for Internet products to attain and maintain user growth and satisfaction, according to Benjamin's (2012) research. The Wang et al. (2019) study highlighted how the use and satisfaction theory may be applied broadly to the study of TikTok usage. Avornyo et al. (2019) discovered a neutral influence on the link between customer satisfaction and retention intention in mobile banking in China. The desire to purchase a product is influenced by consumer satisfaction, according to a study by Bergmann et al. (2023). Happier customers are more likely to make another purchase, whereas those who are unhappy are more likely to back out. Tsai et al. (2014) claim that user satisfaction mediates the association between ease of use and retention intention.

According to research by Kumari and Biswas (2023), the link between satisfaction with M-payment and willingness to stick with it is positively correlated with the perceived usefulness of security risks but negatively correlated with the perceived severity of security threats. According to Loh et al. (2022), consumers' expectations affect how satisfied they are with technology before using it and how reliable and quality they perceive M-payment services to be. Based on the above literature, the following research hypotheses emerged from this paper.

H5: Satisfaction has a significant impact on intention to use.

2.6 Attitude

Lin (2011) found that behavioral intention and attitude have a significant and favorable link that helps to explain why people embrace or continue to utilize mobile banking. According to Chawla and Joshi (2019) research, it makes sense to believe that differences in demographic traits like age, gender, income, work status, and education significantly impact how consumers feel about and intend to use technology. The model also shows how the PU affects BI's ability to embrace technology and its attitude. According to Hew et al. (2015), customers' attitudes may be shaped by using applications that are easy to use.

According to Padmavathy et al. (2012), who investigated these aspects, users' and consumers' evaluations of a system's usefulness, attitude, convenience of use, and past interactions all impact their intention to use it or behavior in a particular way. According to Davis (1989) research, a person's attitude toward usage may be defined as the extent to which they examine and associate the target system with their employment. According to Zaharia and Wurfel (2020), attitude toward all hedonic motives is significantly predicted by felt enjoyment.

Chawla and Joshi (2019) study is unique in that it examines the impact on both intention and attitude. As a result, it makes an effort to reconsider components and offer fresh viewpoints that influence consumer attitudes and intentions around the use of mobile wallets. According to the TRA developed by Fishbein and Ajzen (1975), an individual's positive and negative feelings about acting in a certain way may be used to characterize behavioral intention. Importantly, the above literature has led to the emergence of practical research hypotheses from this paper.

H6: Attitude has a significant impact on intention to use.

3. Research Methods and Materials

3.1 Research Framework

This study references several foundational theories. It utilizes a research model based on the Social Support Theory (SST) developed by Lin and Lee (2022), which explores how artificial intelligence (AI) features influence user behavior from a social support perspective. The Technology Acceptance Model (TAM), introduced by Davis (1989), examines the relationships between adoption objectives, attitudes, and perceptions of usefulness and usability. Additionally, the Unified Theory of Acceptance and Use of Technology (UTAUT), formulated by Venkatesh et al. (2003), includes four core elements that predict behavioral intention and usage behavior. A conceptual framework for this study, illustrated in Figure 1, has been developed by the researcher.

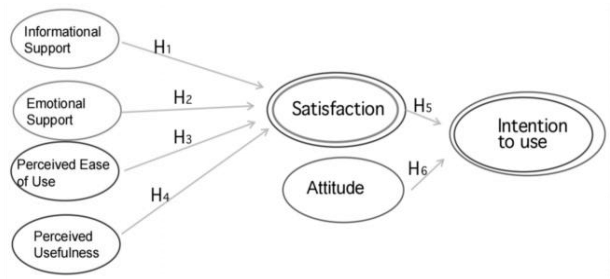

Figure 1: Conceptual Framework

H1: Informational support has a significant impact on satisfaction.
H2: Emotional support has a significant impact on satisfaction.
H3: Perceived ease of use has a significant impact on satisfaction.
H4: Perceived usefulness has a significant impact on satisfaction.
H5: Satisfaction has a significant impact on intention to use.
H6: Attitude has a significant impact on intention to use

3.2 Research Methodology

Using a quantitative non-probability sampling method, the researcher used an internet platform to distribute questionnaires to the target demographic (Steffens et al., 2014). The target population of this study was undergraduates in four art programs in Chengdu. We analyzed the feedback data to explore the factors impacting Undergraduate satisfaction and intention to use Artificial Intelligence in Chengdu, China. The questionnaire for this study was divided into three pieces. The first section consisted of screening questions. Each variable was given a 5-point Likert scale rating in the second section. The scale items measured each of the six research hypotheses. The range of measures was (1) strongly disagree to (5) strongly agree. The third section contained the demographic questions. These issues include gender, major, and experience in using AI. Before conducting the large-scale questionnaire, the pilot test questionnaire met the expert's Item-Objective Consistency Index (IOC) score, and the results are over 0.6. Furthermore, the researcher administered a pilot test to 50 respondents with the results of all constructs of over 0.7.

3.3 Population and Sample Size

Using Cronbach's Alpha method, the study's questionnaire passed validity and reliability evaluations (Den Hartog & Verburg, 2004). After distributing the questionnaires to the intended respondents, the researcher obtained 500 satisfactory answers. We used the SPSS AMOS statistical tests to analyze this feedback data. We used confirmatory factor analysis (CFA) to assess the correctness and validity of the convergence. These measures validated that the conceptual framework of this study was appropriate for the data and ensured the validity and reliability of the model. The researcher employed structural equation modeling (SEM) to examine the causal relationships between the variables in light of these attempts.

3.4 Sampling Technique

The researchers chose undergraduate students in Chengdu, China, majoring in four distinct areas of art. We used non-probability sampling, judgmental sampling, and quota sampling to select participants. We then disseminated questionnaires using an internet platform. Table 1 demonstrates the specific sampling for this study.

Table 1: Sample Units and Sample Size

Major	Population Size	Proportional Sample Size
Digital Media	412	126
Animation and Game Design	276	84
Visual Communication Design	591	181
Product design	357	109
Total	**1636**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

A questionnaire was distributed to 500 undergraduates majoring in art at the Sichuan University of Media and Communications in Chengdu. Among them, 312 were female and 188 were male, accounting for 62.4 % and 37.6 % respectively. Among them, 126 (25.2%) were in digital media, 84 (16.8%) were in animation and game design, Visual Communication Design 181 (36.2%), Product Design 109 (21.8%). Two hundred fourteen people had been using AI for three months, and 286 people had been proficient in using AI for more than 3 months, accounting for 42.8% and 57.2%, respectively. Table 2 presents demographic information for this study.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Female	312	62.4%
	Male	188	37.6%
Major	Digital Media	126	25.2%
	Animation and Game Design	84	16.8%
	Visual Communication	181	36.2%

Demographic and General Data (N=500)		Frequency	Percentage
	Design		
	Product design	109	21.8%
Experience in using AI	3 months	214	42.8%
	More than 3 months	286	57.2%

4.2 Confirmatory Factor Analysis (CFA)

Every variable in the conceptual framework was measured in this study using confirmatory factor analysis (CFA). The measurement results showed how important each scale item was for each variable. Additionally, the factor loading values of each scale item were within acceptable boundaries, indicating that the study's conceptual framework was a good fit. All factor loading values were better than 0.30, all p-values were less than 0.05, all mean extracted variances were larger than 0.50, and all construct reliabilities were more than 0.70 for this inquiry. Each of these projections had importance.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Informational support (IS)	Lin and Lee (2022)	4	0.841	0.708-0.836	0.842	0.573
Emotional support (ES)	Lin and Lee (2022)	5	0.867	0.681-0.838	0.868	0.569
Perceived ease of use (PEU)	Aiolfi et al. (2023)	4	0.712	0.610-0.799	0.828	0.549
Perceived Usefulness (PU)	Aiolfi et al. (2023)	4	0.846	0.703-0.852	0.851	0.590
Satisfaction (SA)	Yüce and Dost (2019)	4	0.861	0.756-0.796	0.862	0.609
Attitude (AT)	Kim and Qu (2014)	4	0.857	0.739-0.845	0.859	0.604
Intention to use (IU)	Aiolfi et al. (2023)	3	0.838	0.762-0.823	0.839	0.634

Table 4 displays the square roots of the extracted level differences. These results imply that all the study's variables had appropriate correlations. This study used GFI, AGFI, NFI, CFI, TLI, and RMSEA as metrics of model fit in the CFA test.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1977)	555.052/329 or 1.687
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.929
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.913
NFI	≥ 0.80 (Wu & Wang, 2006)	0.919
CFI	≥ 0.80 (Bentler, 1990)	0.965
TLI	≥ 0.80 (Sharma et al., 2005)	0.960
RMSEA	< 0.08 (Pedroso et al., 2016)	0.037
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

Table 5. presents the study's convergent and discriminant validity. These two values' acceptability was verified. All of the data verified that the structural model developed in this inquiry was accurate.

Table 5: Discriminant Validity

	IS	ES	PEU	PU	SA	AT	IU
IS	**0.760**						
ES	0.172	**0.754**					
PEU	0.209	0.228	**0.741**				
PU	0.166	0.138	0.230	**0.768**			
SA	0.254	0.198	0.352	0.362	**0.780**		
AT	0.232	0.220	0.225	0.218	0.208	**0.777**	
IU	0.296	0.325	0.371	0.215	0.372	0.334	**0.769**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

According to Wheaton et al. (1977), The Chi-square/degrees of freedom (CMIN/DF) ratio for model fit should be less than or equal to 5.00.

According to Sica and Ghisi (2007), the AGFI should be larger than 0.80, and the GFI should be greater than 0.85. According to Wu and Wang (2006), the NFI ought to be higher than 0.80. It was recommended by Bentler (1990) and Sharma et al. (2005) that the TLI and CFI should both be higher than 0.80. According to Pedroso et al. (2016), the RMSEA was less than 0.08. The researchers modified the model using SPSS AMOS version 26 for the SEM computations. The fit index results for this study presented a good fit. CMIN/df = 2.199, GFI = 0.897, AGFI = 0.876, NFI = 0.889, CFI = 0.936, TLI = 0.930 and RMSEA = 0.049. Table 6 demonstrates these values.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1977)	756.494/344 or 2.199
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.897
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.876
NFI	≥ 0.80 (Wu & Wang, 2006)	0.889
CFI	≥ 0.80 (Bentler, 1990)	0.936
TLI	≥ 0.80 (Sharma et al., 2005)	0.930
RMSEA	< 0.08 (Pedroso et al., 2016)	0.049
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The researcher determined the study model's relevance based on each variable's regression weights and R2 variances. The computation results are shown in Table 7. These findings validated all of the study's assumptions. Informational support influenced Satisfaction (β=0.188), Emotional support influenced Satisfaction (β=0.114), Perceived ease of use influenced Satisfaction (β=0.322), Perceived usefulness influenced Satisfaction (β=0.313), Satisfaction influenced Intention to use (β=0.391) and Attitude influenced Intention to use (β=0.304).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: IS→SA	0.188	3.861*	Supported
H2: ES→SA	0.114	2.404*	Supported
H3: PEU→SA	0.322	6.377*	Supported
H4: PU→SA	0.313	6.159*	Supported
H5: SA→IU	0.391	7.466*	Supported
H6: AT→IU	0.304	6.005*	Supported

Note: * $p<0.05$
Source: Created by the author

According to the results in Table 7., the researcher concluded that establishing H1 indicated that Informational support was one of the key drivers of Satisfaction with a criterion coefficient value of 0.188 in its structural path. The establishment of H2 indicated that Emotional support was one of the key drivers of Satisfaction, with a criterion coefficient value of 0.114 in its structural path. The establishment of H3 indicated that Perceived ease of use was one of the key drivers of Satisfaction, with a criterion coefficient value of 0.322 in its structural path. The establishment of H4 indicated that Perceived usefulness was one of the key drivers of Satisfaction, with a criterion coefficient value of 0.313 in its structural path. The establishment of H5 indicated that Satisfaction was one of the key drivers of Intention to use, with a standard coefficient value of 0.391 in its structural path. The establishment of H6 indicated that Attitude was one of the key drivers of Intention to use, with a standard coefficient value of 0.304 in its structural path.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The aim of this study was to conduct a comprehensive analysis of the factors influencing undergraduate students' satisfaction and intention to use Artificial Intelligence (AI) in Chengdu, China. The University of Chinese Academy of Sciences (UCAS) established the first AI talent training institute in China in May 2017. Following this, AI-focused colleges and institutes were set up by Tsinghua University, Peking University, Renmin University of China, and Nanjing University. AI has the potential to profoundly impact educational reform in China by accelerating the informatization of education, fostering development and innovation, and ultimately creating a new intelligent education system. This study proposes six hypotheses and examines the relationships between these factors.

The study targeted undergraduate art students at Sichuan University of Media and Communications in Chengdu. A survey was conducted with 500 undergraduates who had used AI and were majoring in various art disciplines. The collected data was analyzed to support the conceptual framework of the study. The sample data passed the measurement analyses performed using SPSS and JAMOVI, and the conceptual framework was validated through AMOS testing. Confirmatory Factor Analysis (CFA) confirmed the suitability of the factor structure and validation model, demonstrating a satisfactory fit between the data and the proposed model.

The data collected from the 500 questionnaires underwent CFA, which affirmed the validity and reliability of the study's conceptual model. Convergent validity tests, including discriminant validity, factor loading, mean variance extraction, composite reliability, Cronbach's alpha reliability, and discriminant validity, supported the study's validity (Steigenberger, 2015). Structural Equation Modeling (SEM) was used to examine the factors affecting undergraduate students' satisfaction and intention to use AI in Chengdu. The findings validated all six research hypotheses.

Results indicate that information support, emotional support, perceived ease of use, and perceived usefulness of AI directly influence student satisfaction. Furthermore, student satisfaction and attitudes directly impact students' intention to use AI. These findings provide a theoretical foundation for AI developers and researchers, and offer a model reference for future studies on the impact of AI learning.

5.2 Recommendation

Develop Real-World AI Courses: Create additional courses that demonstrate the practical applications of AI in various industries. These courses should be grounded in real-world scenarios to help students understand and appreciate the utility of AI. Encourage project-based learning, where students tackle real-world problems to enhance their understanding and interest in AI.

Enhance Instructor Training: Recommend that instructors receive ongoing training in AI technology and pedagogy to improve their professionalism and teaching skills. Invite AI experts to give lectures at schools to provide students with insights into cutting-edge technology and real-world applications.

Upgrade Learning Resources: Provide students with advanced computing equipment and software to facilitate effective AI learning and practice. Establish and maintain an online learning platform with extensive AI resources. Focus on optimizing information support, emotional support, perceived ease of use, and perceived usefulness to positively influence students' attitudes toward AI. Ensure continuous feedback is provided to enhance students' satisfaction and intention to use AI.

5.3 Limitation and Further Study

The limitations of this study include the fact that the variables were measured at an individual level and the data were collected from a centralized period (Glick, 1985). The data provided by teachers came from a limited number of specific schools, which may only partially represent the broader educational context. This potential lack of generalizability could affect the applicability of the findings to other settings or populations.

Several improvements should be considered to enhance the robustness of future research. First, future studies could incorporate variables like those examined in this study but explore them across a broader range of institutions and contexts to increase generalizability. A longitudinal or experimental design could provide a more comprehensive understanding of the factors influencing AI usage over time. Collecting data at multiple points throughout the academic year or over several years would help capture temporal variations and more accurately reflect the dynamic nature of AI integration in education.

Moreover, expanding the sample to include a more diverse set of schools and educational environments is crucial. This step would not only strengthen the study's findings but also enhance its applicability. By incorporating data from various educational levels and geographic locations, the study could provide a more nuanced perspective on how AI impacts student satisfaction and usage intentions across different contexts, thereby increasing its potential impact.

These enhancements are not just about improving the study but about contributing to a more thorough investigation of AI's effects on education. By doing so, the study can provide valuable insights for developing more effective AI integration strategies, underscoring its significance, and keeping the audience focused on its potential impact.

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