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Study on the Factors Influencing the Usage Behavior of International Education Cloud Platform in China

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Abstract

Purpose: The purpose of this research is to investigate the factors influencing the usage behavior of International Education Cloud Platforms (IECPs) in China. The study employed a quantitative method, utilizing a questionnaire for data collection from the target population,which allocating 500 samples from 10 higher vocational and technical education institutions across various regions of China, including East, South, West, North, and Central. To ensure content validity and reliability, Item-Objective Congruence (IOC) and a pilot test of Cronbach's Alpha were conducted before distributing the questionnaire. Data analysis involved Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to assess the model's goodness of fit and confirm the causal relationships among variables for hypothesis testing. The results indicated that the research conceptual model effectively predicted and explained the actual usage (AU) of IECPs in higher vocational and technical education. All seven hypotheses proposed were supported, meeting the research objectives. The finding of this study suggests that developers of IECP courses and management in higher vocational education institutions should concentrate on enhancing the quality factors of IECP. This focus would enable students to perceive the system as useful, fostering a positive attitude and behavioral intention toward using IECP.

Keywords: International Education Cloud Platforms, usage behavior, Higher Vocational Education

JEL Classification Code: D83, I25, J24

1. Introduction

The rapid integration of digital technologies into education has revolutionized traditional pedagogical practices, with cloud-based platforms emerging as critical enablers of cross-border collaboration and resource sharing. In China, the International Education Cloud Platform (IECP) has become a cornerstone for higher vocational colleges to deliver online learning, manage transnational programs, and foster global partnerships, particularly during the COVID-19 pandemic and its aftermath.

Despite its transformative potential, challenges such as uneven technological adoption, varying user engagement, and gaps in infrastructure persist, underscoring the need to systematically examine the drivers of IECP acceptance and utilization. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Planned Behavior (TPB), this study investigates the factors influencing international students' behavioral intention and actual usage of IECP in Chinese vocational education contexts.

This study primarily analyzes the influencing factors and effects of using IECP in the process of conducting international education cooperation projects in higher vocational colleges of China. As China's vocational education internationalization process continues to develop and the post-pandemic era brings changes to international education, understanding new educational technologies and models to provide a better educational environment for vocational colleges, educators, and international students becomes particularly important.The main objective of this study is to elucidate the causal relationship between several factors, including performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward behavior, perceived behavioral control, intention to use, as well as actual usage of IECP in higher vocational colleges of China. To achieve this goal, we employ UTAUT model and TPB model, which have been widely used to explain and

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predict individual adoption and usage behaviors of new technologies.

2. Literature Review

2.1 Performance Expectancy

The concept of performance expectancy, which refers to an individual's belief about the enhancement of job performance or productivity through using a particular technology or system, is crucial in technology acceptance and adoption research, shedding light on users' attitudes and intentions toward incorporating a specific technology into their workflows. As articulated by various scholars in the field, including Catherine et al. (2018), understanding the intricacies of performance expectancy provides valuable insights into the dynamics of technology acceptance, particularly within educational contexts. Building upon their seminal work, this paper further explores the multifaceted dimensions of performance expectancy in the specific context of learning management systems, offering a comprehensive analysis of how users' beliefs influence the adoption of these technologies and, consequently, impact educational processes and outcomes.

Grounded in the seminal work of Venkatesh et al. (2003), the establishment of performance expectations is identified as a crucial catalyst for fostering the adoption of information technology (IT) systems and shaping behavioral intentions to utilize them effectively. Mensah (2019) further underscores the significance of performance expectancy, defining it as a robust belief that harnessing technological systems will inevitably lead to an overarching improvement in performance.

2.2 Effort Expectancy

Effort expectancy refers to the perceived level of difficulty or effort required to use a particular technology or system. It is a construct commonly used in technology acceptance models, to understand users' expectations and attitudes towards using a technology (Venkatesh et al., 2003). Users with high effort expectancy may perceive a technology as difficult to learn and use, which can negatively impact their behavioral intentions to adopt and use the technology.

Effort expectancy has been a focal point in the extensive research conducted in the field of technology acceptance and adoption. Many researchers have explored the importance of effort expectancy as a key factor in predicting technology adoption and usage. Venkatesh and Zhang (2010) provided further evidence supporting the role of effort expectancy as a significant predictor of technological adoption. It underscored the importance of perceived ease of use and complexity as reliable and valid constructs in comprehending users' expectations and attitudes towards technology. Venkatesh et al. (2003) emphasized the significance of effort expectancy as an independent variable in the learning management systems (LMS) model emphasizing its positive correlation with users' behavioral intentions and behavior. Cigdem and Ozturk (2016) further identified a positive relationship between users' behavioral intentions regarding effort expectancy and social isolation in an LMS, underscoring the variable's significance in influencing user behavior.

2.3 Social Influence

Social influence refers to the impact that the opinions, attitudes, and behaviors of others have on an individual's own beliefs, attitudes, and actions. It is the process through which individuals are influenced by the social norms, expectations, and pressures of their social environment. Social influence can occur through direct interactions with others, such as friends, family, and peers, as well as through indirect influences, such as media, advertising, and societal norms. In the context of technology adoption and usage, social influence plays a significant role in shaping individuals' intentions and behaviors.

Venkatesh et al. (2003) highlight the significance of social influence and subjective norms in predicting technological adoption and behavioral intentions. They emphasize the impact of influential individuals, group standards, and the opinions of peers, teachers, and other significant members of a group on individuals' behavioral goals and intentions. Furthermore, Kaye et al. (2020) study examines the impact of system navigation, system learnability, and the assessment of instructional effort expectations, linking these factors to both social influence and subjective norms. Additionally, the study by Bervell et al. (2020) examine students' perceptions of using E-Classroom and how their expectations can be altered with adequate internet use and platform development, which can also be linked to social influence and subjective norms. Therefore, combining Social Influence and Subjective Norm can provide a more comprehensive understanding of the social factors that influence individuals' intentions and behaviors in adopting and using learning management systems (LMS).

2.4 Facilitating Conditions

Facilitating conditions refer to the perception of an advanced technological infrastructure that exists to facilitate the use of a system. Facilitating conditions include factors such as the availability of necessary hardware and software, technical support, training, and access to relevant information and resources (Venkatesh et al., 2003). It also involves the removal of obstacles or barriers that may hinder the use of the system. In the context of new technology application in education field, facilitating conditions play a crucial role in promoting user satisfaction, adoption, and long-term viability of the system. Facilitating conditions are a critical component in technology acceptance models, such as UTAUT, where they are believed to directly influence users' intention to use a system and their actual usage behavior.

Many researchers emphasized the importance of facilitating conditions (FC) as a factor that influences individuals' intentions to use LMS. Abdulrahim and Mabrouk (2020) emphasized that favorable conditions were the key factor in ensuring the long-term sustainability and successful adoption of LMS during the COVID-19 pandemic in Saudi. This suggests that when individuals perceive favorable conditions, such as technical support and available resources, they are more likely to intend to use LMS. The study found that favorable conditions, such as access to necessary resources and technical support, positively influenced students' usage of the platform. Overall, the literature indicates that facilitating conditions, including the availability of resources and support, significantly positively impact students' behavioral intentions to use LMS. When individuals perceive these favorable conditions, they are more likely to intend to use LMS and enjoy a positive user experience.

2.5 Attitude toward Behavior

Attitude toward Behavior refers to an individual's subjective evaluation or reaction to a specific behavior. It is influenced by various factors such as beliefs, experiences, social norms, and personal values (Ajzen, 1991). Attitude toward Behavior reflects an individual's positive or negative inclination towards engaging in a particular behavior. It plays a crucial role in shaping behavioral intentions and subsequent actions. Attitudes can be formed through direct personal experiences, observation of others, or information received from various sources.

Krueger et al. (2000) exploration of competing models of entrepreneurial intentions emphasized the significant and positive impact of personal attitudes on fostering entrepreneurial intentions. This seminal study laid a foundation for understanding the intricate interplay between individual attitudes and the inclination toward entrepreneurial pursuits. In a multi-country study by Al-Mamary and Alraja (2022), factors influencing students' attitudes toward entrepreneurship were scrutinized. Their findings underscored the diverse influences stemming from cultural disparities and educational backgrounds, shedding light on the nuanced nature of attitudes toward entrepreneurship across different contexts. Al-Mamary and Shamsuddin (2015) research delved into the transformative effect of entrepreneurship programs on raising entrepreneurial intentions among science students. This study elucidated that the amalgamation of learning, inspiration, and resources provided by such programs wielded a positive influence on shaping entrepreneurial aspirations. Integral to understanding these nuanced attitudes and intentions is Ajzen's Theory of Planned Behavior (TPB), as developed in 1991.

2.6 Perceived Behavioral Control

Perceived behavioral control (PBC) refers to an individual's perception of their ability to control and perform a specific behavior. It is a concept derived from the Theory of Planned Behavior (TPB) and is closely related to self-efficacy and learning autonomy. PBC encompasses the belief that individuals have in their own capabilities to overcome obstacles and successfully engage in a particular behavior (Ajzen, 2002).Perceived Behavioral Control (PBC) is a construct that reflects an individual's perception of the ease or difficulty of performing a specific behavior, and it is considered a crucial determinant of both intentions and actions.

Ajzen (1991) laid the foundation for the Theory of Planned Behavior, shedding light on the role of perceived behavioral control in predicting behavior. Al-Mamary and Alraja (2022) extended this exploration by investigating how perceived behavioral control influences entrepreneurial intentions. Their study involved a comparative analysis of different models of entrepreneurial intentions, providing valuable insights into the multifaceted nature of perceived cehavioral control. Pan et al. (2021) contributed to the understanding of Perceived Behavioral Control by examining its influence, along with desirability and feasibility. Their research utilized a structural equation model to unravel the complex dynamics at play in shaping entrepreneurial aspirations. This study adds a practical dimension to the theoretical underpinnings of perceived behavioral control, emphasizing its significance in the entrepreneurial context.

2.7 Intention to Use

Intention to Use refers to an individual's planned or expected future use of a particular technology or system which is a key predictor of actual usage behavior in many theoretical models. Intention to use captures the motivational factors that influence a person's decision to engage with a technology and can be shaped by various cognitive and affective processes. Intention to Use represents an individual's conscious plan or decision to use a specific technology or system in the future. It is considered a proximal determinant of actual behavior, meaning that the stronger an individual's intention to use a technology, the more likely they are to follow through and use it (Ajzen, 1991). This construct is central to many behavioral models because it bridges the gap between attitudes and actual behavior.

2.8 Actual Use

Actual use refers to the extent to which individuals actually use a particular technology or system in their real-life settings. It is a measure of the actual behavior of individuals in terms of their engagement and interaction with the technology. The assessment of Actual usage typically involves objective measures, encompassing parameters such as the frequency and duration of interaction, the nature of tasks executed using the technology, and the comprehensive utilization of its functionalities (Venkatesh et al., 2003). These quantitative metrics not only provide a nuanced understanding of users' engagement but also offer valuable insights into the technology's impact on users' daily activities. In essence, Actual Usage stands as a crucial juncture in the technology adoption continuum, representing the culmination of users' real-world experiences and interactions with the technology.

3. Research Method

3.1 Conceptual Framework

The conceptual framework of this research has been established with the foundation of existing theories and prior empirical studies to form an integrated conceptual model. It encompasses all variables utilized in this study. This conceptual framework illustrates the causal relationships among the variables, with the primary goal of examining the influencing factors and impacts associated with the utilization of International Education Cooperation Platforms (IECP) in the implementation of international education cooperation projects within Chinese higher vocational colleges. The components of TPB, which effectively predict behavioral intentions, and the factors of UTAUT, which evaluate technology acceptance, enhance the integrated model. Employing multiple theoretical perspectives is essential for thoroughly understanding the relevant factors. By merging these factors and integrating elements from both theories, the integrated conceptual model aims to enhance the prediction of technology usage and assess the willingness to use new techology in education. In this research, the independent variables encompassed performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward behavior and perceived behavioral control. This study had one mediate variables: intention to use, and with only one dependent variable-actual usage.

In this study, UTAUT&TPB are two key models, and investigate seven relationships among the variables within the framework shown in Figure 1.

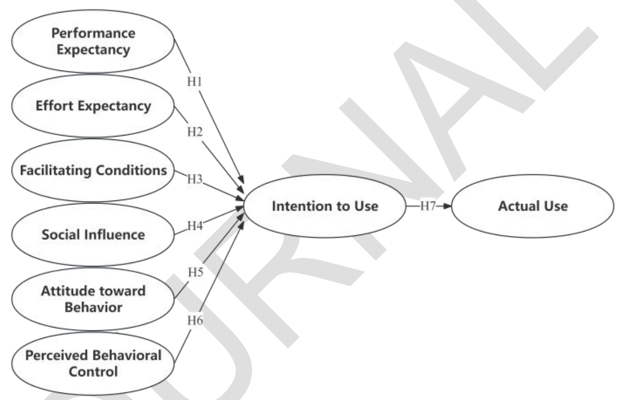

Figure 1: Conceptual Framework

3.2 Research Hypothesis

Hypothesis is a statement proposed to validate researchers' predictions based on findings or insights from a study. It assumes a relationship between independent and dependent variables , and arise from research questions or problem statements and can be confirmed through scientific or statistical research. Within the conceptual framework of this research, seven hypotheses have been formulated and are slated for testing.

H1: Performance expectancy has significant influence on intention to use international education cloud platform.

H2: Effort expectancy has significant influence on intention to use international education cloud platform.

H3: Facilitating conditions has significant influence on intention to use international education cloud platform.

H4: Social influence has significant influence on intention to use international education cloud platform.

H5: Attitude toward behavior has significant influence on intention to use international education cloud platform.

H6: Perceived behavioral control has significant influence on intention to use international education cloud platform.

H7: Intention to use has significant influence on actual use of international education cloud platform.

3.3 Methodology

This study, grounded in empirical analysis and quantitative methods, employs a questionnaire survey to collect sample data, investigating the factors that influence the willingness of international students in China's higher vocational education to use the International Education Cloud Platform (IECP).This study employed a Likert five-point scale to design the questionnaire, aiming to identify factors influencing students' use of the IECP for learning, and obtaining numerical results for statistical analysis. As the questionnaire was targeted at international students, the questions were translated into English for respondents to read and comprehend. The survey questionnaire comprises 31 items, and each construct contained 3-4 items.

The questionnaire was created using the Questionnaire Star online survey tool, facilitating convenient and rapid distribution and collection of data. Before administering the questionnaire to the target population, researchers performed an Item-Objective Consistency (IOC) analysis and conducted a pilot test to validate the reliability of each construct. To validate the questionnaire, three experts who with the doctoral degree and the professional title at least associate professor, which in the filed of education have evaluated the questionnaires with the index of IOC. For the entire scale items, 31 items obtain the point 1.00, and 4 items obtain the point 0.67, which providing the validity of the questionnaire.In this study, the researcher evaluated the reliability of each sub-scale among 50 respondents by using Cronbach's Alpha to assess inter-item reliability. This statistical method examined the Cronbach's Alpha coefficients for each parameter. During pilot testing, the reliability test results for each variable shown in Table 1. These findings robustly validate the internal consistency of the questionnaire's structure and its overall reliability.

Data analysis involved Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to assess the model's goodness of fit and confirm the causal relationships among variables for hypothesis testing.

Table 1: Result of Pilot Test

Variables	Before Pilot Test	After Pilot Test	Cronbach's Alpha	Strengths o f Association
Performance Expectancy	4	4	0.851	Very Good
Effort Expectancy	4	4	0.840	Very Good
Facilitating Conditions	4	4	0.882	Very Good
Social Influence	4	4	0.869	Very Good
Attitude toward Behavior	4	4	0.775	Good
Perceived Behavioral Control	3	3	0.834	Very Good
Intention to Use	4	4	0.795	Good
Actual Use	4	4	0.848	Very Good

3.4 Population and Sample Size

The target population of this study consists of international students who have experienced the use of IECP in Chinese higher vocational education institutions. All ten selected institutions are Chinese higher vocational and technical colleges, recognized for their exemplary international education cooperation efforts within China and the region. The sample size for Structural Equation Models suggested minimum sample size was 444. The survey was given to 500 respondents. After the data screening process, 500 responses were used in this study.

3.5 Sampling Technique

This study employed a multistage sampling approach that integrated both probability and non-probability sampling techniques. The process first started with judgmental or purposive sampling, then proceeded with stratified random sampling, and finally finished with convenience sampling. This comprehensive method aimed to capture a wide range of perspectives and increase the overall robustness of the study.

For this study, the judgmental sampling method was used to select 10 higher vocational and technical education institutions across various regions of China, including East, South, West, North, and Central. This approach was chosen to ensure the sample accurately represents the geographical diversity of China.

In the second step, the population was divided into strata using stratified random sampling, with each stratum representing a specific college. To guarantee representativeness, a proportional stratified sampling method was employed, allocating 500 samples to each stratum. Following this, the survey was disseminated to each college in accordance with the sample proportions.

The questionnaire was created and distributed through the "Survey Star" which is an online survey platform. Compared to other methods, collecting data through online channels offers numerous advantages. Online distribution is an effective and fastest way to achieve the desired number of respondents defined for each selected university.

4. Results and Discussion

4.1 Demographic Information

The questionnaire survey collected demographic information from respondents, including gender, age, and year of study. Among the respondents, there were 382 male students, accounting for 76.4% of the total, and 118 female students, accounting for 23.6%. The age distribution included 117 students aged 18 or younger, making up 23.4%, and 383 students aged 19 or older, making up 76.6%. The year of study distribution was as follows: 131 first-year students, accounting for 26.2% of the total; 140 second-year students, accounting for 28%; 123 third-year students, accounting for 24.6%; and 106 students who had graduated or completed their training, accounting for 21.2%.

Table 2: Demographic Characteristics of Respondents

Demographic Data (N=500)		Frequency	Percentage
Gender	Male	382	76.4%
	Female	118	23.6%
Age	18 years old or under	117	23.4%
	19 years old and above	383	76.6%
Grade	Freshman	131	26.2%
	Sophomore	140	28%
	Junior	123	24.6%
	Graduated	106	21.2%

4.2 Confirmatory Factor Analysis (CFA)

In this study, Confirmatory Factor Analysis (CFA) was performed to assess the measurement model. All items associated with each variable demonstrated significance and exhibited factor loadings that were used to evaluate discriminant validity. The factor loadings for each item were significant, with values exceeding 0.30 and p-values below 0.05, indicating an acceptable goodness of fit (Hair et al., 2006). Additionally, the construct reliability exceeded the threshold of 0.7, and the average variance extracted (AVE) surpassed the cutoff value of 0.5 (Fornell & Larcker, 1981), as detailed in Table 3. All estimates were found to be statistically significant.

To evaluate the model fit in CFA testing, several indices were utilized, including GFI, AGFI, NFI, CFI, TLI, and RMSEA. Both convergent validity and discriminant validity were confirmed, as the values obtained in this study (shown in Table 3) exceeded the acceptable thresholds. Furthermore, the square root of the average variance extracted (AVE) was calculated, confirming that all correlations exceeded the corresponding correlation values for each variable, as presented in Table 4. Consequently, the convergent and discriminant validity of the constructs was established. These results not only support the discriminant validity of the model but also provide a robust foundation for validating subsequent structural model estimations, shown in Table 5.

Table 3: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Awang, 2012; Al-Mamary & Shamsuddin, 2015)	723.282 / 406 or 1.781
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.916
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.898
NFI	≥ 0.80 (Wu & Wang, 2006)	0.891
CFI	≥ 0.80 (Bentler, 1990)	0.949
TLI	≥ 0.80 (Sharma et al., 2005)	0.941
RMSEA	< 0.08 (Pedroso, 2016)	0.040
Model Summary		Acceptable Model Fit

Table 4: CFA Result, CR and AVE

Variables	CA	Factors	t-value	CR	AV
Performance E	0.828			0.834	0.5
PE1		0.629	-		
PE2		0.787	13.475*		
PE3		0.783	13.438*		
PE4		0.780	13.403*		
Effort Expectan	0.839			0.840	0.5
EE1		0.773	-		
EE2		0.785	16.667*		
EE3		0.775	16.480*		
EE4		0.676	14.424*		
Facilitating Co	0.854			0.856	0.5
FC1		0.761	-		
FC2		0.784	16.769*		
FC3		0.763	16.351*		
FC4		0.785	16.787*		
Social Influenc	0.854			0.859	0.6
SI1		0.826	-		
SI2		0.833	19.518*		
SI3		0.729	16.960*		
SI4		0.714	16.544*		
Attitude toward	0.798			0.816	0.5
AB1		0.756	-		
AB2		0.610	12.566*		
AB3		0.829	16.077*		
AB4		0.695	14.289*		
Perceived Beha	0.761			0.770	0.5
PBC1		0.644	-		
PBC2		0.680	11.901*		
PBC3		0.845	12.118*		
Intention to Us	0.793			0.797	0.4
IU1		0.727	-		
IU2		0.705	13.615*		
IU3		0.696	13.462*		
IU4		0.687	13.328*		
Actual Use (A	0.813			0.822	0.5
AU1		0.663	-		
AU2		0.717	13.109*		
AU3		0.753	13.576*		
AU4		0.792	13.989*		

Table 5: Discriminant Validity

	PE	EE	FC	SI	AB	PBC	IU	AU
PE	0.748							
EE	0.249	0.754						
FC	0.137	0.210	0.773					
SI	0.059	0.111	0.132	0.777				

	PE	EE	FC	SI	AB	PBC	IU	AU
AB	0.132	0.137	0.213	0.068	0.727			
PBC	0.121	0.174	0.220	-0.003	0.139	0.728		
IU	0.303	0.303	0.234	0.168	0.224	0.316	0.704	
AU	0.200	0.257	0.190	0.105	0.166	0.159	0.354	0.733

4.3 Structural Equation Model (SEM)

The researcher used SEM to validate the casual relationship among variables in a proposed model and encompasses measurement inaccuracy in the structure coefficient. The goodness of fit indices for Structural Equation Model (SEM) is measured as demonstrated in Table 6. The selected indices are the same as those used in CFA, which evaluate 8 latent variables of PE, EE, FC, SI, AB, PBC, IU, and AU. The values were as followed (listed in Table 6): CMIN/DF = 2.070, GFI = 0.896, AGFI = 0.879, NFI = 0.867, CFI = 0.926, TLI = 0.920, and RMSEA = 0.046. All of these values fell within the acceptable range, thereby confirming the fitness of the structural model.

Table 6: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Awang, 2012; Al-Mamary & Shamsuddin, 2015)	883.903 / 427 or 2.070
GFI	≥ 0.85 (Sica & Ghisi , 2007))	0.896
AGFI	≥ 0.80 (Sica & Ghisi, 2007))	0.879
NFI	≥ 0.80 (Wu & Wang, 2006))	0.867
CFI	≥ 0.80 (Bentler, 1990))	0.926
TLI	≥ 0.80 (Sharma et al., 2005)	0.920
RMSEA	< 0.08 (Pedroso, 2016))	0.046
Model Summary		Acceptable Model Fit

4.4 Research Hypothesis Testing Result

Research hypothesis testing is the process of validating whether the hypotheses proposed by the researcher hold true through data analysis. Researchers formulate hypotheses based on theoretical frameworks and research objectives, and then use statistical analysis methods to test whether these hypotheses align with the actual data. The results of hypothesis testing are typically evaluated by significance levels (p-values), and if the p-value is below the predetermined significance level (usually 0.05), the hypothesis is considered supported. As presented in Table 7.

Table 7: Hypotheses Testing Result of Structural Model

Hypothesis	Standardized path coefficient (β)	t-value	Testing result
H1: Performance Expectancy has significant influence on Intention to Use International EducaCP.	0.279	5.168*	Support
H2: Effort Expectancy has significant influence on Intention to Use IECP.	0.248	4.770*	Support
H3: Facilitating Conditions has significant influence on Intention to Use IECP.	0.103	2.074*	Support
H4: Social Influence has significant influence on Intention to Use IECP.	0.144	2.889*	Support
H5: Attitude toward Behavior has significant influence on Intention to Use IECP.	0.157	3.084*	Support
H6: Perceived Behavioral Control has significant influence on Intention to Use IECP.	0.303	5.401*	Support
H7: Intention to Use has significant influence on Actual Use of IECP.	0.433	7.063*	Support

Note: * = $p < 0.05$

Performance expectancy, effort expectancy, and perceived behavioral control exert the strongest influence on intention to use. In Hypothesis H1, Performance Expectancy has a standardized path coefficient of 0.279 (t-value = 5.18), reflecting learners' belief that using the system enhances learning outcomes or job performance by improving efficiency, deepening knowledge, speeding up tasks, and optimizing the learning experience, thereby increasing their intention to use IECP. In Hypothesis H3, Effort Expectancy shows a coefficient of 0.248 (t-value = 5.18), indicating users' expectation that the system is easy to use, enabling quick mastery, smooth navigation, and seamless interaction, which boosts their intention to adopt IECP. In Hypothesis H6, Perceived Behavioral Control has a coefficient of 0.303 (t-value = 5.401), reflecting users' confidence in their technical skills, resources, and ability to overcome obstacles, ensuring task completion and goal achievement, further enhancing their intention to use IECP. Social Influence and Attitude toward Behavior have a significant but secondary impact on IU. In Hypothesis H4, Social Influence has a coefficient of 0.144 (t-value = 2.889), showing that external suggestions, encouragement, or pressure from peers and social norms influence users' decisions to adopt IECP. In Hypothesis H5, Attitude toward Behavior also has a coefficient of 0.144 (t-value = 2.889), reflecting users' overall positive or negative perceptions of the system, including its perceived benefits, enjoyment, and convenience, which shape their intention to use it. Facilitating Conditions have the third-strongest impact on IU. In Hypothesis H5, its coefficient is 0.103 (t-value =

2.074), indicating that users value technical support, device availability, network stability, and sufficient learning resources. Access to these resources increases their confidence and willingness to use IECP, highlighting the role of external support in influencing usage intentions. Finally, Intention to Use significantly impacts Actual Use of IECP. In Hypothesis H7, the coefficient is 0.433 (t-value = 7.063), aligning with findings by Selim (2007) that technology acceptance and usage intentions are critical challenges for educational institutions. A strong intention to use IECP directly influences actual usage behavior, especially when users plan to continue using it over time.

5. Conclusions and Recommendation

5.1 Conclusion

This research integrated UTAUT model and TPB model, investigated the factors influencing the usage behavior of International Education Cloud Platforms (IECP) in China, including performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward behavior, perceived behavioral control, intention to use, as well as actual usage. The study employed a quantitative method, utilizing a questionnaire for data collection from the target population. To ensure content validity and reliability, Item-Objective Congruence (IOC) and a pilot test of Cronbach's Alpha were conducted before distributing the questionnaire.Data analysis involved Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to assess the model's goodness of fit and confirm the causal relationships among variables for hypothesis testing. The results indicated that the research conceptual model effectively predicted and explained the actual usage (AU) of IECPs in higher vocational and technical education. All seven hypotheses proposed were supported, meeting the research objectives.

The study suggests that developers of IECP courses and management in higher vocational education institutions should concentrate on enhancing the quality factors of IECP. This focus would enable students to perceive the system as useful, fostering a positive attitude and behavioral intention toward using IECP.

5.2 Findings and Recommendation

The study's findings revealed that each of the six factors significantly influenced the intention to use IECP. Performance expectancy, effort expectancy, and perceived behavioral control are the strongest predictors of students' intention to use IECP. Other factors that also have significant impact include social influence, attitude toward behavior, and facilitating condition. These findings can assist administrators of higher vocational education colleges who implement international education programs, teachers involved in curriculum development and teaching, as well as developers of international education cloud platforms, in paying greater attention to and emphasizing the factors that influence usage intention and actual usage.

To enhance the effectiveness of the International Education Cloud Platform (IECP) in international education, administrators, teachers, and developers should focus on several key areas. These include improving the accessibility of course materials and resources, strengthening communication and collaboration tools, and optimizing the learning experience to ensure better understanding of course content. Additionally, efforts should be made to assist users with time management and task organization, simplify platform usability, and save time and effort for learners. Enhancing technical support and system reliability is also crucial, as is boosting social influence and user motivation to foster greater engagement and adoption of the platform. These improvements will collectively create a more efficient, engaging, and user-friendly learning environment.

5.3 Limitation and Further Study

While this study has achieved its objectives and offers valuable insights into the application of educational information technology in the internationalization of vocational education, certain limitations should be acknowledged and addressed in future research. To expand and refine the findings, future studies could broaden the scope of research subjects, diversify research methods, and incorporate additional data sources. For instance, the current study was limited to 10 vocational colleges in China, excluding a wider range of higher education institutions. Expanding the sample to include diverse types of institutions could yield more comprehensive results. Additionally, this study primarily examined IECP usage behavior from the perspective of international students. Future research could explore usage patterns and influencing factors among teachers and administrators to better understand the platform's role in teaching and management. Moreover, while this study relied on a cross-sectional survey approach, longitudinal research could be employed to track dynamic changes in IECP usage behavior and analyze influencing factors more deeply. Furthermore, the study focused exclusively on IECP; future research could investigate other educational informatization technologies, such as AI-driven education tools and virtual simulation labs, to provide a broader understanding of digital technologies in international education. Lastly, while self-reported questionnaires were used for data collection, combining these with objective usage data, such as login records and usage duration, could offer a more accurate assessment of IECP's actual use. Addressing these limitations would enhance the depth and applicability of future research in this field.

References

Abdulrahim, H., & Mabrouk, F. (2020). COVID-19 and the digital transformation of Saudi higher education. *Asian Journal of Distance Education, 15*(1), 291-306.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, *32*(4), 665-683.

Al-Mamary, Y. H. S., & Shamsuddin, A. (2015). The impact of management information systems adoption in managerial decision making: A review. *Management Information Systems*, *8*(4), 10-17.

Al-Mamary, Y. H. S., & Alraja, M. M. (2022). Understanding entrepreneurship intentions and behavior in the light of TPB model from the digital entrepreneurship perspective . *International Journal of Information Management Data Insights, 2*(2), 100106.

Awang, Z. (2012). *Structural Equation Modeling Using AMOS Graphic*. Penerbit Universiti Teknologi MARA.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238-246.

Bervell, B., Nyagorme, P., & Arkorful, V. (2020). LMS-enabled blended learning use intentions among distance education tutors: Examining the mediation role of attitude based on technology-related stimulus-response theoretical framework. *Contemporary Educational Technology, 12*(2), 273.

Catherine, N., Geofrey, K. M., Moya, M. B., & Aballo, G. (2018). Effort expectancy, performance expectancy, social influence and facilitating conditions as predictors of behavioral intentions to use ATMs with fingerprint authentication in Ugandan banks. *Global Journal of Computer Science and Technology, 17*(5), 5-22.

Cigdem, H., & Ozturk, M. (2016). Factors affecting students' behavioral intentions to use LMS at a Turkish post-secondary vocational school. *International Review of Research in Open and Distributed Learning, 17*(3), 276-295.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Pearson Prentice Hall.

Kaye, S. A., Lewis, I., Forward, S., & Delhomme, P. (2020). A priori acceptance of highly automated cars in Australia, France, and Sweden: A theoretically-informed investigation guided by the TPB and UTAUT. *Accident Analysis and Prevention, 133*, 105441.

Krueger, N. F., Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. *Journal of Business Venturing, 15*(5-6), 411-432.

Mensah, I. K. (2019). Factors influencing the intention of university students to adopt and use e-government services: an empirical evidence in China. *Sage Open, 9*(2), 2158244019855823.

Pan, Y., Huang, Y., Kim, H., & Zheng, X. (2021). Factors influencing students' intentions to adopt online interactive behaviors: Merging the theory of planned behavior with cognitive and motivational factors. *The Asia-Pacific Education Researcher, 32*(1), 1-10.

Pedroso, R. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry*, *43*(3), 37-40.

Selim, H. M. (2007). Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers & Education*, *49*(2), 396-413.

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research*, *58*(7), 935-943.

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. *Comprehensive Psychiatry*, *48*(3), 326-333.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology—toward a unified view. *MIS Quarterly, 27*(3), 425-478, http://dx.doi.org/10.2307/30036540.

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management*, *13*(1), 5-27.

Wu, J. H., & Wang, S. C. (2006). What drives mobile commer ce? An empirical evaluation of the revised technology acce ptance model. *Information & Management*, *43*(5), 711-729.