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Résumé de l'article

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Artificial Intelligence in Higher Education: A Cross-Cultural Examination of Students' Behavioral Intentions and Attitudes

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Abstract

Artificial intelligence (AI) has undergone considerable advancement in the contemporary period and represents an emerging technology in higher education. Cultural contexts significantly shape individuals' perceptions, attitudes, and behaviors, particularly in the realm of technology acceptance. By adopting a cross-cultural lens, this research explores the potential variations across Chinese and international students from diverse countries in terms of attitudes and their behavioral intentions toward AI use. With a technology acceptance model (TAM) framework, the research used a survey approach, employing questionnaires as the primary means of data collection. The data were then analyzed through structural equation modeling and descriptive statistics. A substantial discrepancy was found in the prevalence, attitudes, and behavioral intentions toward AI use between Chinese and international students. Findings further revealed a stronger effect of perceived ease of use on both attitudes and behavioral intentions among international students compared with their Chinese counterparts. Findings suggest that cultural backgrounds and prior technological exposure play intricate roles in shaping perceptions of AI technology. The study emphasizes the need for tailored educational strategies to regulate diverse cultural perspectives, provide language-specific support, and ensure user-friendly interfaces. These insights contribute to the evolving discourse on technology acceptance in higher education and offer practical implications for educators and institutions toward optimizing AI integration in pedagogical practices.

Keywords: artificial intelligence, higher education, technology acceptance model, attitudes, behavioral intentions

Artificial Intelligence in Higher Education: A Cross-Cultural Examination of Students' Behavioral Intentions and Attitudes

Over the last few years, artificial intelligence (AI) has emerged as a transformative force, reshaping various aspects of our lives. Its influence has extended into the realm of education, promising to revolutionize traditional teaching and learning methods. The integration of AI in higher education stands out as a beacon of innovation, holding the potential to produce sustainable growth in students' learning experiences (Ouyang & Jiao, 2021), foster retention (L. Chen et al., 2020), strengthen academic motivation (Yilmaz & Yilmaz, 2023), increase academic performance (Zhou, 2023), promote self-directed learning skills (Lasfeto & Ulfa, 2023), support language learning (Crompton & Burke, 2023), and develop problem-solving skills (Zhang & Zhu, 2022). AI refers to the development of computers that can perform tasks that are normally associated with human intelligence (Ertel, 2018) and encompasses a wide array of functions such as problem-solving, language understanding, visual perception, and decision-making. In the context of education, AI presents an exceptional opportunity to tailor learning experiences to individual needs, providing personalized pathways for students to explore and master their academic pursuits (Alam, 2021).

The integration of AI in education is a multifaceted process influenced by various factors, such as technological infrastructure (Matsika & Zhou, 2021), institutional policies (Cheng & Wang, 2022), self-efficacy (Yilmaz & Yilmaz, 2023), and pedagogical approaches (Chan, 2023). In addition to other factors, students' personal perceptions and attitudes play essential roles in the successful implementation of AI in higher education. Studies have constantly shown that students' learning experiences are greatly affected by their beliefs about using or engaging with technologies in their educational practices (Akinoso, 2023; Zulaiha & Triana, 2023). As active participants in the learning process, students show preferences for technological applications that correspond with their attitudes and strategies for learning (Abdelrady & Akram, 2022; Guo et al., 2023). This alignment stems from a desire to improve their educational experience via the effective incorporation of technology (Akram et al., 2022; Linardatos & Apostolou, 2023). On the other hand, individuals with a negative attitude toward technology are less likely to be interested in technology-driven learning and hold negative views of tech-based resources, hindering their abilities to effectively incorporate technology into their learning (Akram, Yingxiu, et al., 2021a; Y. Wang, 2023). Therefore, individuals' willingness and ability to use AI in education are key factors that determine how well the technology is integrated. Furthermore, the debut of new technology requires a thorough examination of individuals' attitudes toward it and the elements that shape those perceptions (Makumane, 2023). In terms of AI in higher education, examining students' perspectives is a critical step in understanding the dynamics of their relationship with this novel technology.

Cultural differences can also greatly influence attitudes toward technology in the educational process. Diverse cultures exhibit different policies regarding and accessibility toward digital technologies (Akram & Yang, 2021), leading to gaps in digital competences such as computational thinking and AI literacy between people of different backgrounds (Kayalar, 2016; Savicki, 2023). These differences can result in distinct ways of interacting with technology, which can influence people's attitudes, perceptions, and beliefs (Vargo et al., 2021). Over time, these disparities may lead to significant differences in professional paths, economic standing, and various other aspects of life.

Over the last few decades, the landscape of higher education in China has undergone a revolutionary transition due to significant growth in the number of international students arriving to study (Akram et al., 2020; Jiani, 2017). This influx has brought cultural diversity to Chinese institutions, offering a robust platform for intellectual enrichment and signifying China's dedication to globalization and cross-cultural interactions (Dai & Hardy, 2023). The interaction between cultures brings different elements or characteristics to the academic landscape, making it an interesting area for research, especially concerning how new technologies like AI can be introduced and used in education. As the landscape of AI in education continues to evolve, it is crucial to understand how students from diverse cultural backgrounds, sharing the common space of Chinese educational institutions, view and engage with it. Therefore, the study aims to address the following research objectives (ROs):

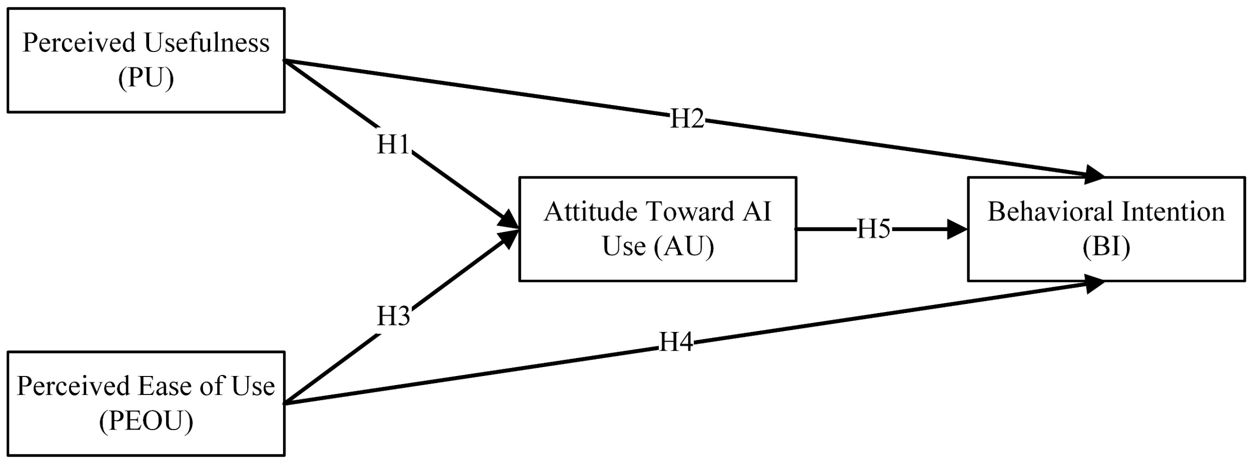
> RO1: To explore and compare the attitudes and behavioral intentions of both Chinese and international students regarding the integration of AI in higher education.
>
> RO2: To identify and analyze the key determinants influencing the attitudes and behavioral intentions of students toward using AI in higher education.

Theoretical Framework and Hypotheses

Examining individuals' attitudes is crucial to determining the success rate of newly introduced technology. Several theories have been developed to investigate and explain the reasons that lead users to embrace, reject, or continue to use a new technology (Venkatesh & Davis, 2000; Venkatesh et al., 2003). The technology acceptance model (TAM) is a widely recognized theoretical framework that helps explain users' intentions and attitudes to use technology (see Figure 1). In the context of students' intentions and attitudes to use AI in higher education, the TAM is particularly relevant as it offers insights into the factors that influence users' decisions to integrate AI into their learning practices (Davis, 1989). This model consists of two primary constructs, which are believed to be the most important factors in determining the level of user approval.

Figure 1

Conceptual Framework



Perceived Usefulness

Perceived usefulness (PU) refers to the extent to which individuals believe that using a specific technology will enhance their ability to accomplish their work (Davis, 1989). Students who perceive technological applications as useful in their studies are more likely to integrate them into their educational practices (Akram, Aslam, et al., 2021). In the current study, PU refers to how AI can improve students' learning and conserve their time and energy. Conversely, individuals who do not perceive technology as useful may find it challenging to use (Davis, 1989). X. Chen et al. (2020) found that PU significantly influenced students' behavioral intentions to use ChatBot in Chinese learning. Similarly, Alfadda and Mahdi (2021) demonstrated a positive and significant correlation between PU and students' attitudes about using Zoom in language learning. Anthony et al. (2022) also established a strong correlation between the perceived advantages of technical courses and their effective adoption. This suggests that students are more likely to incorporate technology into their learning process if they view it as useful and applicable. Therefore, the following hypotheses were put forward:

> H1: PU would significantly and positively influence users' attitudes toward the use of AI in both Chinese and international students.

> H2: PU would significantly and positively influence users' behavioral intentions toward the use of AI in both Chinese and international students.

Perceived Ease of Use

Perceived ease of use (PEOU) refers to a user's comfort and ease with using technology (Davis, 1989). It influences students' behavioral predisposition of ultimate use (Sathye et al., 2018). Several studies provide evidence that PEOU plays a key role in shaping users' attitudes and behavioral intention toward use of technology (e.g., Al-Hattami, 2023; Elfeky & Elbyaly, 2023). Elfeky and Elbyaly (2023) conducted a quasi-experimental study and found PEOU as a significant determinant of students' attitude toward and their behavioral intention to use a learning management system. In agreement with this finding, Barrett et al. (2023) emphasized that perceived technological barriers might prevent users from successfully embracing and accepting technology. Similarly, a study conducted in the Chengdu region of China brought forth a noteworthy revelation regarding the influence of PEOU on the behavioral intention of students (Min et al., 2023), underscoring the significance of promoting the benefits and user-friendliness of online learning systems to encourage students' adoption and boost their satisfaction when using digital learning resources. Therefore, the following were hypothesized:

> H3: PEOU significantly and positively influences users' attitudes toward the use of AI in both Chinese and international students.

> H4: PEOU significantly and positively influences users' behavioral intentions toward the use of AI in both Chinese and international students.

Attitudes Toward Use

A growing body of research supports the idea that users' attitudes toward system usage (AU) strongly influence their behavioral intentions, which ultimately affect their behavior (Al-Mamary, 2022; Yang et al., 2022). This synchronization underscores the critical significance of attitudes in influencing the intentions of users and, eventually, their subsequent behaviors with diverse systems (Akram, Yingxiu, et al., 2021b). Considering this, Almaiah et al. (2022) observed that students often find themselves with insufficient knowledge and incapable of making effective use of newly introduced technologies. Al-Mamary (2022) believes that assessing students' intentions to adopt a new technology is important for analyzing their actual use. In another study, Yang et al. (2022) revealed that across various regions in China, college students' attitudes toward using metaverse technology contributed 33% of the influence on their behavioral intention to use the technology. In other words, students' attitudes about using technology affect how they respond to the technology, leading to the final hypothesis:

> H5: AU significantly and positively influences users' behavioral intentions toward the use of AI in both Chinese and international students.

Methodology

To examine the research objectives and suggested research hypotheses, this study employed a quantitative research method. An online survey consisting of two sections and 16 items was used to collect empirical data. The first section collected the demographic characteristics of the participants, including gender, age, educational level, major, nationality, and the AI platform they used, using a nominal scale. The second section included items derived from the four-construct TAM model and included five items to measure PU and PEOU, adapted from Lewis (2019). It also included three items each measuring AU and BI, adopted from Venkatesh et al. (2003) and Teo (2009). All questions were rated on a 5-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement.

The aim of this cross-sectional study was to investigate the attitudes and behavioral intentions of both Chinese and international students toward the use of AI. To ensure translation quality and consistency, a professional translator first wrote the questionnaire in English, which was then translated into Chinese. The Chinese version was retranslated into English by another translator (Epstein et al., 2015).

This study employed convenience sampling, a non-probability sampling method that allows a researcher to collect data from accessible respondents (Emerson, 2021). An online survey was distributed through the WeChat platform in a Chinese university, targeting both Chinese and international students. Furthermore, to ensure content validity of the self-administered questionnaire, the researchers consulted one English and one Chinese linguistic expert. The questionnaire's clarity and readability were checked through a pilot study involving 50 prospective participants, including both Chinese and international students (Taherdoost, 2016). Based on the pilot study results, two questions were removed. All participants voluntarily participated in the study and were informed of their right to withdraw at any time. The online survey included a cover letter explaining the study's purpose and the participants' rights. No monetary incentives or rewards were provided for participation.

Participants

After screening the data, the study included 689 valid cases from diverse schools of a Chinese university to examine students' attitudes and behavioral intentions toward AI usage. The participants consisted of 372 Chinese and 317 international students.

Table 1 shows the demographic characteristics of participants. Among Chinese participants, 54.8% were female and 45.2% were male, with the majority between the ages of 17 and 24. All Chinese students were pursuing undergraduate education, with over 50% from applied sciences fields and over 40% from social sciences. Of international students, 63.1% were male and 36.9% were female, with the majority (58.1%) between the ages of 21 and 24. Most international participants were pursuing undergraduate education, and 12.6% were postgraduate students. Over 40% of international participants were from natural sciences fields, about 36.5% from applied sciences, and over 20% from social sciences. Most international students were from Asia (66.9%) and Africa (32.5%), with only a few from Australia (0.3%) and Europe (0.3%).

We found a substantial discrepancy in the adoption rate of AI between Chinese and international students. International students showed a higher adoption rate (78%) compared with Chinese students (53%). Diverse preferences for AI platforms were also revealed among both groups. Among Chinese students, ChatGPT was the most widely used platform, followed by Baidu and Bing AI. Other platforms including ChatBot, Google, Youdao, Zhidao, and Bard were used by smaller percentages, and 47.1% of Chinese students did not use any specific AI platform. Similarly, ChatGPT emerged as the top choice for 47.3% of international students, followed by Bing AI and Google. Other platforms including ChatBot, Baidu, Freenome, Midjourney, Nova, Perplexity AI, and QuillBot were used by smaller percentages, and 22.4% of international students expressed reluctance to use any particular AI platform.

Table 1

Demographic Features of Both Samples

Demographic category	Chinese		International	
	Frequency	%	Frequency	%
Gender				
Male	168	45.2	200	63.1
Female	204	54.8	117	36.9
Age				
17–20	281	75.5	72	22.7
21–24	89	23.9	184	58.1
25–28	1	0.2	41	12.9
29+	1	0.2	20	6.3
Educational level				
Undergraduate	372	100.0	277	87.4
Postgraduate	0	0.0	40	12.6
Major				
Social sciences	174	46.7	71	22.4
Applied sciences	198	53.3	116	36.5
Natural sciences	0	0.0	130	41.1
Nationality				
African	0	0.0	103	32.5
Asian	0	0.0	212	66.9
Australian	0	0.0	1	0.3
European	0	0.0	1	0.3
AI platform				
ChatBot	4	1.07	6	1.89
Baidu	52	13.97	9	2.8
Bing AI	59	15.8	35	11.0
ChatGPT	72	19.3	150	47.3
Google	3	0.8	29	9.14
Freenome	0	0.0	1	0.31
Midjourney	0	0.0	4	1.3
Nova	0	0.0	3	0.9
Perplexity AI	0	0.0	2	0.6

QuillBot	0	0.0	2	0.6
None	175	47.1	71	22.4
Youdao	2	0.6	0	0.0
Zhidao	2	0.6	0	0.0
Bard	3	0.8	0	0.0

Data Analysis

Structural equation modeling (SEM) is a statistical technique that allows researchers to estimate connections within a conceptual model and to find correlations between independent and dependent variables (Y. A. Wang & Rhemtulla, 2021). This multivariate approach is an integration of factor analysis and multiple regression that estimates several associations in a single step (Breitsohl, 2019). Given its capacity to manage complex mathematical models and its confirmatory modeling approach (Hair & Alamer, 2022), SEM is ideal for investigating attitudes toward the use of technology and behavioral intentions, especially when dealing with changes between independent and dependent variables (J. Wang & Wang, 2019). Therefore, this study used SEM to analyze the proposed model's data, employing a maximum-likelihood covariance-based SEM approach (SPSS Amos v.26.0), which aligns with the study's emphasis on theory testing and confirmation. Using all constructs treated as latent variables, this study modeled PU and PEOU as predictors, AU as mediator, and BI as outcome. Each of these constructs was measured by uniting distinct indicators—namely, questionnaire items assessing participants' insights.

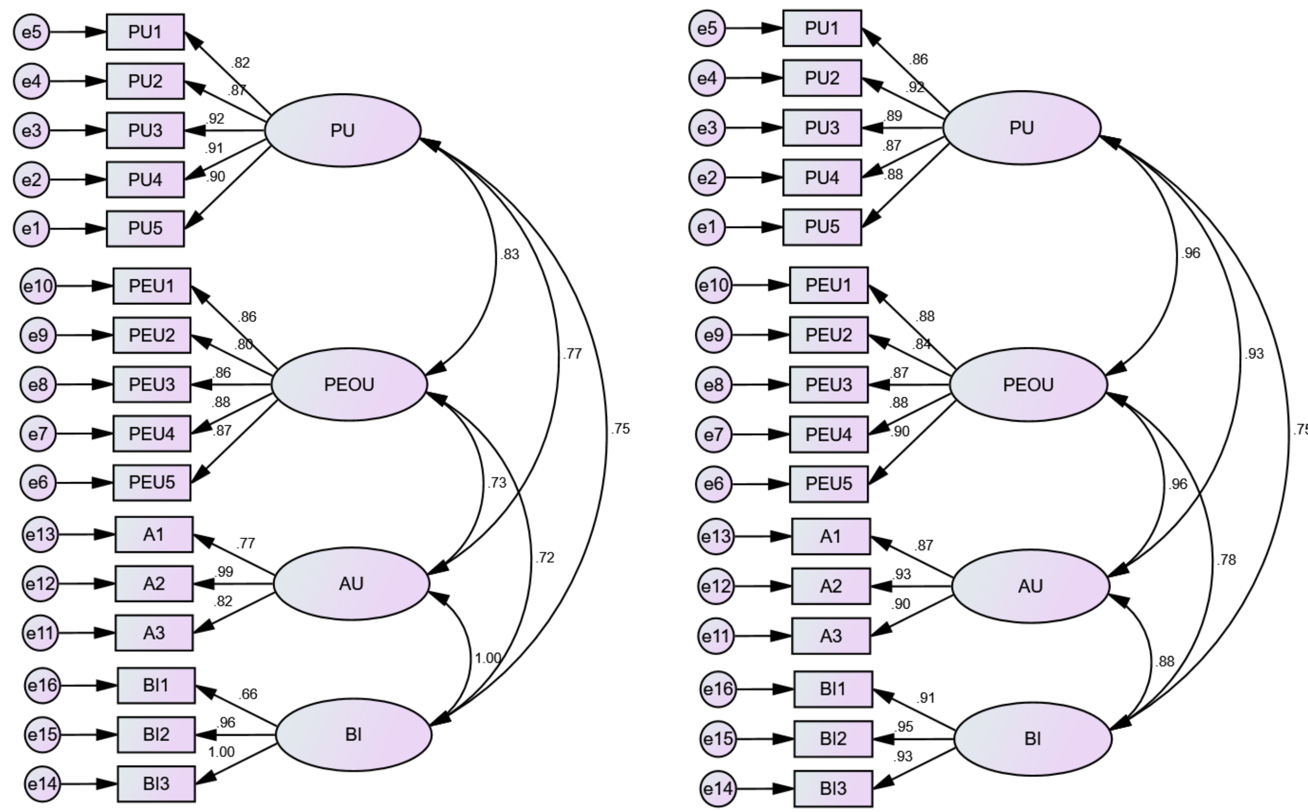
Results

Assessment of the Model

The study conducted a comprehensive examination of all constructs across both samples to evaluate the consistency of the research model, as outlined by Hair and Alamer (2022). Critical measures were used to assess the model: goodness of fit and reliability and validity. The initial model demonstrated a remarkable degree of consistency with the collected data, and all items showed strong factor loadings across both Chinese and international students' samples, as depicted in Figure 2. Notably, each obtained value exceeded the recommended threshold of 0.6, in line with the guidelines provided by Alavi et al. (2020).

Figure 2

Confirmatory Factor Analysis Model of Both Samples



(a) Chinese students' sample (b) International students' sample

Note. PU = perceived usefulness; PEOU = perceived ease of use; AU = attitude toward use; BI = behavioral intention to use.

Table 2 presents a comprehensive assessment of the model fit indices, which includes chi-square (χ^2/df), Root Mean Square Residual (RMSR), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and Tucker-Lewis Index (TLI). All seven indicators were statistically significant across both samples and fell within the recommended range, consistent with the criteria outlined by Sarstedt et al. (2021). The consistency observed across these various indices strongly supports the reliability and validity of the model for both samples, affirming its appropriateness for the study's intended research objectives.

Table 2

Fit Indices Summary

Fitting indices	Recommended values	Model values for Chinese sample	Model values for international sample
χ^2/df	< 3	2.51	2.62
RMSR	< 0.08	0.071	0.75
RMSEA	< 0.08	0.067	0.072
CFI	> 0.90	0.92	0.94
GFI	> 0.90	0.93	0.94
AGFI	> 0.8	0.83	0.86
TLI	> 0.90	0.91	0.93

Note. RMSR = Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; GFI = Goodness of Fit Index; AGFI = Adjusted Goodness of Fit Index.

To assess the consistency of the research measurement model across both Chinese and international students' samples, reliability and validity assessments were conducted. Cronbach's alpha was used to ensure the reliability of the variables, and all constructs achieved a satisfactory level exceeding 70% across both samples, in line with the guidelines by Taber (2018) (Table 3).

Validity was evaluated using both convergent and discriminant validation tests. A convergent validity test was conducted to determine the degree of alignment among all instrument constructs from two distinct perspectives: composite reliability (CR) and average variance extracted (AVE). All variables across both samples were validated, as the obtained values exceeded the predefined thresholds, specifically, CR > .70 and AVE > .50 (Lai, 2021). In parallel, a discriminant validity test was conducted to explore the distinctions among the overlapping constructs. The acquired values for each construct across both samples were found to be consistent with the established threshold values (> .7) (Hair and Alamer, 2022). All variables exhibited significant correlations with each other. In the Chinese sample, correlation coefficients ranged from .76 to .82, and in the international students' sample, they ranged from .79 to .83, demonstrating high correlation.

Table 3

Reliability and Validity Matrix of Both Samples

S.No	Variables	Chinese sample							International sample						
		α	CR	AVE	1	2	3	4	α	CR	AVE	1	2	3	4
1	PU	.79	.90	.78	**.88**				.77	.90	.76	**.87**			
2	PEOU	.78	.90	.79	.78*	**.88**			.78	.91	.77	.83*	**.87**		
3	AU	.80	.91	.79	.80*	.76*	**.88**		.79	.92	.79	.85*	.87*	**.88**	
4	BI	.81	.90	.80	.78*	.77*	.82*	**.89**	.80	.90	.75	.70*	.73*	.80*	**.86**

Note. Bold values reflect discriminant validity. CR = composite reliability; AVE = average variance extracted; PU = perceived usefulness; PEOU = perceived ease of use; AU = attitude toward use; BI = behavioral intention to use.

*p < .01.

Descriptive Analysis

Table 4 and Figure 3 illustrate the descriptive results for both samples. Chinese students' reported mean values were 3.46 for PU, 3.23 for PEOU, 3.38 for AU, and 3.41 for BI. Meanwhile, international students indicated slightly higher mean values across all constructs: 3.72 for PU, 3.58 for PEOU, 3.64 for AU, and 3.69 for BI. To assess the normality of the data distribution, both skewness and kurtosis were examined using descriptive statistics. All the obtained values were within the determined range, with skewness between −3 and +3 and kurtosis between −10 and +10 (Matore & Khairani, 2020). Following established criteria, especially when using SEM, ensures the appropriateness of the data distribution (Demir, 2022).

Table 4

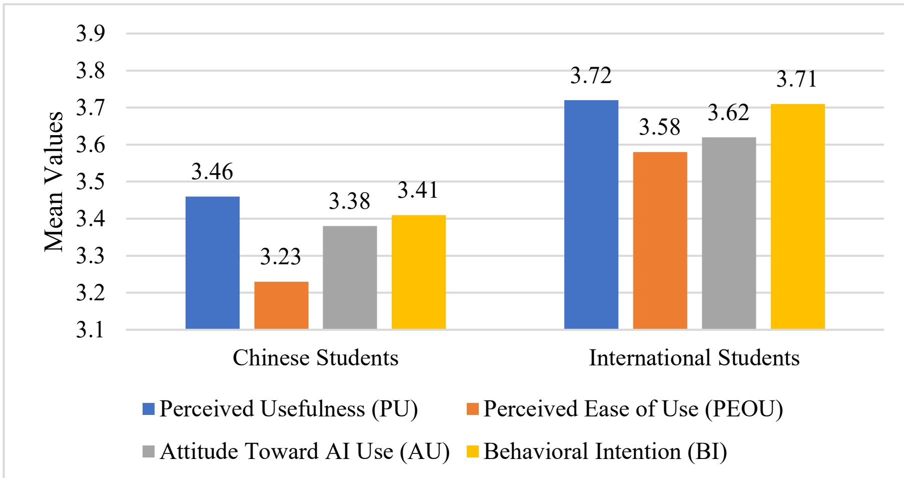
Descriptive Statistics

Participants	Chinese students				International students			
Variables	PU	PEOU	AU	BI	PU	PEOU	AU	BI
M	3.46	3.23	3.38	3.41	3.72	3.58	3.62	3.71
SD	0.81	0.82	0.81	0.83	0.96	0.93	0.99	0.84
Skewness	−0.27	0.10	−0.71	−0.82	−0.97	−0.71	−0.83	−0.87
Kurtosis	1.11	0.89	0.97	0.92	0.87	0.57	0.41	0.67

Note. CR = composite reliability; AVE = average variance extracted; PU = perceived usefulness; PEOU = perceived ease of use; AU = attitude toward use; BI = behavioral intention to use.

Figure 3

Comparison of Mean Values of Constructs Across Chinese and International Students



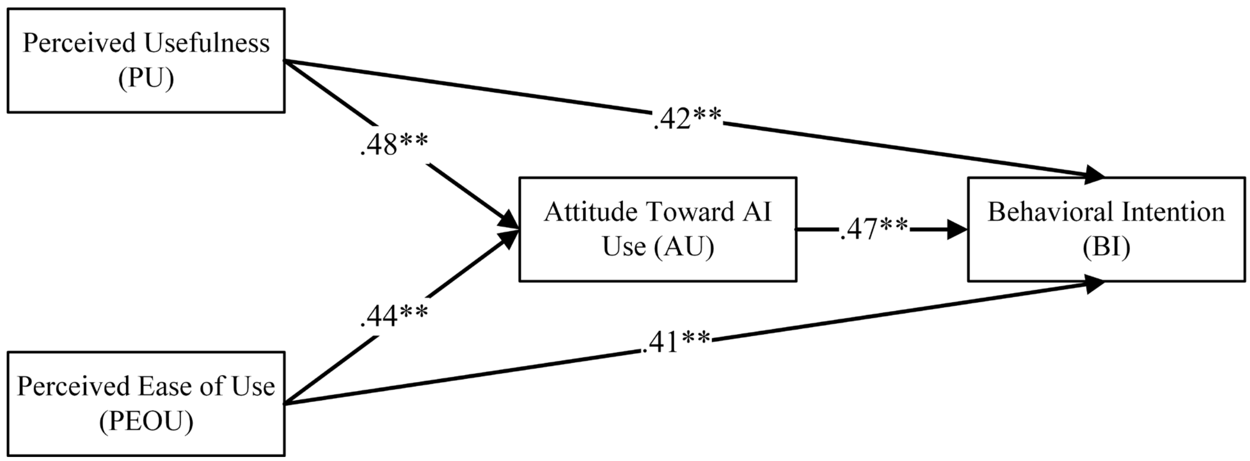
Structural Model Assessment

After ensuring the reliability and validity of the constructs, the study employed the structural model approach to evaluate relationships between the outlined hypotheses (see Figure 4). The results indicate that PU and PEOU significantly impact both Chinese and international students' attitudes and behavioral intentions toward AI use. In the Chinese sample, the influence of PU on attitude was .48, and the influence on their behavioral intentions was .42, supporting H1 and H2 respectively. In the international students' sample, the influence of PU on their attitude was .39, and the influence on their behavioral intentions was .44, supporting H1 and H2 respectively. In the Chinese sample, the influence of PEOU on attitude was .44, and the influence on their behavioral intentions was .41, supporting H3 and H4 respectively. . In the international students sample, the influence of PEOU on their attitude was .54, and the influence on their behavioral intentions was .43, respectively supporting H3 and H4. Results also show that attitude toward AI use significantly influenced the behavioral intentions of both Chinese (.47) and international students (.45) at a significance level of .01, providing support for H5.

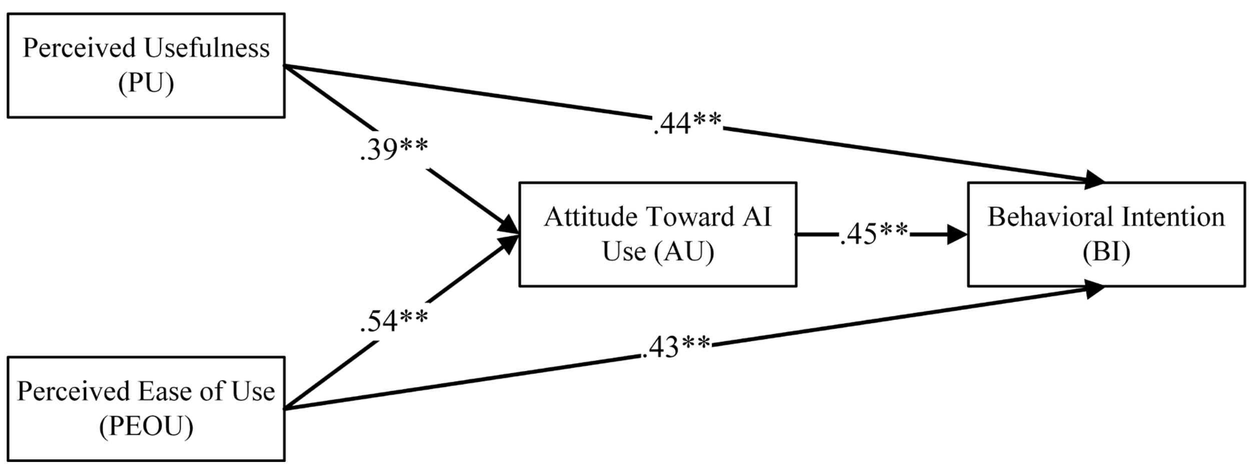
After confirming the reliability and validity of the constructs, the study used the structural model approach (see Figure 4) to explore the relationships outlined in the hypotheses. The results revealed significant insights into the impact of PU and PEOU on the AU and BI of Chinese and international students concerning use of AI.

Figure 4

Structural Model Assessment



(a) Chinese students' sample



(b) International students' sample

$^{**}p < .01$.

In the Chinese student sample, the study found a substantial influence of PU on AU (.48) and BI (.42), providing robust support for H1 and H2. Correspondingly, the group of international students demonstrated a similar pattern, whereby PU had a substantial impact on both AU (.39) and BI (.44), thereby confirming the veracity of H1 and H2. Exploring the robustness of H3 and H4, Chinese students demonstrated a significant impact of PEOU on AU (.44) and BI (.41). A noticeable effect was shown for international participants, on the other hand, with PEOU significantly shaping both AU (.54) and BI (.43), robustly supporting H3 and H4 in this unique cultural setting.

Finally, the study examined the interplay between attitude and behavioral intentions. The results indicated that both Chinese and international students' attitudes toward AI significantly impacted their behavioral intentions (.47 and .45, respectively) at a high significance level (.01), providing robust support for H5. These findings offer a multifaceted understanding of how students from different cultural backgrounds adopt and use AI in their educational practices.

Discussion

In the current educational landscape, AI integration has become a pivotal determinant of students' learning experiences. The success of implementing AI in higher education largely hinges on students' attitudes and perceptions (Al-Adwan et al., 2022; Linardatos & Apostolou, 2023). As new technologies continue to emerge, it becomes crucial to investigate individuals' attitudes toward using them and analyze the factors that shape these perceptions (Akram & Abdelrady, 2023). Additionally, diverse cultural backgrounds may lead to varying preferences regarding technology use in education (Savicki, 2023). Consequently, individuals may hold complex attitudes toward the adoption of technology. Therefore, it is imperative to comprehend these dynamics.

In the context of China, the landscape of higher education has undergone a significant transformation in recent decades due to a substantial increase in the number of international students. This transformative shift motivated the study to provide empirical evidence regarding students' attitudes and behavioral intentions toward AI use across both Chinese and international contexts using the technology acceptance model as the guiding framework. This study not only revealed the intricate dynamics but also highlighted the reliability of the theoretical framework within both Chinese and international contexts, establishing a solid foundation for potential applications in diverse cultural settings. The insights obtained from this study can inform the development of educational interventions to help foster a more enriching educational experience that is tailored to the diverse needs of students in our technology-driven era.

Regarding the prevalence of AI usage, the identification of a notable discrepancy between Chinese and international students reveals an intriguing aspect of the technological landscape in higher education. This coincides with the consensus of Kim and Lee (2023), who highlighted the significant role of sociocultural factors on students' attitudes toward AI. The observed prevalence of, attitudes toward, and behavioral intentions to using AI use among international students reflect the global trend in which students from diverse cultural backgrounds are more likely to employ the latest technologies in their learning (T. Wang et al., 2023). One reason may be that they come from different academic backgrounds and want to have globalized educational experiences (Xiong et al., 2022). International students may perceive AI adoption as essential for staying competitive in a globally connected job market, while Chinese students might see it as an opportunity to align with global educational standards.

Language proficiency also plays a key role in shaping students' interactions with technology. Students with more advanced language skills can better understand instructions and navigate user interfaces, enhancing their overall experience with AI-driven tools (Lee, 2022). Additionally, the fact that technological tools are generally rendered in English makes them easier for international students to use, since they usually possess better English proficiency (Huang et al., 2023). Conversely, Chinese students may have different perspectives on the use of AI in higher education because they may not be as fluent in English and may thus encounter more obstacles when trying to make full use of AI technologies (Galloway & Ruegg, 2020). This linguistic component adds another degree of intricacy to AI technology use, emphasizing the necessity for a detailed comprehension of language-related aspects of technology acceptance.

The observation regarding the significantly elevated levels of both key elements—PU and PEOU—among international students compared with Chinese students marks a noteworthy trend with implications rooted in prior research. Existing literature on technology adoption suggests that positive perceptions of usefulness and ease of use are fundamental predictors of technology acceptance (Park & Kim, 2023). These positive perceptions often lead to increased intentions to use technology and foster a more favorable disposition toward its integration into daily practices (Elfeky & Elbyaly, 2023). Prior studies have also emphasized the importance of positive perceptions in driving technology adoption and use (e.g., Al-Hattami, 2023). For both international and Chinese students to optimize PU and PEOU, it is essential to prioritize the enhancement of user interfaces through a multifaceted approach. Concerned authorities should initiate the process by conducting comprehensive user experience assessments, gathering feedback from diverse student groups to inform targeted improvements. Design features that match international and Chinese students' cultural preferences and educational backgrounds should be implemented, guaranteeing simple access and adaptable design for device accessibility.

The findings reveal a compelling narrative on the intricate relationships between PU and PEOU on AU and BI. The significant role of PU in shaping students' attitudes and intentions toward AI use is consistent with prior studies (Anthony et al., 2022). The strong effect of PU on both AU and BI for Chinese students aligns with studies emphasizing the importance of perceived usefulness in technology adoption (Xiao & Goulias, 2022). Similarly, international students also exhibited a high level of PU, with a few minor differences, indicating that PU of AI is a global driver that transcends cultures.

This study further examined the impact of PEOU on students' attitudes and intentions toward AI use. The findings underline the significance of user-friendly interactions, consistent with prior research (Granić, 2022). We observed a stronger effect of PEOU on AU and BI among international students compared with Chinese students. This difference can be attributed to cultural dissimilarities, which affect how people perceive technology and its ease of use. International students' familiarity with diverse technological tools in their home countries may make AI easier for them to use (Sutrisno & Lubis, 2022). Additionally, different levels of previous technology exposure may also contribute to this difference: international students might have more experience with modern technologies than Chinese students (Steyn & Gunter, 2023).

The intricate connection between attitude and behavioral intentions, as examined in H5, reveals a recurring pattern in existing research. The results of earlier research are reflected in the data, with a significant correlation between both Chinese and international students' attitude toward interacting with AI and their behavioral intentions to use it (Papakostas et al., 2023). This provides evidence for the notion that cultivating a positive attitude is not only a precondition but also a strong indicator of future interactions with AI technology.

Recognizing the influence of students' cultural backgrounds, institutions should design interventions that cater to the unique perspectives of both Chinese and international students, fostering a shared understanding of AI technology. Providing language-specific support and user-friendly interfaces can bridge potential language barriers, ensuring that international students, in particular, feel comfortable and empowered in interacting with AI. Moreover, incorporating cross-cultural workshops and technology training programs tailored to people with varying levels of technological exposure can further enhance positive perceptions and ease of use, contributing to a more inclusive and globally aware educational environment.

Conclusions

This study provides empirical evidence regarding the attitudes and behavioral intentions toward the use of AI among Chinese and international students in higher education. Results shed light on the complex dynamics among PU, PEOU, AU, and BI in a cross-cultural setting in a Chinese university. The findings emphasize the pivotal role of PU and PEOU in influencing both AU and BI of students toward AI use. Moreover, the study revealed notable disparities, particularly in the influence of PEOU on AU and BI. International students exhibited a stronger effect of PEOU on both AU and BI than their Chinese counterparts. These findings underscore the intricate interplay of cultural backgrounds, prior technological exposure, and language considerations in shaping perceptions of AI technology. Tailoring educational strategies to regulate the number of cultural perspectives, providing language-specific support, and ensuring user-friendly interfaces are crucial for fostering positive attitudes and intentions toward using AI, especially among international students. The insights gleaned from this research contribute to a nuanced understanding of the factors influencing technology acceptance in a cross-cultural higher education context, offering practical implications for educators and institutions seeking to optimize AI integration in their pedagogical approaches.

Declarations

Ethics Approval and Consent to Participate

Informed consent to participate was obtained from all individual participants included in the study. The responses were collected after getting approval from the Institutional Review Board in North China University of Water Resources and Electric Power.

Consent for Publication

Informed consent for publication was obtained from all individual participants included in the study.

Availability of Data and Materials

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no competing interests.

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