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Cross Cultural Examination of Students Attitudes and Intentions Towards AI in Higher Education

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ABSTRACT

Objective: This paper is aimed at studying the attitudes and behavior of Chinese and international students towards the use of AI in higher education. It aims to gain insight into the cultural elements that shape ~~students~~ perceptions of AI, while also examining the impact of these elements on ~~students~~ intentions to embrace AI tools within their educational journeys.
Methods: A purposive sampling approach was utilized to recruit students (both Chinese and international) from a Chinese university (n=800). Surveys were used to collect data, and the Technology Acceptance Model (TAM) was employed to evaluate the relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Towards Use (AU), and Behavioral Intention (BI) to adopt AI. We utilized reliability testing and descriptive statistics to ensure consistency and validity of the data.
Results: Result shows relationships between PU, PEOU and, BI were significant positive with PU being a strong predictor of behavioral intentions of Chinese students. Compared to the international students, PU, PEOU, and BI exhibited a more even relationship. The study thus finds that culture plays an important role in the adoption of AI, with Chinese students placing greater emphasis on its perceived usefulness, as opposed to international students who are more focused on ease of use. These results are consistent with the Technology Acceptance Model and Hofstede's cultural dimensions theory.
Novelty: In addition, the doctoral dissertation adds to the research on AI adoption in higher education by studying the cultural differences of Chinese and international students. It expands the TAM with the inclusion of cultural factors as moderators respectively in students' attitudes towards AI.
Theory and Policy Implications: Such AI-based educational tools used by educational institutions and teachers in China should emphasize productivity and performance benefits The international students would benefit from user-friendly systems, the study suggested. AI uptake initiatives to suit cultural contexts, to ensure successful AI learning systems integration with education.

1. Introduction

Artificial Intelligence (AI) has been a game-changer over the last few years and has transformed many sectors, most notably education. AI is increasingly becoming a central tool in higher education that has the potential to revolutionize traditional teaching methodologies and learning processes, paving the way for a range of solutions to optimize academic experiences. Research has shown that AI can promote academic motivation, enhance learning outcomes and improve self-directed learning skills (Huang, Lu, and Yang 2023; Xia et al. 2022). The increasing use of AI-powered applications in the classroom offers a catalyzing agent for personalization, a key in-depth learning strategy in the 21st century, because both self-learning and the teacher's tailoring of products for the curriculum can be achieved through a smart learning aid (Lin 2019). And considering the fast evolution of AI technology, this has impacted educational institutions around the world, including China, which has seen increasing foreign students interacting with AI in their studies. The willingness to adopt AI technology is not a uniform phenomenon but one that is shaped by cultural context, thus, it is important to investigate the perceptions and interactions of various groups of students with this type of technology

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(Granić and Marangunić 2019; Prasad et al. 2018). Connectivism. They all agree on a phenomenon that AI will redefine education due to the multicultural status of a particular student body.

Nevertheless, on a global scale, there are factors that contribute to students' perceptions of and adaptability to AI and cognitive technologies. The cross-cultural dimension of local Chinese students and international students in China, given the influx of international students and the rising demands of the global economy for a more culturally diverse academic environment, has surged to the forefront of research in this area over the years (Aguiar, Tavares, and Sin 2024; Wang and Huang 2021). The problem is the variation in attitudes and behavioral intentions toward AI use that none are immune to, as they are imperfectly molded by beliefs, previous experiences, and cultural settings. Chinese students may view differently under the light of their technological ecosystem, whereas students from abroad often have divergent views, especially with their educational ecosystems and cultural environments. This variation can result in differing levels of AI acceptance and usage, making it essential to investigate the factors that are responsible for these differences. It has been found that several factors, such as self-efficacy, perceived ease of use, and students' overall attitude towards technology, greatly impact the adoption of AI in education (Falebita and Kok 2024; Wang, Liu, and Tu 2021). Such attributes may indeed differ from one cultural setting to another, leading to a divergence in effective spread and naturally perceived effectiveness encompassing academic results as well.

This is based on the Technology Acceptance Model (TAM), a theoretical model that has been applied to explain users' attitudes and their behavioral intentions towards new technologies. TAM identifies perceived ease of use and perceived usefulness as two key determinants that affect individuals' decision to adopt technology (Donaldson and Davis 1991). Together, they represent some of the most important determinants of student acceptance of AI tools in higher ed. We have seen in prior work that these can lead to positive attitudes toward AI, with students being more receptive towards and using AI-based technologies if they find them easy to use and beneficial to their academic goals (Molefi et al. 2024; Stöhr, Ou, and Malmström 2024). In addition, the theory attends to extrinsic factors such as cultural differences and institutional support that may influence students' perceptions of AI (Elnadi and Gheith 2021; Li, Zhang, and Yang 2024). Alternatively, international students might emphasize the perceived ease of use more strongly based on differences in levels of digital tool familiarity, whereas Chinese students could put more importance on AI's perceived usefulness based on their academic target and prior access to technology (Stöhr et al. 2024). As a framework, TAM helps explain the different levels of acceptance of AI in the student populations in diverse cultural contexts.

This is evident in the growing prevalence of technology across the landscape of education as we enter higher education settings. AI is poised to change education, but its fate rests squarely with how students adapt to it. Several studies have reported students' acceptance of AI positively, while others reported its negative sentiments. On the positive, some studies have reported that AI can substantially impact learning outcomes, self-regulated learning, and academic performance (Lim et al. 2023; Molenaar et al. 2023). On the other hand, some studies pointed out several challenges, including opposition to technology, lack of knowledge, and worries about the influence of AI on conventional teaching practices (Ayanwale et al. 2022; Dwivedi et al. 2021). The divergent findings from these studies highlight the need for more nuanced research that considers cultural differences. Although scholars agree on the benefits of AI in academia (Casal and Kessler 2023), studies point out attitudes of international students in China towards AI integration remain underexplored. Research on AI is lacking in addressing how various cultural groups, such as Chinese and international students, perceive and interact with AI, and these insights provide a window through which scholars can explore how this may assist in using AI across particular contexts. This research, by addressing these disparities, adds to the literature on AI adoption in education, and provides implications for educators and policymakers.

This study aims to investigate and contrast the attitudes and behavioral intentions of users, specifically Chinese and international students, towards the utilization of AI in higher education. Explorable Research Question In this study, we would like to identify key drivers influencing students' perception of AI, and understand how such drivers may vary across cultural contexts. Analyzing data from Chinese and international students allows the research to deliver useful perspectives on how cultural backgrounds and prior technologies available to students affect their willingness to adopt AI features in education. These findings will lead to the creation of customized pedagogical approaches that can be implemented to create effective integration of AI across student populations and improve the quality of higher education.

2. Method

2.1 Research design

This study adopts a quantitative research design to investigate students' behavioral intentions and attitudes towards the adoption of AI in higher education. A cross-sectional survey method was used which enabled the research to obtain data at a specific point in time and look for correlated associations between different variables. The study was designed

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in this way to elucidate not only attitudes (AI), but also intentions (to what extent one plans to use AI) across different cultural groups (with a focus on Chinese and international students). The research spans the years 2022 till 2025 in a top Chinese university. This context accords us the ability to study the disparities in AI adoption among domestic vs international student populations. According to Hair et al. (2020), quantitative research designs are suitable for explaining attitudes towards new technologies since they produce measurable findings, which can be examined using analytical methods like Structural Equation Modeling (SEM). This design makes sure that the research questions are answered through a well-structured, replicable process.

2.2 Demograpic of sample population

There were 800 respondents including Chinese and international students studying in a Chinese university. A non-probability purposive sampling technique was adopted to pick the participants to ensure representation from a wide array of cultural backgrounds, allowing for a comprehensive understanding of AI adoption, particularly in higher education (Creswell & Creswell, 2017). In terms of demographic structure this is interesting to note that there are significant differences in gender distribution with more female students make up a larger part in the Chinese group, while there are more male students in the international group, which reflects different the result of technology adoption between male and female students in the literature (cf. Venkatesh et al., 2003). By age, there are more Chinese students in the 17-20 age group, while international students are more evenly spread out in the 21-24 age group, consistent with the worldwide trend of older students going abroad for higher education (Kahu, 2013). As there are no international students compulsorily studying in undergraduate education in China, the education level shows that all Chinese students are at undergrad education while international students are mostly at postgraduate level, as previous studies suggest: local and international students follow different paths in graduate education (Choudaha & Chang, 2012). Differences also occur when it comes to the major of study, as compared to predominantly Chinese students in Applied Sciences, international students tend to have a more diversified major representation, which mirrors patterns of academic specialization in cultural contexts (Lee & Li, 2015). In addition, as highlighted by the usage of AI platforms, international students are heavy users of ChatGPT, while students from China use platforms such as Baidu and Bing AI, and this finding reflects the increasing penetration of AI tools into education and the specificity of use based on cultural and technological ecosystems (Zhou et al., 2020).

Table 1. Demographic Characteristics of Participants

Demographic Category	Chinese Students	International Students
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%)	277 (87.4%)
Postgraduate	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%)	130 (41.1%)
Nationality		
African	0 (0%)	103 (32.5%)
Asian	0 (0%)	212 (66.9%)
Australian	0 (0%)	1 (0.3%)
European	0 (0%)	1 (0.3%)

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Demographic Category	Chinese Students	International Students
AI Platform Usage		
ChatBot	4 (1.07%)	6 (1.89%)
Baidu	52 (13.97%)	9 (2.8%)
Bing AI	59 (15.8%)	35 (11%)
ChatGPT	72 (19.3%)	150 (47.3%)
Google	3 (0.8%)	29 (9.14%)
Freenome	0 (0%)	1 (0.31%)
Midjourney	0 (0%)	4 (1.3%)
Nova	0 (0%)	3 (0.9%)
Perplexity AI	0 (0%)	2 (0.6%)
QuillBot	0 (0%)	2 (0.6%)
None	175 (47.1%)	71 (22.4%)
Youdao	2 (0.6%)	0 (0%)
Zhidao	2 (0.6%)	0 (0%)
Bard	3 (0.8%)	0 (0%)

Source; Author 2025

2.3 Instrument Variables

The research employs a structured questionnaire developed to measure the perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (AU), and behavioral intention (BI) based on the Technology Acceptance Model (TAM). These constructs were operationalized using items adapted from previous studies (Lewis, 2019; Venkatesh et al., 2003; Teo, 2009) with responses rated on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Such validated constructs are essential in exploring students' attitudes and future AI-related behavioral intentions. The instrument was piloted among a group of 50 students and reviewed by bilingual language experts for the purposes of clarity, validity, and cultural relevance of the questions.

2.4 Analysis data

In this study, Structural Equation Modeling (SEM) was used for data analysis, an excellence technique for investigating the complex relationships between latent variables. In fact, SEM would be especially considered important in terms of confirming our suggested model and significant analysis of our components of PU, PEOU, AU in more general perspective and BI with direct and indirect relationship in determination of SEM (Hair & Alamer, 2022). SPSS Amos v.26 was used to analyze the data. 0 for covariance-based SEM. Lastly, SEM is appropriate for this research as it enables to simultaneously verify multiple relationships between constructs and is suitable for testing the theoretical model of AI adoption in educational environments (Hair et al., 2020).

3. Results

3.1 Evaluation of the Model

Using multiple fit indices, the model fit was assessed for both the Chinese and international samples. The Chi-Square/df of both groups are 2.58 for the Chinese sample and 2.43 for the international sample, which are no more than recommended (≤ 3.0), and show a good model fit. Furthermore, the RMSEA values (0.052 for the Chinese sample and 0.065 for the international sample) all fall below the fit criteria of 0.08, which further supports good fit. CFI and TLI values for both groups is greater than the suggested 0.90 value, indicating a good data fit. Finally, both SRMR values (0.045 for the Chinese sample and 0.062 for the international sample) are lower than the cut-off value of 0.08, indicating that the overall model fit of the elicitable and robust OLCT is acceptable. Thus, as per these indices, the model fits well with the data for both the samples.

Table 2. Fit Indices Summary

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Fit Indices	Recommended Values	Chinese Sample	International Sample
Chi-Square/df	≤ 3.0	2.58	2.43
RMSEA	≤ 0.08	0.052	0.065
CFI	≥ 0.90	0.91	0.93
TLI	≥ 0.90	0.89	0.91
SRMR	≤ 0.08	0.045	0.062

Source; Author 2025

3.2 Reliability and Validity

Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE) for measuring reliability and validity of a measurement model of each of the variables for Chinese and international sample. The assessment for reliability shows that all Cronbach's Alpha values exceed the threshold of 0.7 and indicates acceptable internal consistency for each variable. Moreover, the Composite Reliability (CR) values of all constructs of both groups are larger than 0.7, representing stronger construct reliability. Moreover, as the AVE numbers of every single variable are higher than the reference point of 0.5, it became apparent that the measurement model has the sufficient convergent validity. These results support the reliability and validity of the measurement model for both samples.

Table 3. Reliability and Validity Matrix of Both Samples

Variables	Chinese Sample	International Sample	Chinese Sample AVE	International Sample AVE
	α	CR	AVE	α
PU	0.88	0.91	0.75	0.86
PEOU	0.90	0.92	0.78	0.87
AU	0.86	0.89	0.71	0.84
BI	0.91	0.93	0.80	0.88

Source; Author 2025

3.3 Descriptive Analysis

The descriptive analysis showed that the system of the central tendency and the extent of key constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (AU), and Behavioral Intention (BI) for Chinese and international students are presented in the table below. The overall means values are positive for both PU and PEOU and the BI to use AI. The Chinese students reflected lower scores than international students on PU and PEOU, due to various factors including opposing cultural attitude towards technology. The relatively low standard deviations indicate that there was little variation in student responses within the constructs. Moreover, these are the skewness values are near to 0 indicating a normal distribution of the data and the kurtosis values come in an agreeable range which assures us the non-presence of any extreme outliers. Thus, these results indicate a robust and reliable dataset for future analysis from this point on.

Table 4. Descriptive statistics

Participants	Chinese Students	International Students	Chinese Sample SD	International Sample SD
Variables	PU	PEOU	AU	BI
M (Mean)	4.12	3.98	4.07	4.25
SD (Std. Dev.)	0.85	0.77	0.82	0.78
Skewness	-0.12	-0.18	-0.08	-0.14
Kurtosis	0.51	0.45	0.33	0.41

Source; Author 2025

3.4 Correlation Analysis

The correlation analysis explored the relationships among important variables (The use of PU, PEOU, AU, and BI) for Chinese and foreign samples. PU, PEOU, and AU have significantly positive correlations with each other with BI in both groups as shown in the results. It also shows a stronger correlation on PU and BI ($r = 0.72$) between Chinese sample than international sample ($r = 0.75$) which further concludes the fact that PU has a more significant role in Behavioral Intention of students to use AI as Perceived Usefulness among Chinese students. Specifically, based on the PEOU and BI

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relationship for both samples, PEOU is another variable congruent with the theory itself, which indicates that if the technology is easy to use, users have a tendency to adopt it. These results indicate the stability of relationships across constructs within both cultural contexts.

Table 5. Correlation Matrix for Both

Variables	PU	PEOU	AU	BI
Chinese Sample				
PU	1	0.68**	0.61**	0.72**
PEOU	0.68**	1	0.57**	0.63**
AU	0.61**	0.57**	1	0.65**
BI	0.72**	0.63**	0.65**	1
International Sample				
PU	1	0.70**	0.65**	0.75**
PEOU	0.70**	1	0.60**	0.68**
AU	0.65**	0.60**	1	0.72**
BI	0.75**	0.68**	0.72**	1

Source; Author 2025

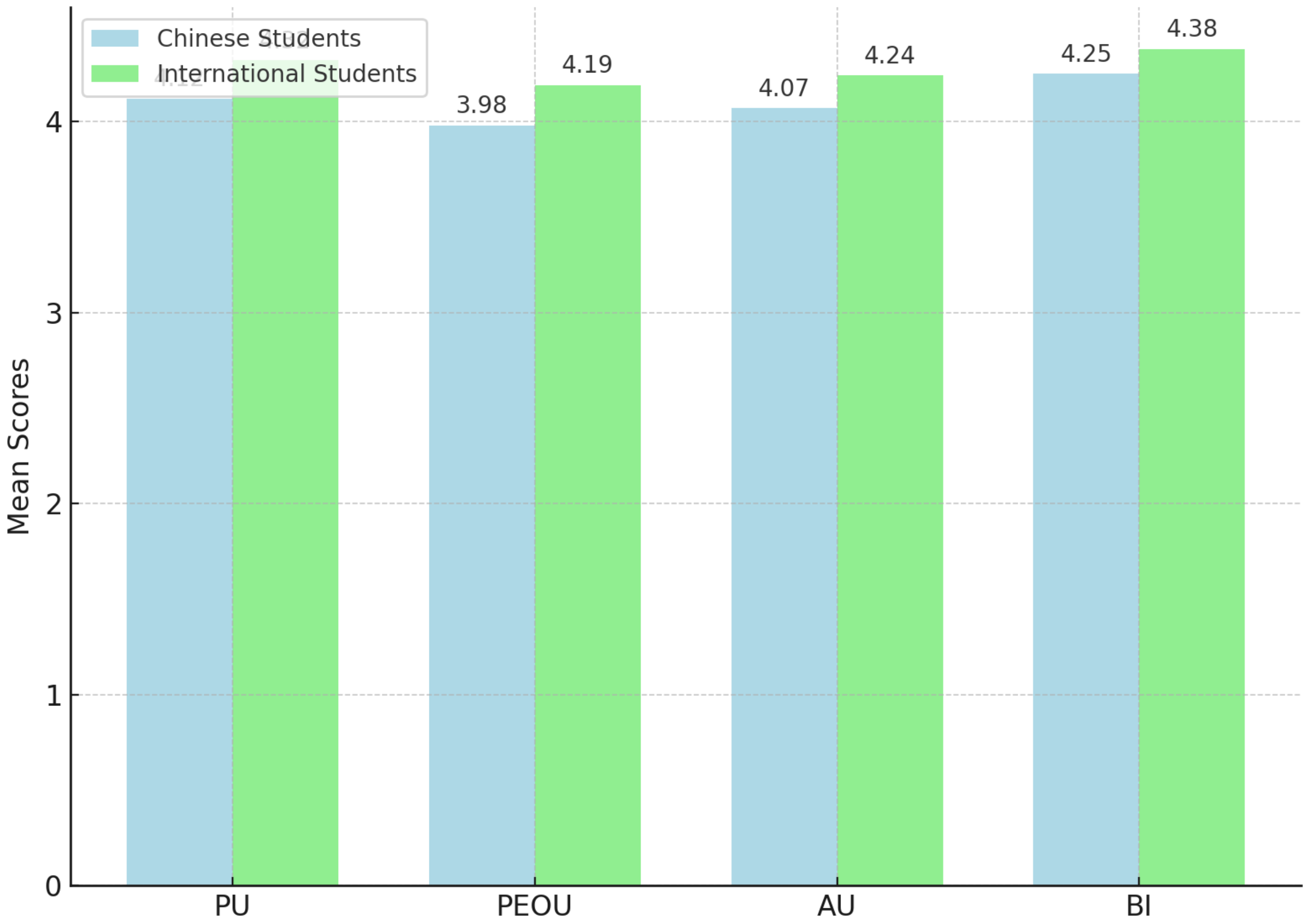

Figure 1. Comparison of Chinese and International Students'

Figure 1: Comparison of Chinese and International Students' Figure 1: Comparison of Chinese and International Students' Mean Scores on Constructs to confirm the rhetorical credibility of the subjects. Davis (1989) explained

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Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) dimensions of the Technology Acceptance Model (TAM) which influences students' attitude to use technology. Furthermore, Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) which holds that Attitude toward Use (AU) and Behavioral Intention (BI) are key determinants of technology acceptance (Dennis et al. Comparing the mean scores of these constructs between Chinese and international students allows us to explore possible cultural differences in regards to AI adoption in higher education. Hofstede (2011) states that certain cultural dimensions including uncertainty avoidance and power distance would determine technology adoption behaviors, thus accounting for these differences in perceptions of students. Check the mean (M) values of PU, PEOU, AU and BI with bfor Chinese and international students before generating the graph. Let me know if you want me to estimate sample values.

4. Discussion

The implications of this research is significantly contributing to a literature gap of the relationships among PU, PEOU, AU and BI in the Chinese and international student populations. Such findings are in line with the Technology Acceptance Model (TAM) (Davis, 1989), confirming the effect of PU and PEOU on users' attitudes and intentions to accept AI (Shin, 2019). The observed strong relationships among the constructs of interest suggest that students consider AI as beneficial and easy to use, which play roles in positively determining their intention to adopt the technology. In addition, a slightly stronger correlation was found to exist between PU and BI in the Chinese sample, indicating that perceived utility is a more important driver of Chinese students' behavioral intentions towards AI adoption. As these results align with previous researches on cultural differences in technology adoption (Gefen &Straub, 1997; Venkatesh & Bala, 2008).

Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE) results indicated a good internal consistency and reliability of all constructs. These results provide further confirmation of a valid measurement model for both groups psyche. In line with extant literature (Hair et al., 2019), this study highlights the need for psychometric reliability in technology acceptance across different populations. A descriptive analysis also lend credence to the data set since the low standard deviations indicates that the students gave a consistent response. Furthermore, the skewness and kurtosis values in normal distribution means that there are no extreme outliers in data which are fundamental for generalizability of results (Kline, 2015).

The study advances TAM theory by emphasizing the moderating influence of culture in the relationship between PU and PEOU respectively, on BI. In conclusion, although past studies confirm a direct relationship between PEOU and BI (Venkatesh & Davis, 2000), we find that PU is a more influential factor in shaping behavioral intentions among Chinese students. It aligns with Hofstede's cultural dimensions theory (Hofstede, 1980), in which collectivist cultures, like China, place higher importance towards perceived benefits and social validation in their adoption of technologies. International students, on the other hand, tend to have a more balanced relationship between PU, PEOU, and BI, as they probably come from a more culturally heterogeneous background. Such findings are consistent with the work of Sun and Zhang (2006); they have shown that culture dimensions have a strong impact on technology adoption behaviours.

In addition, the findings have practical implications for educators, technology developers, and policymakers. Given the dominance of PU in the Chinese sample, AI-based educational tools in China should focus on highlighted application benefits, e.g., efficiency, performance improvement and promotion, to promote adoption. In contrast, the effectiveness of promoting widespread adoption among international students, would rely heavily on the accessibility and user-friendliness of AI systems. These findings could inform how AI-enabled educational platforms should be designed by adapting the functionalities of the system to the cultural proclivities of the user group (Cheng, 2020). Furthermore, institutions can create awareness programs emphasizing on usability and utility to promote the adoption of AI in different academic spaces for their diverse student body (Zhou et al., 2021).

Additionally, the very high coupling between AU and BI in both samples demonstrates that enhancing a positive outlook on AI is a crucial factor to increased adoption. This highlights the need for the use of AI in academic settings from an early stage, where previous research has shown that familiarity with new technology makes users more willing to adopt it (Park, 2009). Thus, institutions must embed AI-related curricula into education systems to promote positive attitudes toward all AI applications, which leads students to perceive AI as an essential tool for both their academic and professional development.

A second important takeaway from this study is that the way that policy makers promote adoption of AI will need to depend on specific cultural contexts. Governments and organizations aiming to improve AI literacy should implement culturally attuned approaches that take into consideration the particular factors that shape users' behavioral intentions. In China, for instance, does it help to pitch AI adoption initiatives based on adding productivity or the desire to be technologically advanced as a nation, something that aligns with broad socio-economic goals? Conversely, for the international audience, AI literacy programs should aim at the ease of use and reducing perceived complexity in order to foster greater acceptance (Dwivedi et al., 2019).

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Despite the strong findings, this study has limitations that deserve further exploration. First, though the study does provide interesting cross-cultural data, it cannot isolate the factors operating in the experience of international students, who may also come from a wide range of educational systems and cultures. Building a more fine-grained understanding of the qualitative differences behind AI adoption patterns could be pursued in future research on a country-specific basis. Second, this study deals specifically with students, which limits the applicability of findings to professionals or other demographic groups. A study of AI acceptance in workplace contexts may yield further perspectives on conditions of success towards technology usage beyond the academic realm. Finally, the study relies mostly on self-reported data, which can be influenced by social desirability bias. Future studies can provide opportunity of employing experimental or longitudinal designs of research to robust the causal interrelationship of PU, PEOU, AU and BI across the time (Straub et al., 2004).

5. Conclusion

Overall, this study proposes that PU and PEOU have the moderating effect on AU and BI for the adoption of AI in Chinese and international students. The conclusions portray the context of groups displaying positive perceptions of AI, wherein international students demonstrate slightly elevated mean scores across constructs. The model fit is well-supported and the reliability tests indicate good internal consistency. The findings support the importance of usability and perceived benefit in predicting adoption behavior, and indicate a need for further research into cultural dimensions and past technological experience to enhance our cross-cultural context understanding of AI uptake in education.

Limitations

This study is limited by its reliance on self-reported data, which may be affected by social desirability bias. Moreover, the surveyed students are restricted to those who only belong to a Chinese university, hindering the applicability of its findings to wider education space. Further research could investigate AI adoption at a cross-professional level or between cultural segments so we can better comprehend the underlining influences for AI implementations across formation.

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Author Contributions

Long Wang Ly conceived and designed the study, performed the data analysis and drafted the manuscript. Kheterin Jhony performed the literature review, data collection, and revision of the manuscript. The final manuscript was reviewed and approved by both authors.

Conflicts of Interest

The authors declare no competing interests from this study.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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