pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 - 868x © 2021 AU-GSB e-Journal.
https://assumptionjournal.au.edu/index.php/AU-GSB

Factors Shaping Students' Attitudes and Adoption Intentions Toward Artificial Intelligence Applications: A Case Study at a Private University in Zhanjiang, China

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Received: September 18, 2024. Revised: December 9, 2024. Accepted: February 22, 2025

Abstract

Purpose: This research aimed to investigate the key factors impacting students' attitudes and adoption intentions toward artificial intelligence applications at a private university in Zhanjiang, China. The conceptual framework delineates the cause-and-effect relationships among Perceived Usefulness, Perceived Ease of Use, Trust, Effort Expectancy, Performance Expectancy, Attitude, and Adoption Intention. **Research design, data, and methodology:** The researcher employed a quantitative methodology with a sample consisting of 500 students from a private university in Zhanjiang, China. Non-probability sampling methods were used, including judgmental sampling to select four colleges, quota sampling to determine the sample size, convenience sampling for data collection, and online questionnaire distribution. Data analysis was conducted using structural equation modeling (SEM) and confirmatory factor analysis (CFA) to evaluate model fit, reliability, and construct validity. **Results:** The findings reveal that attitude is a significant mediating variable that substantially impacts adoption intention. Among the factors affecting attitude, Trust has the most pronounced effect, followed by perceived usefulness. additionally, performance expectancy, effort expectancy, and perceived ease of use also influence attitude. **Conclusions:** These results indicate that enhancing students' trust, perceived usefulness, perceived ease of use, performance expectancy, and effort expectancy regarding artificial intelligence applications is an effective strategy for promoting their acceptance and use in educational settings.

Keywords: Trust, Effort Expectancy, Performance Expectancy, Attitude, Adoption Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Artificial Intelligence is a sophisticated technological system that demonstrates intelligence by applying machine learning techniques and computer models inspired by human behavior, primarily addressing complex problems (Coppin, 2004). Emerging as a pivotal technology for the coming decade, artificial intelligence offers substantial benefits, especially in the domain of Independent or partially independent processing, understanding, and application of significant amounts of data (Gado et al., 2022). Over the past twenty years, artificial intelligence has significantly enhanced the operational efficiency of the manufacturing and service sectors, leading to its widespread adoption and recognition as one of the most transformative advancements (Bhosale et al., 2020). According to Zhai et al. (2021), artificial intelligence is considered the fourth industrial revolution, with the potential to initiate a new transformation in education as key institutions responsible for shaping society's future; colleges and universities play a crucial role in researching attitudes towards artificial intelligence and its applications.

In higher education, artificial intelligence applications serve as practical educational technologies that optimize users' learning process while alleviating educational challenges (Loeckx, 2016). According to Zhu and Ren (2022), artificial intelligence (AI) is a disruptive technology capable of autonomously perceiving, interpreting, predicting,

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and acting. This capability greatly improves the adaptability and effectiveness of using computers as central elements in the pedagogical process. As the primary learners in higher education, students must acquire and apply knowledge through collaborative efforts between humans and computers facilitated by educators and AI applications (Timms, 2016). The integration of artificial intelligence has transformed the traditional teaching and learning paradigm by enabling computers to simulate human-like thinking and actions, thereby fostering student-centered learning and practice (Cox, 2021). The ongoing utilization of artificial intelligence in education is anticipated to promote increased customization and personalization in the delivery of higher education and transform the future professional environment (Ahmad, 2019).

The application of artificial intelligence in higher education demonstrates its inherent capabilities and potential but also raises some concerns (Chatterjee & Bhattacharjee, 2020; Zhu & Ren, 2022). Unlike previous technological advances, implementing AI technology introduces new challenges, including control issues and ethical considerations. Concerns have been raised about the risk of students' personal information being leaked or misused during AI applications, which poses significant challenges to user trust and attitudes (Zhai et al., 2021).

As a representative private university of higher education in Zhanjiang, the attitudes and adoption intentions of students at the university reflect the current acceptance of technology within the educational environment and offer valuable insights into how the new generation perceives and engages with emerging technologies. This study investigates students' attitudes toward artificial intelligence (AI) and their intentions to adopt it in practical applications at this private university. Additionally, it seeks to explore the key factors impacting these attitudes and intentions, providing a scientific basis for the future development of AI education and related policies in higher education institutions.

Research indicates that factors impacting students' acceptance of artificial intelligence applications include performance expectancy, perceived ease of use, trust, usefulness, and effort expectancy. The above variables substantially and favorably impact attitudes toward artificial intelligence and the intention to adopt it in educational contexts (Kelly et al., 2023). This research explores the elements impacting students' attitudes toward artificial intelligence applications, drawing on existing literature and theoretical frameworks. To this end, a questionnaire was developed to systematically collect, analyze, and synthesize data on the various factors impacting students' attitudes and adoption intentions at a private university in Zhanjiang, China.

In conclusion, this paper proposes to study the factors impacting the attitudes and adoption intentions of students at a private university in Zhanjiang toward artificial intelligence applications to promote the broader application of artificial intelligence. By investigating and analyzing these factors, this paper will provide valuable insights for educators and technology developers, helping them better understand and address students' attitudes and adoption intentions of artificial intelligence applications.

2. Literature Review

2.1 Perceived Ease of Use

In the context of AI applications, perceived usefulness reflects students' belief that these tools can improve their academic outcomes (Almaiah et al., 2022). Perceived ease of use involves users' assessments of how simple or complex it is to interact with AI applications (Lin et al., 2022). This perception influences their intention to use AI and indirectly affects perceived usefulness by shaping their overall view of the technology (Saadé & Bahli, 2005).

Perceived ease of use and perceived usefulness are closely linked, with the ease of use often determining the perceived usefulness—easier-to-use technologies are generally seen as more beneficial (Abdullah et al., 2016; Almarashdeh & Alsmadi, 2016; Tsai et al., 2021; Wojciechowski & Cellary, 2013). However, this relationship can change as users gain more experience with AI applications (Chai et al., 2020). This study hypothesizes that perceived ease of use significantly impacts perceived usefulness, which aligns with previous research (Dutot et al., 2019).

Attitudes towards technology are consistent cognitive and psychological tendencies that significantly impact technology acceptance and educational outcomes (Huang, 2020). In technology acceptance models, perceived ease of use predicts user attitudes (Dutot et al., 2019). It can mediate and partially moderate the relationship between ease of use and adoption intention (Osman et al., 2016). Research indicates that a student's knowledge of AI influences their confidence and attitudes, which can shift before and after acquiring substantial knowledge (Chai et al., 2020; Dai et al., 2020). Generally, users have positive attitudes toward technologies they find easy to use (Trayek & Hassan, 2013). However, the effect of perceived ease of use on attitudes may not always be consistent across studies or user groups (Chien et al., 2019; Rahmat, 2019; Tajudeen Shittu et al., 2011; Wojciechowski & Cellary, 2013). Given the limited research on students' attitudes toward AI, further validation of these relationships is needed. Therefore, we propose the following hypotheses:

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived ease of use has a significant impact on attitude.

2.2 Perceived Usefulness

Comprehending learners' perspectives on technology utilization is a pivotal concern for enhancing the efficacy of technology integration and education (Liaw, 2008). Attitude significantly impacts adoption intention, while comprehending students' attitudes toward artificial intelligence applications helps to create an appropriate learning environment for teaching and learning (Chatterjee & Bhattacharjee, 2020). As a mediating factor, attitude is impacted by factors like perceived usefulness and also serves as a predictor for students' inclination toward embracing artificial intelligence applications (Gado et al., 2022). Therefore, altering individuals' perspectives on the practical applications of artificial intelligence necessitates addressing several dimensions of their perceptions (Chang et al., 2021; Kashive et al., 2020).

Based on the research that has been done on technology acceptance modeling, users' attitudes toward the usage of new technology can often be predicted based on how useful they believe the new technology will be (Dutot et al., 2019). It has been demonstrated that students' perceptions of the usefulness of artificial intelligence applications have a significant role in determining their attitudes towards these technologies (Kim et al., 2020). However, the impact of perceived usefulness on attitudes may vary depending on their mastery of the technology. At the initial stage of acquiring knowledge, students may not be able to use artificial intelligence applications well, contributing to their negative attitudes towards artificial intelligence applications (Chai et al., 2021; Dai et al., 2020). These connections have received limited exploration, and it is crucial to give specific consideration to utilizing these emerging technologies in artificial intelligence (Chai et al., 2020, 2021). Therefore, we formulate hypotheses:
H3: Perceived usefulness has a significant impact on attitude.

2.3 Trust

In educational systems based on artificial intelligence applications, trust refers to the user's belief in the application's capacity to provide accurate information, protect their privacy, and give effective learning methods to help them achieve their educational goals (Qin et al., 2020). Trust plays an essential function in virtual environments, as it relates to the user's willingness to exchange important information with the virtual system during information exchange and knowledge integration (Ridings et al., 2002). It is a crucial aspect that influences the adoption of artificial intelligence applications by students, as users need to demonstrate trust to have a good attitude towards it and, in turn, to accept and apply the new technology, which can only be achieved with the appropriate awareness and knowledge (Roy et al., 2022).

Trust has been proven to be a necessary condition that must first be met before certain attitudes can become visible and people are motivated to conduct themselves positively (Chu et al., 2014). Research shows that trust is one of the determinants of attitude (Lien & Cao, 2014; Moorman et al., 1992; Nam, 2014). However, Watzdorf et al. (2010) observed that trust did not significantly influence users' inclination to utilize mobile applications. Yoo et al. (2017) argued that content with prior experience or knowledge creates trust in technology, which leads to positive attitudes, and that trust is one of the determinants of attitudes; however, users' different experiences and knowledge backgrounds can lead them to trust technology differently, which affects technology adoption attitudes. In conclusion, trust can change students' attitudes toward artificial intelligence applications and ultimately lead to their adoption of this technology. Research and analysis of trust and attitudes towards artificial intelligence applications for different groups of students can provide valuable information for the study of adoption intention. Drawing from the reviewed literature, the following hypotheses are formulated:
H4: Trust has a significant impact on attitude.

2.4 Performance Expectancy

Performance expectancy pertains to an individual's view of how employing the system can boost their performance and, as a result, elevate the quality of their work (Venkatesh et al., 2003). Research indicates that performance expectancy positively influences attitudes, shaping intentions and, subsequently, driving behavior (El-Gayar & Moran, 2006; Liebenberg et al., 2018; Nassuora, 2013). Furthermore, performance expectancy significantly predicts attitudes (Bervell et al., 2020; Pangaribuan & Wulandar, 2019). Higher expectations of benefits from a technology increase the likelihood that potential users will accept and utilize it (Thomas et al., 2013).

Performance expectancy refers to the belief held by students that the integration of instructional technology would contribute to the attainment of their learning objectives, and it is assumed that a positive performance expectancy will lead to positive attitudes toward the use of the technology (Robinson, 2006). Researchers have studied the relationship between students' performance expectations and attitudes when adopting new technologies in higher education. Studies indicate that performance expectancy is the primary driver of student technology adoption (Alshare & Lane, 2011; Altalhi, 2021; Chatterjee & Bhattacharjee, 2020; Šumak et al., 2010). So, we anticipate the following hypotheses:

H5: Performance expectancy has a significant impact on attitude.

2.5 Effort Expectancy

The adoption of novel technologies is contingent upon prospective users' perceptions and attitudes on the usability level in practical work settings for accomplishing their objectives (Bervell et al., 2020). While attitude refers to a user's subjective impression of their behavior towards adopting technology (Fishbein & Ajzen, 1977), it is notable that the UTAUT model does not incorporate this construct. Many UTAUT-based studies have incorporated the influence of attitudes in education and have found significant associations with effort expectancy and behavioral intentions (El-Gayar & Moran, 2006; Natasia et al., 2022; Thomas et al., 2013). It was found that technology adoption attitudes mediate the influence of effort expectations and user behavioral intentions, effort expectations positively influence technology adoption attitudes, and attitudes positively impact adoption intentions (Liebenberg et al., 2018; Nassuora, 2013).

Students' effort expectancy is positively correlated with students' attitudes toward using the technology, and students have positive attitudes toward the new technology when they believe that they can achieve their learning goals with a relatively small degree of effort using the new technology (Robinson, 2006). Bervell et al. (2020) found that effort expectancy was a key prerequisite for using LMS attitudes in blended learning and that attitudes significantly mediated effort expectancy and behavioral intentions. In their study on Thai students' acceptance of mobile learning, Jairak et al. (2009) found that effort expectancy significantly improved students' attitudes towards technology acceptance. Based on this finding, we propose the following hypotheses:

H6: Effort expectancy has a significant impact on attitude.

2.6 Attitude

Adoption intention relates to a person's predisposition or readiness to embrace and integrate a specific product into their consumption patterns (Srivastava et al., 2022). Adoption intention is a psychological construct separate from attitude (Eagly & Chaiken, 1993). While adoption intention pertains to an individual's readiness to embrace a new behavior, attitude reflects the individual's general disposition towards engaging in that behavior. Attitude toward technology adoption pertains to the degree of favorability that people exhibit toward the process of adopting technology (Ajzen, 1991). Attitude impacts adoption intention (Davis, 1993; Taylor & Todd, 1995; Venkatesh et al., 2003), further regarded as a factor impacting adoption intentions (Brachten et al., 2021; Mathieson, 1991).

The confirmation of the association between attitudes toward technology adoption and students' cognitive and affective dispositions towards the technology, which are anticipated to influence intentions to embrace the technology, has also been acknowledged (Srivastava et al., 2022; Yeap et al., 2016). Shih (2008) discovered a noteworthy positive correlation between attitude and adoption intention when evaluating adoption intention. Singh et al. (2021) found that individuals' attitudes regarding computer usage influenced their adoption intentions toward technology. According to Kim et al. (2020), the attitudes regarding the application of artificial intelligence teaching assistants have been found to exert a favorable influence on individuals' intent to adopt artificial intelligence-based education. It is evident that in the context of technological innovation, attitudes are likely to be a central driver (Brachten et al., 2021). Therefore, we formulate hypotheses:

H7: Attitude has a significant impact on adoption intention.

2.7 Adoption intention

Adoption intention indicates a user's willingness to accept a product and reflects a person's drive to engage in the desired behavior (Srivastava et al., 2022). Senaratne and Samarasinghe (2019) stated that adoption intention reflects the inclination of students to favor utilizing a learning system when they perceive it as straightforward and valuable. Adoption intention is impacted by many factors, which vary from context to context. Gatzioufa and Saprikis (2022) argued that perceived usefulness, performance expectations, trust, attitudes, and effort expectancy influence users' adoption intention. Research establishes that perceived usefulness, perceived ease of use, and attitude are significant predictors of adoption intention, with attitude identified as the most critical predictor of this intention (Hashim et al., 2015; Ndubisi & Chukwunonso, 2004; Shih, 2008; Srivastava et al., 2022).

3. Research Methods and Materials

3.1 Research Framework

The researcher utilized three theoretical models—the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Theory of Planned Behavior (TPB) (Ajzen, 1991)—to underpin the conceptual framework. Figure 1 displays the framework used in this study. The research aimed to explore how various factors affect undergraduate students' attitudes and adoption intentions toward artificial intelligence (AI) applications at a private university in Zhanjiang, China. The framework incorporates seven variables: perceived usefulness (PU), perceived ease of use (PEOU), trust (TR), effort expectancy (EE), performance expectancy (PE), attitude (ATT), and adoption intentions (ADI).

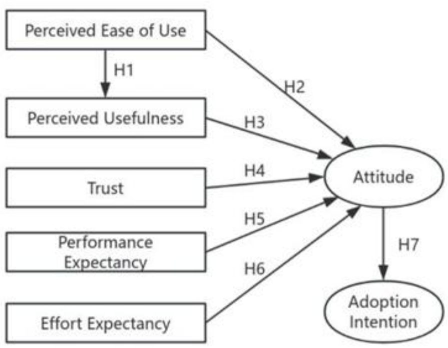

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived ease of use has a significant impact on attitude.
H3: Perceived usefulness has a significant impact on attitude.
H4: Trust has a significant impact on attitude.
H5: Performance expectancy has a significant impact on attitude.
H6: Effort expectancy has a significant impact on attitude.
H7: Attitude has a significant impact on adoption intention.

3.2 Research Methodology

This study employed quantitative methods, covering multiple aspects such as research background, target population and sampling procedures, research instruments, data collection, and hypothesis testing. The researchers initially utilized a non-probability sampling method, distributing the questionnaire through an online survey platform. The target population consisted of students at a private university in Zhanjiang, China, who had previously used artificial intelligence applications. The study aimed to examine the gathered data and investigate the primary factors impacting these students' attitudes toward and intentions to embrace artificial intelligence applications.

The questionnaire was organized into three sections. The first section included screening questions to determine whether participants met the study's criteria. The subsequent section utilized a 5-point Likert scale to assess various aspects of the seven hypotheses, incorporating all study variables. The scale from "1" (strongly disagree) to "5" (strongly agree). The last section concentrated on demographic questions, such as gender, age, academic year, duration of AI application usage, and the channels through which participants encountered artificial intelligence applications. A preliminary poll was undertaken before the main survey, involving a pilot test with 30 participants. Experts evaluated the questionnaire using the Item-Objective Congruence (IOC) index, and its reliability and consistency were confirmed through Cronbach's Alpha.

3.3 Population and Sample Size

To guarantee the precision and content validity of the study, the researchers employed several evaluation techniques before data collection. Afterward, the questionnaire was disseminated to the targeted participants, yielding 500 valid responses. Data analysis was carried out using JAMOVI and SPSS AMOS software. Confirmatory Factor Analysis (CFA) was performed to assess the model's convergent validity and overall fit, affirming its validity and reliability as a foundational step. Building on these validated measures, Structural Equation Modeling (SEM) was subsequently employed to investigate the causal relationships among variables, offering deeper insights into the factors influencing students' attitudes toward and intentions to adopt artificial intelligence applications.

3.4 Sampling Technique

This study employed non-probability sampling methods, including purposive and quota sampling, to select four colleges from a private university in Zhanjiang, China. Questionnaires were distributed via an online survey platform. Table 1 outlines the detailed sampling process. The survey was conducted from January to August 2024, and data screening confirmed that the participants were suitable for the study. The respondents, all students from the selected university, participated voluntarily.

Table 1: Sample Units and Sample Size

College	Population Size	Proportional Sample Size
Management College	2,000	99
Architecture and Engineering College	1,600	79
Accounting College	2,614	129
Intelligent Manufacturing College	3,923	193
Total	**10,137**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Among the 500 valid questionnaires obtained, there were 290 males (58.0%) and 210 females (42.0%). Of these respondents, 165 were aged 19-20 (33.0%), 185 were aged 21-22 (37.0%), and 150 were aged 23 and above (30.0%). There were 125 freshmen (25.0%), 91 sophomores (18.2%), 163 juniors (32.6%), and 121 seniors (24.2%). Additionally, 146 respondents (29.2%) had known about artificial intelligence applications for less than a year, 167 (33.4%) for one to two years, and 187 (37.4%) for three years or more. Among them, 308 respondents (61.6%) learned about artificial intelligence applications through the Internet, 121 (24.2%) through recommendations, and 71 (14.2%) through advertisements. The demographic information is detailed in Table 2.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	290	58.0%
	Female	210	42.0%
Age	19 to 20 years old	165	33.0%
	21 to 22 years old	185	37.0%
	More than 23 years	150	30.0%
Grade	Freshman	125	25.0%
	Sophomore	91	18.2%
	Junior	163	32.6%
	Senior	121	24.2%
Experience	Less than 1 year	146	29.2%
	Between 1-2 years	167	33.4%
	Three years or more	187	37.4%
Channel	network	308	61.6%
	recommended by others	121	24.2%
	advertising	71	14.2%

4.2 Confirmatory Factor Analysis (CFA)

For this research, confirmatory factor analysis (CFA) was employed to evaluate the measurement accuracy of each variable within the conceptual framework. The study revealed that all scale items were statistically significant, with factor loadings within acceptable ranges, suggesting a strong fit of the conceptual framework. Specifically, all factor loadings exceeded 0.60, with p-values below 0.05, construct reliability surpassing 0.70, and average variance extracted (AVE) values above 0.50, thus affirming the statistical significance of these estimates. Detailed values are presented in Table 3.

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
Perceived Ease of Use (PEOU)	Roy et al. (2022)	4	0.865	0.767-0.799	0.865	0.617
Perceived Usefulness (PU)	Roy et al. (2022)	4	0.857	0.738-0.797	0.858	0.601
Trust (TR)	Roy et al. (2022)	4	0.844	0.679-0.803	0.846	0.579
Performance Expectancy (PE)	Chatterjee and Bhattacharjee (2020)	5	0.876	0.718-0.797	0.876	0.585
Effort Expectancy (EE)	Chatterjee and Bhattacharjee (2020)	5	0.879	0.706-0.803	0.880	0.594
Attitude (ATT)	Roy et al. (2022)	4	0.881	0.782-0.844	0.882	0.651
Adoption Intention (ADI)	Pillai et al. (2023)	5	0.897	0.778-0.814	0.897	0.635

Several fit indices, including GFI, AGFI, NFI, CFI, TLI, and RMSEA, were utilized to assess the fit of the CFA model. The CFA indices provided in Table 4 are all deemed acceptable. The metrics collectively substantiate the validity of the structural model estimated in this study, thereby reinforcing its robustness and credibility. By demonstrating consistent performance across various criteria, these measures validate the model's theoretical framework and empirical accuracy.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.642
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.924
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.908
NFI	≥ 0.80 (Wu & Wang, 2006)	0.924
CFI	≥ 0.80 (Bentler, 1990)	0.969
TLI	≥ 0.90 (Hair et al., 2006)	0.965
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

Additionally, Table 5 illustrates the square roots of the AVE values, confirming the appropriateness of the correlations among the variables in this study.

Table 5: Discriminant Validity

	PEOU	PU	TR	PE	EE	ATT	ADI
PEOU	**0.785**						
PU	0.415	**0.775**					
TR	0.423	0.444	**0.761**				
PE	0.470	0.357	0.407	**0.765**			
EE	0.424	0.303	0.274	0.379	**0.771**		
ATT	0.355	0.375	0.397	0.358	0.318	**0.807**	
ADI	0.459	0.340	0.424	0.369	0.356	0.418	**0.797**

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

4.3 Structural Equation Model (SEM)

The researcher employed SPSS AMOS 23.0 to assess the Structural Equation Model (SEM) fit. The analysis demonstrated that the chi-square statistic (CMIN/DF) was 2.879, the goodness-of-fit index (GFI) was 0.855, the adjusted goodness-of-fit index (AGFI) was 0.831, the normed fit index (NFI) was 0.863, the comparative fit index (CFI) was 0.905, the Tucker-Lewis index (TLI) was 0.897, and the root mean square error of approximation (RMSEA) was 0.061. These figures indicate a satisfactory model fit, with all metrics falling within acceptable ranges. Detailed results are summarized in Table 6.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.879
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.855
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.831
NFI	≥ 0.80 (Wu & Wang, 2006)	0.863
CFI	≥ 0.80 (Bentler, 1990)	0.905
TLI	≥ 0.90 (Hair et al., 2006)	0.897
RMSEA	< 0.08 (Pedroso et al., 2016)	0.061
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 importance of the research model was evaluated through the regression coefficients for each variable and the R^2 variance. The results, presented in Table 7, provide detailed calculations. These findings validate all the hypotheses proposed in this research—perceived ease of use impacts perceived usefulness (β=0.483) and attitude (β=0.119). Perceived usefulness also impacts attitude (β=0.192). Trust significantly affects attitude (β=0.285), while performance expectancy (β=0.157) and effort expectancy (β=0.166) also contribute to shaping attitude. Finally, attitude strongly influences adoption intention (β=0.471).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.483	9.113***	Supported
H2: PEOU→ATT	0.119	2.098*	Supported
H3: PU→ATT	0.192	3.331***	Supported
H4: TR→ATT	0.285	5.569***	Supported
H5: PE→ATT	0.157	3.268**	Supported
H6: EE→ATT	0.166	3.454***	Supported
H7: ATT→ADI	0.471	8.932***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

Based on the findings in Table 7, the following conclusions can be drawn: H1 indicates that perceived ease of use significantly impacts perceived usefulness, with a Standardized path coefficient (β) of 0.483. H2 demonstrates that perceived ease of use is a key attitude driver, with a β value of 0.119. H3 reveals that perceived usefulness is another crucial attitude driver, with a β value of 0.192. H4 establishes that trust is the most significant factor impacting attitude, with a β value of 0.285. H5 identifies effort expectancy as a major determinant of attitude, with a β value of 0.157. H6 confirms that effort expectancy is a critical factor influencing attitude, with a β value of 0.166. Lastly, H7 shows that attitude is a key determinant of adoption intention, with a β value of 0.471. These findings collectively support all seven hypotheses.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study seeks to thoroughly examine the elements impacting students' attitudes and adoption intentions toward artificial intelligence applications at a private university in Zhanjiang, China. Building on previous research, the study developed a conceptual framework and proposed seven hypotheses to explore the primary factors affecting students' attitudes and adoption intentions.

This research focuses on students from a private university in Zhanjiang, China, as its target population. A questionnaire survey was conducted among students from four colleges within the university, employing a five-point Likert scale. The questionnaire's reliability and consistency were confirmed through expert assessment and a pilot study. A preliminary test with 30 samples demonstrated high internal consistency and reliability. A sum of 500 valid questionnaires was obtained, and the data analysis supported the conceptual framework outlined in this research. The data were examined using SPSS and JAMOVI, while AMOS was employed to test the conceptual framework, validating the study's factor structure. The confirmatory factor analysis (CFA) further validated the factor structure and the model's suitability, with the data showing a good fit.

The information gathered from 500 surveys was evaluated through Confirmatory Factor Analysis (CFA), which confirmed the accuracy of the theoretical model. Assessments of consistency and validity—including composite reliability, Cronbach's alpha, factor loadings, and average variance extracted (AVE) analyses—along with discriminant validity tests all affirmed the strength of the theoretical framework. Structural Equation Modeling (SEM) was employed to examine the factors impacting students' attitudes and adoption intentions regarding artificial intelligence applications at the university. The results validated the research hypotheses and supported all seven proposed hypotheses.

The analysis shows that perceived ease of use (PEOU) directly and significantly affects perceived usefulness (PU). Furthermore, PEOU, PU, trust (TR), performance expectancy (PE), and effort expectancy (EE) all exert direct and significant influences on attitude (ATT), which subsequently has an indirect effect on adoption intention (ADI). The study highlights that trust and perceived usefulness significantly impact students' attitudes, while PEOU, EE, and PE indirectly affect adoption intention through mentality. These findings suggest that enhancing students' trust in and perceived value of artificial intelligence applications is an effective way to promote their acceptance and use in educational settings.

5.2 Recommendation

The results of the investigation lead to the following proposed recommendations. First, developers of artificial intelligence applications and educational administrators should focus on and refine five key factors: trust, perceived usefulness, effort expectancy, performance expectancy, and perceived ease of use. These factors significantly impact students' attitudes toward the adoption intention of artificial intelligence applications. By enhancing students' trust in these applications, increasing their perceived usefulness and ease of use, and reducing their perceived effort expectancy, educational administrators can effectively promote the adoption and positive utilization of artificial intelligence systems.

Second, this study clarifies the relationships among seven variables and integrates them into a comprehensive conceptual framework. This framework elucidates the mechanisms influencing students' attitudes and adoption intentions toward artificial intelligence applications in private universities. Specifically, increasing trust can significantly improve students' positive attitudes toward artificial intelligence, while perceived usefulness and ease of use directly impact their willingness to use these applications. Additionally, effort and performance expectancy indirectly impact users' attitudes and adoption intentions.

Finally, creators of artificial intelligence applications and educational policymakers in China can leverage this conceptual framework to refine strategies for integrating artificial intelligence technologies into educational settings. By enhancing system credibility, improving user-friendliness, and simplifying the usage process, developers can reduce students' perceived difficulties when using these technologies, thereby fostering more positive attitudes and higher adoption intentions. Furthermore, educational administrators should provide more training and support to help students better understand and utilize these technologies, maximizing their academic potential.

In summary, these recommendations offer valuable guidance for higher education institutions, helping them harness artificial intelligence technologies to enhance educational quality and student experience in a rapidly evolving technological environment. By systematically addressing and managing these influencing factors, institutions can effectively advance the integration and application of intelligent technologies, achieving a more modern and efficient educational system.

5.3 Limitation and Further Study

The constraints of this study include the fact that the data were gathered exclusively from students at a particular university and within certain colleges. The variables examined are at the individual level, and the data were collected simultaneously. Due to the rapid advancement of technology and changes in the social environment, the results of this study may vary over time. To address these limitations, future research should increase sample diversity, address potential biases, and collect data at multiple time points to achieve more comprehensive and accurate findings.

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