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Research on University Students' Intention to Use AI Assistance in Cross-Cultural Learning

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ABSTRACT

This study aims to explore university students' intention to use AI-assisted tools in cross-cultural learning and the factors influencing this intention. Based on the Technology Acceptance Model (TAM), a survey was designed covering variables such as perceived usefulness, perceived ease of use, satisfaction of personalized learning needs, subjective norms, and perceived risk. Statistical analysis was conducted using SPSS and AMOS, and the results showed that perceived ease of use significantly positively impacts perceived usefulness and further enhances the intention to use AI tools by satisfying personalized learning needs. Although perceived usefulness is considered a key factor, the study found its direct impact on personalized learning needs is not significant, suggesting that the satisfaction of these needs relies more on the ease of use of the tools. Additionally, subjective norms significantly influence students' intention to use, indicating that social environment and peer expectations play a major role in decision-making. The study also found that perceived risk does not significantly negatively impact the intention to use, likely due to the maturity of AI technology and the promotion efforts by educational institutions, which have reduced students' risk perception and increased their trust in AI tools. The findings of this study are of significant importance for the development and promotion of educational technology, especially in designing AI tools that meet students' personalized learning needs. The study also suggests further exploration of other influencing factors, such as perceived cost and trust, to gain a more comprehensive understanding of students' acceptance of AI-assisted learning tools.

Keywords: TAM model, cross-cultural learning, AI assistance, intention to use.

INTRODUCTION

Cross-cultural learning refers to the process by which individuals acquire knowledge and skills by understanding and adapting to cultural differences within diverse cultural contexts. This type of learning not only enhances an individual's language abilities and cultural literacy but also fosters global competence, enabling them to effectively communicate and collaborate in multicultural environments (Smith, 2020). As globalization accelerates, the importance of cross-cultural learning becomes increasingly prominent. Globalization strengthens connections between nations, leading to frequent cultural exchanges, making cross-cultural learning a vital component of modern education. It plays a crucial role in cultivating individuals with international perspectives and cross-cultural communication skills (Deardorff, 2006). University students, as the backbone of future society, must not only continuously improve their professional knowledge and skills but also develop the ability to engage in cross-cultural communication to address the various challenges and opportunities presented by globalization. However, in the process of cross-cultural learning, students often face obstacles such as language barriers, cultural differences, and access to learning resources, which can limit their ability to understand and embrace diverse cultures.

In recent years, the introduction of artificial intelligence (AI) tools has provided new possibilities and opportunities for university students engaged in cross-cultural learning. In the field of cross-cultural learning, AI tools can assist students in quickly and accurately understanding learning materials from different cultural backgrounds by offering intelligent translation and cultural explanations, thereby overcoming language barriers and improving learning efficiency (Zhao & Cao, 2022). Additionally, AI technology can offer personalized learning suggestions based on students' progress and interests, catering to their individual learning needs and enhancing both satisfaction and motivation in the learning process (Chen et al., 2020). Furthermore, virtual communication platforms and simulated learning environments can offer students more opportunities for cross-cultural interaction, thereby enhancing their cross-cultural communication skills (Wang et al., 2021). However, despite the vast potential of AI technology, there are numerous factors influencing students' willingness to use AI-assisted tools in cross-cultural learning. Understanding these factors and how they impact students' intentions to use AI in this context is of significant practical and academic importance.

Therefore, this study aims to explore university students' intention to use AI-assisted tools in cross-cultural learning and the factors that influence this intention. Specifically, the study focuses on analyzing how variables such as perceived usefulness, perceived ease of use, perceived risk, satisfaction of personalized learning needs, and subjective norms impact the intention to use these tools. By examining relevant research and actual survey data, the study seeks to reveal how these factors influence students' intention to use AI in cross-cultural learning, as well as the challenges and issues encountered during the process. The findings are intended to provide valuable insights for educational institutions and technology developers, aiding in the optimization of AI-assisted learning tools, enhancing students' cross-cultural learning experiences, and expanding the effective application of AI in education.

RESEARCH FOUNDATION AND LITERATURE REVIEW

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is widely used to explain technology usage behavior. AI is an emerging technology, and the TAM model is applicable for interpreting university students' behavior regarding the use of AI assistance in cross-cultural learning. Developed by Davis (1986) based on the Theory of Reasoned Action (TRA), TAM includes five key elements: perceived usefulness, perceived ease of use, attitude toward using, behavioral intention to use, and actual system use. According to the TAM model, learners' intention to use information technology is influenced by perceived ease of use and perceived usefulness, which in turn affects their acceptance and usage of new technologies. Recent studies have confirmed this, particularly in the context of educational technology, where these two variables significantly impact students' intention to use AI tools (Lee, 2020). The influence mechanism of this model is illustrated in Figure 1. This classic behavioral science theory is widely used to explain and predict individuals' attitudes and intentions toward technology and behavior. Cross-cultural learning involves acquiring knowledge and skills related to different cultural backgrounds, values, beliefs, customs, and behaviors. The vastness of cross-cultural knowledge makes it a challenging task to master. AI technology can facilitate learners by utilizing algorithms such as machine learning and data analysis. However, students' acceptance and use of AI-assisted learning depend on the fulfillment of their learning needs and the applicability of AI technology. Therefore, this study will use the TAM model as a foundation to explore university students' intention to use AI assistance in cross-cultural learning.

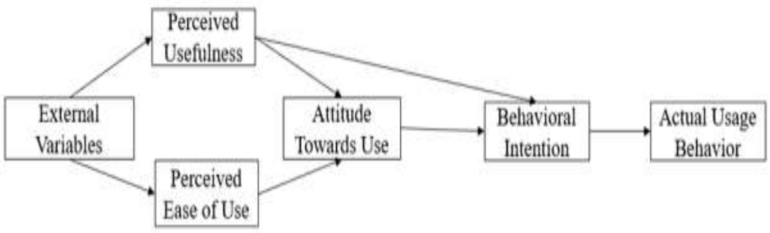


Figure 1: TAM Model

Satisfaction of Personalized Learning Needs, Perceived Risk, Subjective Norms, and Intention to Use

Intention to use refers to an individual's plan or intention to use a specific technology or system at a future point in time. It is a key variable in the Technology Acceptance Model (TAM) that predicts actual usage behavior (Davis, 1989). Intention to use is typically measured through subjective assessments in surveys, reflecting users' attitudes and expectations towards the technology. The Theory of Planned Behavior (TPB) emphasizes the importance of intention, suggesting that intention is the immediate precursor to behavior, influenced by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1980).

Subjective norms refer to the perceived expectations and pressures from significant others regarding an individual's behavior. According to the extended TAM theory, subjective norms can also influence an individual's acceptance and intention to use technology (Venkatesh & Davis, 2000). In the context of cross-cultural learning, students' intention to use AI tools may be influenced by peers, teachers, and parents (Park et al., 2021).

Perceived risk, as a negative factor, also impacts students' intention to use AI tools. Perceived risk includes concerns such as privacy breaches and technical failures, which can decrease students' trust in AI tools and thereby affect their intention to use them (Luo et al., 2019). Research has shown that perceived risk in educational technology significantly negatively impacts students' intention to use, highlighting the need to carefully address and mitigate these risks when designing and promoting AI tools (Kim et al., 2018).

Satisfaction of personalized learning needs is another important variable. Personalized learning can tailor content and learning paths to students' individual needs and interests, significantly enhancing learning outcomes and satisfaction (Zhu & Liu, 2018). AI technology, through data analysis and machine learning algorithms, enables personalized learning recommendations, providing resources and activities that align with students' individual needs (Chen et al., 2020). Research indicates that personalized learning not only improves students' learning efficiency but also enhances their intention to use learning tools (Gong et al., 2021).

Although previous studies have explored the impacts of perceived usefulness, perceived ease of use, perceived risk, and subjective norms on technology acceptance, providing a solid theoretical foundation for this research, the mediating role of satisfaction of personalized learning needs in this process remains under-researched. Additionally, existing research has primarily focused on general educational technology applications, with few studies specifically addressing the context of cross-cultural learning. Therefore, this study aims to fill this gap by investigating how perceived usefulness and perceived ease of use influence the adoption of AI tools in cross-cultural learning through the satisfaction of personalized learning needs. It will also examine the impact of perceived risk and subjective norms on university students' intention to use these tools, thereby further enriching the application of the Technology Acceptance Model (TAM) in the educational field.

RESEARCH HYPOTHESES AND MODEL CONSTRUCTION

Research Hypotheses

Perceived Usefulness (PU), Perceived Ease of Use (PEU), Satisfaction of Personalized Learning Needs (SPLN), and Intention to Use (IU)

In the current era of smart technology, artificial intelligence has become a focal point. Personalized learning in this smart era refers to self-directed learning that is supported by adaptive systems, which are tailored to the individual's needs, interests, and abilities (Leng Jing, Fu Chuxin, & Lu Xiaoxu, 2021). In the process of satisfying personalized learning needs, individual learning demands and preferences should be effectively met. Satisfaction of personalized learning needs reflects the user's satisfaction with the positive outcomes brought about by AI technology. Perceived ease of use and perceived usefulness are two key factors, as greater ease of use often enhances perceived usefulness. Previous studies have shown that perceived ease of use positively influences perceived usefulness (Yu Kunpeng & Li Wei, 2023). In the context of cross-cultural learning, both perceived ease of use and perceived usefulness jointly influence the satisfaction of personalized learning needs, which in turn affects users' intention to use the technology. In the adoption and use of AI-assisted cross-cultural learning models, personalized learning needs include language support, customization of cultural background knowledge, and adjustment of learning pace. When these needs are effectively met, students feel that their learning experience aligns with their expectations and needs, thereby enhancing their overall learning satisfaction. This satisfaction not only boosts learning motivation but also potentially improves learning outcomes and the intention to use the associated learning tools. If AI technology can satisfy users' personalized learning needs, they are more likely to embrace the technology. Therefore, the satisfaction of personalized learning needs is an effective measure of an individual's intention to accept and use AI-assisted cross-cultural learning. Based on the above analysis, this study proposes the following hypotheses:

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

H2: Perceived usefulness has a significant impact on the satisfaction of personalized learning needs.

H3: Perceived ease of use has a significant impact on the satisfaction of personalized learning needs.

H4: Satisfaction of personalized learning needs has a significant impact on university students' intention to use AI assistance in cross-cultural learning.

Perceived Risk (PR)and Intention to Use (IU)

Perceived risk was first introduced from a psychological perspective by Bauer at Harvard University in 1960, suggesting that all consumer behaviors have outcomes that are not entirely predictable, and some of these outcomes may be unpleasant (Bauer, R.A., 1960). Perceived risk has been shown to have a significant negative impact on intention to use, and it is widely applied in fields such as management and sociology (Liang Taixin & Liu Shifeng, 2022). When faced with new technology, users often perceive risk due to uncertainties related to its performance, stability, and compatibility. This uncertainty directly affects their intention to use the new technology or product. In the context of cross-cultural learning, university students may perceive uncertainties associated with AI, which can influence their intention to use the technology. Therefore, the following hypothesis is proposed:

H5: Perceived risk has a significant impact on university students' intention to use AI assistance in cross-cultural learning.

Subjective Norms(SN)and Intention to Use(IU)

Subjective norms, a concept in psychology and sociology, refer to the perceived social pressure that individuals experience regarding whether to perform or not perform a particular behavior (Ajzen, 1991). Subjective norms primarily influence behavior decisions through the social pressure individuals perceive. This pressure can come from significant others, such as family, friends, or colleagues, as well as from broader social groups, including media, experts, or third-party organizations. Research has shown that subjective norms significantly impact individuals' acceptance and use of technology (Y. K. Choi & J. W. Totten, 2012; Huang Jie, 2013). Therefore, the following hypothesis is proposed:

H6: Subjective norms have a significant impact on university students' intention to use AI assistance in cross-cultural learning.

Research Model

Based on the above analysis, the following model has been established. The model is grounded in the Technology Acceptance Model (TAM), with perceived ease of use, perceived usefulness, and satisfaction of personalized learning needs as the core elements. Additionally, perceived risk and subjective norms are incorporated into the model to explore their impact on university students' intention to use AI assistance in cross-cultural learning. The research model is illustrated in Figure 2.

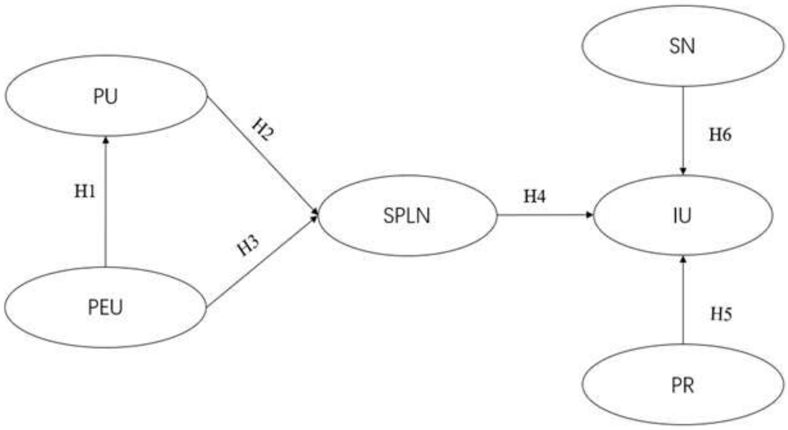


Figure 2: Research Model

RESEARCH DESIGN AND DATA ANALYSIS

Questionnaire Design and Variable Measurement

The questionnaire used in this study is composed of two parts. The first part gathers demographic information from the respondents, including gender, age, the university they attend, and the frequency of AI use in cross-cultural learning. The second part focuses on the measurement of variables. Based on previous research and tailored to the specific needs of this study, the measurement items were appropriately adjusted. This section includes 6 variables with a total of 20 measurement items. A 7-point Likert scale was used for the questionnaire. Data collected were organized and analyzed using SPSS 25.0 and AMOS 24.0, with reliability and validity tests, exploratory factor analysis, confirmatory factor analysis, and structural equation modeling being conducted.

Data Collection and Sample Description

The questionnaire for this study was distributed online, targeting university students. To ensure the quality of the data, a lie detection item was included in the questionnaire to test whether respondents answered seriously. After completing the questionnaire and passing the review, each respondent received a small reward. A total of 350 questionnaires were collected, of which 285 valid responses were retained after screening. The sample included 109 males and 176 females, with the majority of respondents aged between 21 and 24 years, all of whom had experience using AI to assist in cross-cultural learning.

Data Analysis

Reliability and Validity Analysis

The reliability and validity of the questionnaire were assessed through reliability analysis, convergent validity, and discriminant validity. Cronbach’s α coefficient was calculated to determine the reliability of the questionnaire. Generally, the closer Cronbach’s α is to 1, the stronger the reliability. In this study, SPSS 25.0 was used to conduct reliability analysis for each variable in the questionnaire to measure the stability and reliability of the scale. As shown in Table 1, the Cronbach’s α coefficient for each variable was 0.675. For exploratory research, a Cronbach’s α value between 0.6 and 0.7 is considered acceptable (Nunnally & Bernstein, 1994), indicating that the reliability of this scale is acceptable. Additionally, principal component analysis extracted 6 factors.

Table1 Reliability of the Survey Data (n=285)

Variable	Items	Cronbach’s α
PU	4	0.675
PEU	4	
SPLN	4	
PR	3	
SN	2	
IU	3	

As shown in Table 2, the KMO value of the scale is 0.831, and the Bartlett’s test of sphericity is significant ($P < 0.001$), indicating that the scale has good validity and is suitable for confirmatory factor analysis. As shown in Table 3, the reliability coefficients of each factor in the scale are all greater than 0.7, the CR values are greater than 0.7, and the AVE values are greater than 0.3. It is generally accepted that a CR value of ⩾ 0.7 indicates good internal consistency, and an AVE value of ⩾ 0.5 suggests good convergent validity (Hair et al., 2010). However, even if the AVE value is below 0.5, a model can still be considered acceptable if the CR value is high (Malhotra, 2010; Hair et al., 2010). Discriminant validity is determined by comparing the square root of the AVE with the correlation coefficients of the factors. The square root of the AVE must be greater than the absolute value of the correlations with other factors to confirm the discriminant validity of the questionnaire. Table 4 presents the results of the discriminant validity analysis. The bold numbers indicate the square root of the AVE, which must be greater than the corresponding row and column values to verify good discriminant validity. The results show that the square root of the AVE for each variable is greater than the correlations between latent variables, indicating that the questionnaire has good discriminant validity.

Table2 and Bartlett's Test (n=285)

KMO		0.831
	Approx. Chi-square	1758.499
Bartlett	df	210
	P	0.000

Table3 Reliability and Convergence Validity of Survey Data (n=285)

Variable	Items	Cronbach's α	CR	AVE
PU	4	0.751	0.753	0.381
PEU	4	0.711	0.765	0.450
PR	3	0.800	0.805	0.582
SPLN	3	0.711	0.716	0.391
SN	2	0.716	0.718	0.560
IU	3	0.730	0.738	0.486

Table4 Correlation among Constructs and the AVE Square Root (n=285)

	SN	PR	PEU	PU	SPLN	IU
SN	**0.784**					
PR	-0.464	**0.763**				
PEU	0.471	-0.436	**0.671**			
PU	0.159	-0.147	0.338	**0.617**		
SPLN	0.264	-0.244	0.56	0.323	**0.625**	
IU	0.529	-0.281	0.333	0.137	0.313	**0.697**

Model Fit and Hypothesis Testing

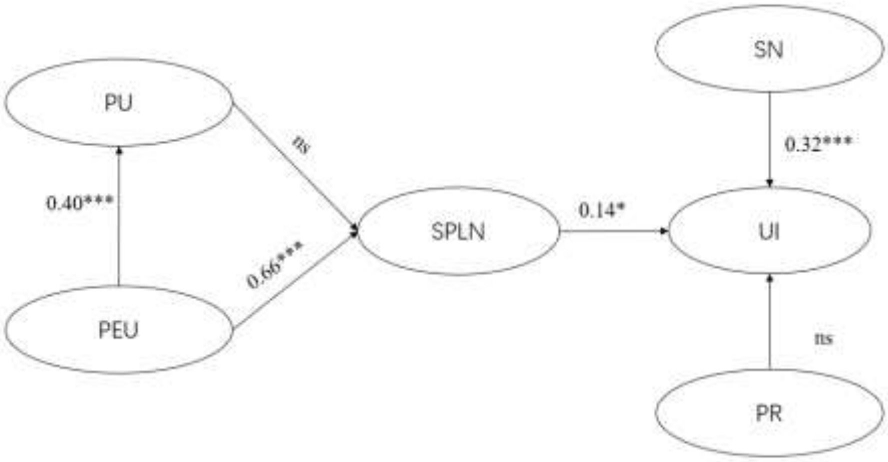
This study used Amos 24.0 for model fitting and hypothesis testing, with the results presented in Table 5. According to Benther's research conclusions, the output indicates that the model fit indices are all within acceptable ranges, suggesting that the overall model fit is good. Based on the hypothesis testing results shown in Figure 3, perceived ease of use has a significant impact on both perceived usefulness and the satisfaction of personalized learning needs; perceived usefulness does not affect the satisfaction of personalized learning needs; the satisfaction of personalized learning needs significantly influences the intention to use; subjective norms significantly influence the intention to use; perceived risk does not influence the intention to use. Therefore, hypotheses H1, H3, H4and H6 are supported, while hypotheses H2 and H5 are not supported.

DISCUSSION

This study focused on university students, using an empirical research approach to examine the factors influencing their intention to accept and use AI-assisted tools for cross-cultural learning. The findings are as follows:

Table5 Model Fit Indices for the Structural Model

Model fit indices	Reference value	Value of this model
CMIN/DF	＜3	1.326
RMSEA	＜0.08	0.043
TLI	＞0.8	0.957
IFI	＞0.8	0.964
GFI	＞0.8	0.926
CFI	＞0.8	0.963
PNFI	＞0.5	0.744
PCFI	＞0.5	0.826



Note: (*:P＜0.05，**:P＜0.01，***:P＜0.001)
Figure3 Structural Model

Perceived ease of use has a significant positive impact on perceived usefulness. This conclusion has been validated across various research fields, particularly in information technology and education. Perceived ease of use and perceived usefulness positively predict the intention to use (Tsai & Liao, 2021). For instance, a study on Korean university students using Zoom in English classes found that perceived ease of use significantly influenced perceived usefulness (Bailey, Almusharraf, & Almusharraf, 2022). The positive impact of perceived ease of use on perceived usefulness indicates that when users find a system or product easy to use, they are more likely to perceive it as useful. This is because ease of use reduces the learning cost and difficulty for users, enabling them to quickly master the system or product's functions and apply them effectively, thereby recognizing the value it provides.

Perceived ease of use has a significant positive impact on the satisfaction of personalized learning needs. Additionally, perceived ease of use positively influences university students' intention to use AI assistance in cross-cultural learning through the satisfaction of personalized learning needs. When AI-assisted tools are perceived as easy to use and can meet students' personalized learning needs, students are more likely to be willing to use these tools to support their cross-cultural learning. This is because ease of use lowers the barriers to entry, while personalization enhances the relevance and effectiveness of learning, increasing students' acceptance of and intention to use AI-assisted tools. This finding highlights the importance of ease of use and personalization in promoting the widespread adoption and application of AI-assisted learning tools.

Perceived usefulness does not impact the satisfaction of personalized learning needs. Personalized learning needs encompass a wide range of factors, including different learning goals, learning styles, interests, preferences, as well as prior knowledge and experiences of the learners. This diversity may cause perceived usefulness to not directly relate to satisfying the personalized needs of some learners. Even if AI-assisted learning tools are generally considered useful, they may not fully address or adapt to all learners' personalized needs. Additionally, perceived usefulness is based on learners' subjective perceptions and judgments, while actual learning outcomes may be influenced by various factors, including the applicability of AI technology, the level of learner engagement, and the learning environment. Therefore, even if learners perceive AI-assisted learning tools as useful, they may not fully satisfy their personalized learning needs in practice, as there could be a gap between perception and actual effectiveness. Based on this analysis, it is essential to consider learners' personalized needs carefully when designing and developing AI technology, ensuring that the AI tools can adapt to these needs to enhance learner satisfaction and improve learning outcomes.

Subjective norms have a significant impact on university students' intention to use AI assistance in cross-cultural learning. Zhai & Ma (2022) confirmed through empirical research that subjective norms significantly influence intention to use. When deciding whether to use AI-assisted tools for cross-cultural learning, university students perceive expectations and pressures from peers, friends, teachers, and experts. Their opinions and attitudes play an important role in influencing the students' behavioral decisions.

The impact of perceived risk on university students' intention to use AI assistance in cross-cultural learning is not significant. Several possible reasons may explain this: First, with the continuous development and maturation of artificial intelligence technology, AI-assisted learning tools have significantly improved in terms of accuracy, stability, and security. These technological advancements reduce the potential risks users might encounter during use, thereby lowering perceived risk. Second, many schools and educational institutions actively promote AI-assisted learning tools, offering training, resources, and support to help students better utilize these tools. This official support and guidance help reduce students' perceived risk of using AI tools. Additionally, when peers and friends are successfully using AI-assisted tools with positive results, this positive social network influence can further lower individuals' perceived risk and increase their intention to use. Finally, prolonged use and positive feedback gradually build trust in AI-assisted tools within the user community. When students find that these tools can reliably and effectively aid their cross-cultural learning, they are more likely to trust them. Even if students are aware of certain perceived risks, they may have already developed strategies to mitigate these risks, such as choosing reliable tool providers, regularly backing up learning data, and carefully managing personal privacy. These strategies help alleviate their concerns and enhance their intention to use the tools.

CONCLUSION

This study focused on university students, using an empirical research approach to deeply explore the factors influencing their intention to accept and use AI-assisted tools for cross-cultural learning. Through systematic analysis and validation, it was found that in the process of cross-cultural learning, when university students perceive AI-assisted learning tools as easy to use, they are more likely to find these tools useful. This indicates that ease of use is an important prerequisite for users to accept AI technology. Additionally, perceived ease of use further enhances students' intention to use AI-assisted tools for cross-cultural learning by satisfying personalized learning needs. While perceived usefulness is valued by users to some extent, this study found that it does not directly influence the satisfaction of personalized learning needs. This could be due to the diversity of personalized learning needs, which may result in perceived usefulness not being directly associated with satisfying the needs of certain learners. Therefore, when designing and developing AI technology, greater attention should be paid to how well it can meet learners' personalized needs, rather than solely focusing on improving perceived usefulness.

Furthermore, subjective norms have been shown to significantly impact students' intention to use AI-assisted tools for cross-cultural learning, indicating that the social environment and group norms play a crucial role in students' decision-making processes regarding the use of AI-assisted learning. Perceived risk did not significantly negatively affect students' intention to use AI-assisted tools in this study, which could be attributed to the continuous development and maturation of AI technology, the promotion by schools and educational institutions, positive social network influences, and the trust built over time through prolonged use and positive feedback. These factors collectively reduced students' perceived risk regarding AI-assisted learning tools.

The findings of this study provide important guidance for the design and development of AI technologies that better meet user needs. However, there are some limitations to this study. First, the research participants were limited to university students and did not include graduate students, doctoral students, or other social groups, whose needs and requirements for cross-cultural learning may differ. The participants' positive attitudes towards cross-cultural learning could have influenced the results of the questionnaire. Therefore, future research could expand the scope of the survey to include more diverse groups to enhance the comprehensiveness and validity of the data. Second, the application of AI in the field of learning is still in its developmental stage, and its potential and effects are worth further exploration. Conducting in-depth interviews could provide a more genuine understanding of students' psychological experiences and actual interactions with AI-assisted learning tools, thereby improving the reliability and validity of the research. This study did not include in-depth interviews with participants, so future research could incorporate this component to gain deeper insights into students' learning needs and expectations, making the research more scientific and rigorous. Finally, the factors influencing the intention to engage in cross-cultural learning are not limited to perceived usefulness, perceived ease of use, performance expectancy, subjective norms, and perceived risk; other factors, such as perceived cost and perceived trust, may also play a role. Future research could further explore these potential factors to gain a more comprehensive understanding of the complexity and diversity of AI-assisted cross-cultural learning.

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