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Determinants of Junior College Students' Satisfaction and Intentions to Adopt Artificial Intelligence in Chengdu, China

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Abstract

Purpose: This article aimed to research the critical factors impacting junior college students' satisfaction with and intention to use artificial intelligence 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:** The researcher used a quantitative technique (n=500) to administer a questionnaire to junior art college students at the Sichuan University of Media and Communications in Chengdu, China. 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 carried out the data analysis, using structural equation modeling (SEM) and confirmatory factor analysis (CFA). **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 intention to use. Also, the attitude has a significant effect on the intention to use. **Conclusions:** This study suggest that to increase the use of AI in higher education, continuous attention should be paid to the factors affecting student satisfaction and intention to use AI, and continuous feedback should be provided to optimize and adapt.

Keywords: Emotional Support, Satisfaction, Attitude, Intention to use, Artificial Intelligence

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Zafari et al. (2022) emphasized the essential question that British logician and mathematician Alan Turing raised in 1950: "Can a machine think?" created the artificial intelligence (AI) framework. Machine learning is the central component of artificial intelligence technology, according to Ermagan and Ermagan (2022). McCarthy (2007) introduced the idea of artificial intelligence (AI), according to research by Russell and Norvig (2010). McCarthy (2007) said that artificial intelligence (AI) is the science and engineering of developing intelligent machines, especially astute computer programs. According to Aydin et al. (2022), artificial intelligence is a technological development starting to be used in many facets of life.

According to Tapalova and Zhiyenbayeva (2022), artificial intelligence-based technologies are necessary to develop personalized learning pathways. According to Yang et al. (2021), as artificial intelligence (AI) grows more and more prevalent in people's everyday lives, it has the potential to be applied in several contexts, such as education, healthcare, and the manufacturing of food and beverages. According to Alam (2021), artificial intelligence (AI) might assist educators by determining the training needed for the teaching profession and assisting with repetitive tasks in the classroom.

According to Zhang and Aslan (2021), large data is a feature of AI and a crucial element that drives AI to improve recognition accuracy and rate. The broad development and application of the Internet of Things has led to a massive

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yearly increase in data output. The number has expanded, but so has the dimensionality of the data. According to Chi-Hsien and Nagasawa (2019), AI learning enables computers to automatically learn from and analyze vast volumes of data to predict and provide decisions on real-world events. According to Agrawal et al. (2018), "machine learning" refers to the artificial intelligence-defining process of teaching computers to learn from sample data or experience. According to Berente et al. (2021), machine learning technologies—embody the essence of contemporary artificial intelligence—have greater autonomy, a deeper capacity for learning, and more enigmatic properties than previous "intelligent" IT artifacts.

According to Stone et al. (2016), there have been notable developments in artificial intelligence (AI) in education during the past fifteen years. Although face-to-face education has always been essential to excellent learning, various applications may be very helpful to professors and students in university settings, though to differing degrees. AI has much promise to enhance education, especially in learner-tailored training. The University of Chinese Academy of Sciences (UCAS) established the first comprehensive AI talent training institute in China in May 2017. Subsequently, Tsinghua University, Peking University, Renmin University of China, and Nanjing University established AI colleges and institutes.

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 as a new age of AI comes closer. Additionally, the nation is creating a thorough AI plan for training qualified workers and civic education. Many of the country's high-tech companies are also researching how AI may change education. 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 focused on art junior college students at Chengdu universities as a target group. This was mainly due to the unique way their research and work were presented. They were the specific users of the artificial intelligence. According to Mazzone and Elgammal (2019), artificial intelligence (AI) can be used to create art. AI can rely on various computer algorithms to finish the art creation assistance during the creation process. AI has been used to create a large number of works of art. Therefore, art students must understand how to apply AI to keep art production current.

This study examined the variables impacting Chengdu, China, junior college students' satisfaction with and intention to use artificial intelligence (AI). This study began by screening variables that could impact junior college students' satisfaction with and intention to use artificial intelligence (AI) in higher education. These elements comprised attitude (AT), perceived utility (PU), perceived ease of use (PEU), emotional support (ES), and informational support (IS). 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 junior art college students. The aim of this study was to investigate the Factors Impacting Junior College Students' Satisfaction and Intention to Use Artificial Intelligence in Chengdu, China, and to further explore the development of creative talent using the art of AI.

2. Literature Review

2.1 Informational Support

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.

According to Sarajärvi et al. (2006), the primary objective of information support, which strives to enhance decision-making processes, is to guarantee that correct and pertinent information is available when required. According to Buis (2008), information support is necessary for efficient decision-making, problem-solving, and organizational success. According to Xing et al. (2018), information support makes information a practical instrument that aids in issue-solving and goal accomplishment by fusing method, technology, and human understanding.

AI-powered M-banking can provide users with personalized assistance and allow them to express concern when encountering banking service difficulties. This can enhance user satisfaction by raising users' emotional evaluation of M-banking (Tajvidi et al., 2020). User satisfaction is a key advantage of IS and ES, influencing users' CI (Li et al., 2021). M-banking users are likelier to stick with it if they are happy (Sharma & Sharma, 2019). 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

According to Guo et al. (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.

According to Lee et al. (2022), AI chatbots may demonstrate empathy by providing emotional support, which includes understanding and positive affect. Additionally, they discovered that when people interact with artificial intelligence, people's perceptions of the emotional support provided by chatbots are positively connected with social attractiveness and emotional credibility. Positive interactions between customers and AI chatbots strengthen the bond between humans and AI by providing emotional support and product or service expertise. Barrington-Trimis et al. (2018) discovered that a critical word, emotional support, captures the positive affective reactions (such as attachment, compassion, and faith) from employees inside groups.

When selecting alternative items, emotional support is described as the perceived usefulness derived from various sentiments, emotions, and states of reality (Kashif et al., 2018). Gelbrich et al. (2021) and Zhu et al. (2016) discovered the direct impact of emotional support on users' happiness in the setting of technology-mediated services and online brand communities. 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

The results showed that perceived usability, perceived ease of use, and information quality all influence user satisfaction, which determines whether or not a user wants to continue using (Legramante et al., 2023). The perceived usefulness and ease of use of new technologies significantly impact customers' attitudes about using them, which in turn influences their intentions to do so (Davis, 1989). Perceived utility and ease of use are the two primary drivers of IT acceptability, making them valuable for predicting or measuring end-user satisfaction with IT (Venkatesh & Davis, 1996).

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.

Positive correlations exist between attitudes about using hotel self-service kiosks, perceived usefulness, perceived ease of use, and satisfaction with using these kiosks (Kim & Qu, 2014). Within TAM, perceived utility and perceived ease of use are linked to the value barrier and use barrier, respectively, whereas consumers' perceived risk is linked to the risk barrier (Ram & Sheth, 1989). 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

According to Ashfaq et al. (2020), TAM antecedents (i.e., perceived usefulness and ease of use) support contentment and continuing intention, whereas information quality and service quality enhance satisfaction. According to Kasilingam (2020), innovativeness, trust, and attitude motivate use intention; however, ease of use, perceived usefulness, enjoyment, cost considerations, perceived risk, and innovativeness all impact attitude. Le (2023) highlighted that perceived usefulness reflects how consumers feel an information system (IS) may help them perform better, while ease of use indicates how easy they feel it is to utilize an IS.

Le (2022) investigated how the adoption of IS is significantly influenced by its perceived usefulness. According to studies already conducted, adoption intentions for ISs are significantly influenced by perceived utility. According to Hess et al. (2014), it is a key component of the Technology Acceptance Model (TAM) and other acceptance models, emphasizing the significance of users' opinions on the worth and utility of a technology. According to Adams et al. (1992), consumers' perceptions of the usefulness of technology have a big impact on whether or not they embrace and utilize it. Users are more likely to accept and use technology if they believe it will enhance their performance and offer genuine benefits.

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

According to Chong (2013) research, utility significantly influences satisfaction, whereas ease of use has less bearing. More research by Susanto et al. (2016) has shown that higher satisfaction may result in future repeat business, which is crucial for creating lasting relationships. Liébana-Cabanillas et al. (2016) reached a similar conclusion, asserting that user trust and continuing mobile banking usage depend highly on pleasure. Yoon (2010) and Yaya et al. (2011) find that security and privacy statistically positively impact online banking user satisfaction.

According to Benjamin (2012) research, recommendation algorithms are crucial in helping Internet products achieve and sustain user growth and satisfaction. The study by Wang et al. (2019) emphasized the general applicability of the use and satisfaction theory to the analysis of TikTok usage. In the context of mobile banking in China, Avornyo et al. (2019) found a neutral impact on the relationship between customer satisfaction and retention intention. According to research by Bergmann et al. (2023), customer satisfaction affects the desire to acquire a product. Happier customers are more likely to repurchase, whereas unhappy customers are more likely to cancel a future purchase. According to Tsai et al. (2014), the relationship between ease of use and retention intention is mediated by user satisfaction.

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

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.

Safa et al. (2015) studied individuals' attitudes, which are directly influenced by their experiences and knowledge. Dinev and Hu (2007) found that one of the key factors influencing attitude is the user's awareness of risks in the context of information technology. According to Vafaei-Zadeh et al. (2019), attitudes about using anti-malware software are influenced by one's perception of the product's pricing and level of information security knowledge. According to Ajzen and Fishbein (1980), a person's action intention results in real conduct, which is dictated by his or her subjective norm and attitude—both of which are influenced by personal beliefs.

The study by Chawla and Joshi (2019) is distinctive in that it looks at the influence of both intention and attitude. Consequently, it reevaluates elements and provides new perspectives impacting customer attitudes and intents about 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. Based on the above literature, the following research hypotheses emerged from this paper.

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

3. Research Methods and Materials

3.1 Research Framework

The foundational theories referenced in this study included a research model based on the social support theory (SST) developed by Lin and Lee (2022) to examine how users' behavior is affected by artificial intelligence (AI) features from a social support perspective. The technology acceptance model (TAM) was developed by Davis (1989) and examined the relationships between three key elements: adoption objectives, attitudes, and perceived usefulness and usability. The model created by Venkatesh et al. (2003) is known as the Unified Theory of Acceptance and Use of Technology (UTAUT). Four basic elements comprise the model that predicts behavioral intention and usage behavior. The researcher has developed a conceptual framework for this study, described in Figure 1.

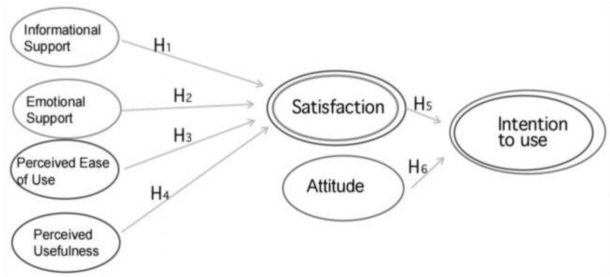

Figure 1: Conceptual Framework

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

The researcher employed a quantitative non-probability sampling approach through an online questionnaire platform to disseminate surveys to the target population (Steffens et al., 2014). The target population of this study was junior college students in four art programs in Chengdu. We analyzed the feedback data to explore the factors impacting junior college students' satisfaction and intention to use Artificial Intelligence in Chengdu, China. There were three sections on the questionnaire for this investigation. Screening questions made up the first segment. In the second part, every variable was rated on a 5-point Likert scale. The scale items measured the six study hypotheses. From (1) strongly disagree to (5) strongly agree, they were the range of measures. The demographic questions were in the third part. These issues include gender, major, and experience in using AI. Before conducting the large-scale questionnaire, the researcher administered a pilot test to 50 respondents. The questionnaire used for the pilot test passed the expert's Item-Objective Consistency Index (IOC) score.

3.3 Population and Sample Size

The study's questionnaire passed validity and reliability assessments using the Cronbach's Alpha technique (Den Hartog & Verburg, 2004). The researcher distributed the questionnaires to the target respondents and received acceptable feedback of 500 responses. We examined this feedback data using SPSS AMOS statistical tests. We employed confirmatory factor analysis (CFA) to evaluate the convergence's validity and accuracy. These measurements guaranteed the model's validity and dependability and confirmed that this study's conceptual framework suited the data. Based on these efforts, the researcher used structural equation modeling (SEM) to investigate the causal linkages between the variables.

3.4 Sampling Technique

Using non-probability, judgmental, and quota sampling, the researchers selected junior college students from four art majors in Chengdu, China. They distributed questionnaires using an online questionnaire 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	231	141
Animation and Game Design	180	110
Visual Communication Design	238	145
Product design	170	104
Total	**819**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

A questionnaire was distributed to 500 junior college students majoring in art at the Sichuan University of Media and Communications in Chengdu. Among them, 276 were female and 224 were male, accounting for 55.2 % and 44.8 % respectively. Among them, 141 (28.2%) were in digital media, 110 (22%) were in animation and game design, Visual Communication Design 145 (29 percent), and Product Design 104 (20.8 percent). 263 people had been using AI for 3 months, and 237 people had been proficient in using AI for more than 3 months, accounting for 52.6% and 47.4%, respectively. Table 2 presents demographic information for this study.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Female	276	55.2%
	Male	224	44.8%
Major	Digital Media	141	28.2%
	Animation and Game Design	110	22%
	Visual Communication Design	145	29%
	Product design	104	20.8%
Experience in using AI	3 months	263	52.6%
	More than 3 months	237	47.4%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was utilized in this study to measure every variable in the conceptual framework. The measurement's findings demonstrated the significance of each scale item for every variable. Furthermore, each scale item's factor loading values were within acceptable bounds, suggesting that the study's conceptual framework was a suitable fit. For this investigation, all construct reliabilities were more than 0.70, all mean extracted variances were greater than 0.50, all p-values were less than 0.05, and all factor loading values were better than 0.30. Every one of these estimations was significant.

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	0.835	0.700-0.825	0.836	0.562
Emotional support (ES)	Lin and Lee (2022)	5	0.872	0.692-0.835	0.817	0.580
Perceived ease of use (PEU)	Aiolfi et al. (2023)	4	0.842	0.692-0.827	0.845	0.578
Perceived Usefulness (PU)	Aiolfi et al. (2023)	4	0.843	0.701-0.860	0.848	0.585
Satisfaction (SA)	Yüce and Dost (2019)	4	0.848	0.727-0.776	0.848	0.583
Attitude (AT)	Kim and Qu (2014)	4	0.861	0.728-0.859	0.862	0.611
Intention to use (IU)	Aiolfi et al. (2023)	3	0.843	0.770-0.822	0.844	0.643

The square roots of the extracted level differences are shown in Table 4, and these values suggest that all of the study's variables had suitable correlations. As measures of model fit in the CFA test, this study employed GFI, AGFI, NFI, CFI, TLI, and RMSEA.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1977)	544.397/329 or 1.655
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.931
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.914
NFI	≥ 0.80 (Wu & Wang, 2006)	0.920
CFI	≥ 0.80 (Bentler, 1990)	0.967
TLI	≥ 0.80 (Sharma et al., 2005)	0.962
RMSEA	< 0.08 (Pedroso et al., 2016)	0.036
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 displays the study's discriminant and convergent validity. These two values were confirmed as acceptable. All of the measurements confirmed the correctness of the structural model derived in this investigation.

Table 5: Discriminant Validity

	IS	ES	PEU	PU	SA	AT	IU
IS	**0.750**						
ES	0.152	**0.762**					
PEU	0.132	0.110	**0.760**				
PU	0.142	0.223	0.183	**0.765**			
SA	0.243	0.216	0.337	0.350	**0.764**		
AT	0.185	0.194	0.186	0.207	0.241	**0.782**	
IU	0.253	0.326	0.204	0.367	0.398	0.320	**0.802**

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

4.3 Structural Equation Model (SEM)

Wheaton et al. (1977) suggested that the Chi-square/degrees of freedom (CMIN/DF) ratio for model fit is less than or equal to 5.00

Sica and Ghisi (2007) suggested that the GFI should be greater than 0.85 and AGFI greater than 0.80. Wu and Wang (2006) suggested that the NFI should be greater than 0.80. Bentler (1990) and Sharma et al. (2005) suggested that the CFI and TLI should be greater than 0.80. Pedroso et al. (2016) considered RMSEA to be less than 0.08. The researchers used SPSS AMOS version 26 for the SEM calculations and adjusted the model. The fit index results for this study presented a good fit. CMIN/df = 2.053, GFI = 0.905, AGFI = 0.876, NFI = 0.888, CFI = 0.944, TLI = 0.938 and RMSEA = 0.046. 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)	706.318/344 or 2.053
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.905
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.876
NFI	≥ 0.80 (Wu & Wang, 2006)	0.888
CFI	≥ 0.80 (Bentler, 1990)	0.944
TLI	≥ 0.80 (Sharma et al., 2005)	0.938
RMSEA	< 0.08 (Pedroso et al., 2016)	0.046
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=0.203), Emotional support influenced Satisfaction (β=0.152), Perceived ease of use influenced Satisfaction (β=0.311), Perceived usefulness influenced Satisfaction (β=0.324), Satisfaction influenced Intention to use (β=0.426) and Attitude influenced Intention to use (β=0.268).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: IS→SA	0.203	4.139*	Supported
H2: ES→SA	0.152	3.196*	Supported
H3: PEU→SA	0.311	6.070*	Supported
H4: PU→SA	0.324	6.558*	Supported
H5: SA→IU	0.426	7.993*	Supported
H6: AT→IU	0.268	5.412*	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 0.203 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 0.152 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 0.311 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 0.324 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 0.426 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 0.268 in its structural path.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The purpose of this study was to provide a comprehensive analysis of the factors impacting junior college students' satisfaction and intention to use Artificial Intelligence in Chengdu, China. In May 2017, the University of Chinese Academy of Sciences (UCAS) set up the first comprehensive AI talent training institute in China, followed by Tsinghua University, Peking University, Renmin University of China, and Nanjing University, which have successively set up AI colleges and institutes. China needs to create a new generation of talented people proficient in AI, and AI should be widely used in basic education, higher education, vocational education, and civic education. Therefore, there is a need for an in-depth study of the factors impacting AI satisfaction and intention to use. This study proposes six hypotheses and explores the relationship between the factors.

The target population of this study is art junior college students in Chengdu, China. In this paper, a survey was conducted at Sichuan University of Media and Communications in Chengdu, China. We administered questionnaires to 500 junior college students from four art majors who used AI. The information gathered from these survey replies was examined. The data analysis supported the conceptual foundation of this article. This study's 500-point sample data passed the JAMOVI and SPSS measurement analyses. This study's conceptual framework supported the item factor structure and passed the AMOS test. The CFA validated that this study's factor structure and validation model were appropriate and that there was an acceptable match between the relevant data (West, 2002).

The confirmatory factor analysis (CFA) assessment was passed on the information gathered by the researcher from the 500 surveys. These findings showed that the study's conceptual model was sound and passed the validity and reliability tests. The notion of this study holding was demonstrated by the outcomes of the convergent validity tests, which included composite reliability, Cronbach's alpha reliability, factor loading, and mean-variance extraction analysis, and discriminant validity (Steigenberger, 2015). This study used structural equation modeling (SEM) to analyze the factors impacting junior college students' satisfaction and intention to use Artificial Intelligence in Chengdu, China. The results indicate that the research hypotheses proposed in this paper are valid. These results support all six research hypotheses of this study.

The results show that in artificial intelligence, information support, emotional support, perceived ease of use, and perceived usefulness directly affect student satisfaction, and student satisfaction and attitudes directly affect students' intention to use artificial intelligence. This effect is direct and significant, and this study provides a theoretical basis for AI developers and researchers and a model reference for future researchers who study the influences on AI learning.

5.2 Recommendation

Based on this paper's findings, we make the following recommendations. First, we suggest designing more courses based on real-world cases to demonstrate the application of AI in various fields so that students can understand its practical use and value. Students are encouraged to participate in project-based learning to solve real-world problems, increasing their understanding of and interest in AI.

Second, we recommend regular training for teachers in AI technology and teaching methods to improve their professionalism and teaching ability. Experts and practitioners in the field of AI should also be invited to give lectures in schools to share cutting-edge technologies and practical work experience with students.

Finally, we suggest Providing students with advanced computing equipment and software to ensure they can successfully learn and practice AI-related skills. Establish and maintain an online learning platform to provide rich AI learning resources. On this basis, AI optimizes information support, emotional support, perceived ease of use, and perceived usefulness to change students' attitudes toward AI and provide continuous feedback on students' satisfaction and intention to use.

5.3 Limitation and Further Study

One of the study's drawbacks was that the variables were measured individually using data from a centralized era (Glick, 1985). The junior college students who provided these data were from specific schools. Further research might benefit from including characteristics comparable to those in this study, the use of an experimental or longitudinal design, and the consistent data collection at several periods.

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