

Factors influencing undergraduate English majors' behavioral intention to use GenAI for Chinese cultural expression in EFL: An extended UTAUT framework

Yining Zheng^{1,a}, Ran Huang^{1,b}, Shuhan Yang^{1,c,*}

¹School of Foreign Languages and Cultures, Panzhuhua University, Panzhuhua, 617000, China

^a2792938403@qq.com, ^b3542353166@qq.com, ^cyangshuhan1908@pzhuh.edu.cn

*Corresponding author

Abstract: The deep integration of artificial intelligence into education has made generative AI (GenAI) a promising instructional tool for supporting foreign language learners' cross-cultural and linguistic expression. Despite its growing pedagogical popularity, few empirical studies have systematically examined English majors' behavioral intentions to adopt GenAI for Chinese cultural expression in English. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), this study extends the original framework by incorporating information quality and system quality to better suit culture-oriented foreign language learning contexts. Based on 521 valid responses, this study employed PLS-SEM to investigate the key determinants of students' intention to use GenAI for enhancing their English-mediated representation of Chinese culture. The results demonstrate that information quality, system quality, performance expectancy, and facilitating conditions positively and significantly shape students' behavioral intention. Unexpectedly, effort expectancy exerts a significant negative influence on usage intention. Mediation analyses further reveal that performance expectancy partially mediates the relationship between information quality and behavioral intention, whereas effort expectancy partially mediates the link between system quality and behavioral intention. The proposed model explains 71.1% of the variance in learners' intention to use GenAI, indicating strong explanatory power. This study extends the theoretical applicability of UTAUT to AI-supported cross-cultural learning and culture-focused foreign language instruction. It also provides practical implications for the design, optimization, and pedagogical implementation of intelligent language learning tools in digital cultural teaching reform.

Keywords: GenAI; UTAUT; Information Quality; System Quality; Behavioural Intention; Chinese Cultural Expression

1. Introduction

In light of the evolving global cultural dynamics and the rapid advancement of artificial intelligence technology, cross-cultural communication encounters new opportunities and challenges^[1]. Developing learners' ability to accurately and systematically articulate the nuances of local culture in English has emerged as one of the core objectives of English language instruction and second language talent cultivation across nations^{[1][2]}. This composite cultural-linguistic competence transcends symbol conversion at the language level but encompasses a comprehensive system of cultural cognitive construction, cross-lingual expression skills, and cross-cultural communicative attitudes.

Research indicates that Chinese undergraduates, even English majors, often struggle when they introduce Chinese culture in English. Many of them produce disjointed writing, make frequent wording errors and fail to organize ideas logically in their expression^[2]. This lack of relevant ability hurts students' performance in cross-cultural exchanges on a personal level. It also slows down the international promotion of local culture to a certain degree. National educational policies now actively push for deeper integration of artificial intelligence into language and cultural courses. Even so, traditional teaching approaches can hardly raise students' English cultural expression ability in a systematic way. GenAI has brought new possibilities to foreign language education and cross-cultural communication since its development^[3]. Unlike earlier discriminative AI, GenAI is able to produce texts, pictures and other varied materials following given prompts. It makes lively interactive learning environments easier to build and works well to support learners' language output while deepening their

cross-cultural awareness^{[4][5]}. Most existing research on GenAI in foreign language teaching only looks at its practical uses and broad industry-level influences^{[5][6][7]}, rarely examining its specific role in helping students talk about Chinese culture properly in English. Fewer studies further discuss learners' willingness to use such tools and the factors that shape this willingness.

To address the gaps in the existing literature, this study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as the core theoretical framework and further incorporates variables related to information quality and system quality to construct an extended model, aiming to answer the following research questions:

RQ1: To what extent do English majors hold behavioral intention to adopt GenAI to strengthen their ability to express Chinese culture in English?

RQ2: Do performance expectancy, effort expectancy, social influence, facilitating conditions, system quality and information quality predict this behavioral intention?

RQ3: Do performance expectancy and effort expectancy mediate the relationships between system quality, information quality and this behavioral intention?

2. Theoretical Framework

This study adopts the UTAUT as its theoretical foundation. By delineating four core constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, the theory provides a robust explanatory framework for understanding individuals' adoption behaviors toward information technology^[8]. However, the classical UTAUT model primarily centers on users' subjective cognitive perceptions and socio-environmental influences, with relatively limited attention to the objective attributes inherent in the technological system itself. When the research focus shifts to GenAI, an information system characterized by complex content generation and dynamic interactivity, and when applied to the specific pedagogical context of expressing Chinese culture in English, which imposes stringent demands on both content accuracy and cultural appropriateness, relying solely on users' subjective expectancy variables proves insufficient to fully elucidate the mechanisms underlying usage intention. To redress this theoretical limitation and construct a more robust explanatory framework, this study substantially extends the UTAUT model by incorporating two critical constructs, information quality and system quality^[9], a theoretical expansion grounded in two principal considerations. From the perspective of theoretical development, the integration of these two constructs represents an inheritance and synthesis of seminal theoretical traditions in the information systems research domain. Information quality, typically defined as the accuracy, completeness, timeliness, and relevance of system output^{[9][10]}, constitutes the cognitive foundation upon which users evaluate the value of the technology^[11]. By embedding these two objective attribute constructs into the UTAUT framework, which is primarily anchored in user subjective cognition, this study establishes a complete theoretical chain linking system characteristics, user cognition, and behavioral intention, thereby contributing to a more holistic explanatory model of technology acceptance.

Given the specificity of the research context, the scenario of using GenAI to enhance the ability to express Chinese culture in English imposes unique requirements on the technological system. In this context, information quality encompasses not only the effectiveness of knowledge transmission, but also the accuracy of cultural representation and the appropriateness of cross-cultural communication. Any informational deviation may potentially lead to profound cultural misinterpretation, rendering content reliability a critical prerequisite in users' technology adoption decisions. Concurrently, system quality acquires a new connotation in this scenario; it not only affects general user experience but also directly relates to the sense of immersion and continuity of thought essential for cross-cultural learning, which is closely associated with the cognitive environment required for the process of cultural internalization.

By integrating information quality and system quality into the UTAUT framework, this study aims to establish a more comprehensive theoretical model to explore the multi-level factors influencing students' technology adoption decisions and the complex mechanisms through which these factors operate in a culture-oriented AI-assisted learning environment.

3. Research Hypotheses

3.1. Performance Expectancy and Effort Expectancy

Performance expectancy, derived from UTAUT, refers to the degree to which an individual believes that using a particular technology will enhance task performance and efficiency. Effort expectancy, in turn, denotes the perceived ease of use associated with the technology, reflecting the amount of effort required for its operation^[8]. In the context of this study, performance expectancy is manifested in English-major students' recognition that GenAI can effectively facilitate the accurate and efficient completion of learning tasks related to expressing Chinese culture in English. Effort expectancy concerns whether students perceive GenAI's interface as user-friendly, its command input as straightforward, and the overall learning and operation process as smooth and effortless.

In technology acceptance research, performance expectancy and effort expectancy have been widely recognized as key cognitive determinants of users' adoption intentions. A substantial body of empirical evidence has confirmed their stable and significant effects on users' continuance intention across various educational technology systems. For instance, studies on learning management systems, mobile learning platforms, and mobile health services have consistently demonstrated that performance expectancy serves as a core predictor of users' continuance intention^{[12][13]}; Effort expectancy, which shares theoretical roots with perceived ease of use, plays a fundamental role in both initial adoption and sustained use of new technologies. More recently, in the context of generative AI adoption, researchers have also found that effort expectancy exerts a significant influence on users' continuance intention, highlighting the importance of ease-of-use perceptions during the early diffusion stage of novel technologies^{[14][15]}.

Based on the theoretical framework and empirical evidence outlined above, the following hypotheses are proposed:

H1: Performance expectancy positively affects English-major students' behavioral intention to use generative AI for enhancing their ability to express Chinese culture in English.

H2: Effort expectancy positively affects English-major students' behavioral intention to use generative AI for enhancing their ability to express Chinese culture in English.

3.2. Social Influence and Facilitating Conditions

Social influence refers to the degree to which an individual perceives that important referent groups, such as instructors, peers, and family members, believe they should or should not use a particular technology^[8]. Facilitating conditions denote the extent to which an individual believes that organizational and technical infrastructure exists to support the use of a technology in terms of resources, knowledge, and assistance^[8]. In the present study, social influence is reflected in English-major students' perceived normative pressure stemming from teacher recommendations, peer usage norms, and successful role-model cases regarding the use of GenAI for learning Chinese cultural expression in English. Facilitating conditions pertain to whether students perceive that they have stable access, adequate learning time, necessary operational guidance, and timely technical support when encountering difficulties. Accordingly, the following hypotheses are proposed:

H3: Social influence positively affects English-major students' behavioral intention to use generative AI for enhancing their ability to express Chinese culture in English.

H4: Facilitating conditions positively affect English-major students' behavioral intention to use generative AI for enhancing their ability to express Chinese culture in English.

3.3. Information Quality

Drawing on the empirical study by Qiu et al. on college students' continuance intention toward generative AI, information quality and system quality have been shown to exert significant positive effects on users' continuance intention^[9]. Information quality refers to the accuracy, completeness, consistency, and other attributes of the information obtained through an information system. In existing research, there is broad scholarly consensus that the quality of information delivered by an information system positively influences users' intention to adopt and continue using the system^[11]. Wu et al. (2021), in their investigation of Facebook users, confirmed that information quality and social influence significantly and positively affect users' usage intention^[16].

Gu et al. (2024), in their study of MOOC platform users' continuance intention, demonstrated that information quality significantly and positively influences user satisfaction and continuance intention^[11]. As GenAI constitutes an emerging information system, the quality of information it provides may similarly affect college students' behavioral intention to use it for enhancing their ability to express Chinese culture in English. The following hypothesis is therefore proposed:

H5: Information quality positively affects students' behavioral intention to use generative AI for enhancing their ability to express Chinese culture in English.

3.4. System Quality

System quality refers to the comprehensive capabilities of a system in terms of reliability, responsiveness, flexibility, and related performance attributes^[11]. In previous research, Wang & Ding, in their study on mobile government services, found that factors such as normal access, operational stability, and the rationality of design and functionality directly affect users' intention to adopt government apps^[17]. Using hierarchical regression analysis, Zhang (2023) investigated college students' continuance intention toward social reading apps and revealed that high system quality, along with its high usability and instant feedback, effectively reduces cognitive burden in human-computer interaction, facilitates immersive experiences, and consequently enhances continuance intention^[18]. With the advent of the artificial intelligence era, GenAI has profoundly influenced college students' learning and creative practices. This study posits that the reliability, responsiveness, and flexibility of GenAI may similarly shape university students' behavioral intention to use it for enhancing their ability to express Chinese culture in English. Accordingly, the following hypothesis is advanced:

H6: System quality positively affects students' behavioral intention to use generative AI for enhancing their ability to express Chinese culture in English.

3.5. The Mediating Role of Information Quality and Performance Expectancy in Behavioural Intention

The process of GenAI-assisted learning for expressing Chinese culture in English is, in essence, a transformation from individuals' cognitive evaluation of technological information output to behavioral motivation. Information quality, as a core attribute of technological output, provides students with a rational basis for assessing the value of the tool. Performance expectancy, as a key utility belief, assumes the mediating role of translating information cognition into behavioral intention. Drawing upon cognitive evaluation theory, which posits that individuals' rational assessment of technology functionality forms the basis for utility beliefs, the accuracy, depth, cultural appropriateness, and logical consistency of GenAI-generated information constitute the foundational elements of students' perceived tool value. This rational assessment is further internalized as a belief in tool utility, namely performance expectancy^[10].

In the process of translating information quality into behavioral intention, performance expectancy plays a critical mediating role. High-quality information does not directly drive usage intention; rather, it first strengthens students' recognition of the tool's utility in enhancing the ability to express Chinese culture in English, thereby converting external informational stimuli into internal psychological motivation, which subsequently drives the formation of behavioral intention. Specifically, information quality influences the cognitive judgment of whether the tool's output is reliable and useful, while performance expectancy influences the belief transformation of whether such usefulness can translate into motivation for use. Together, they constitute a transformation chain of information input, cognitive appraisal, and motivation formation^{[19][20]}. Based on this reasoning, the following hypotheses are proposed:

H7: Information quality positively affects performance expectancy.

H9: Performance expectancy mediates the relationship between information quality and behavioral intention.

3.6. The Mediating Role of System Quality and Effort Expectancy in Behavioural Intention

The process of GenAI-assisted learning for expressing Chinese culture in English is also inherently dependent on the influence of technological platform performance on users' ease-of-use perceptions and behavioral intention. System quality, as a core objective attribute of the technological platform, provides

the material foundation for students' formation of ease-of-use perceptions; Effort expectancy, as a key ease-of-use belief, assumes the mediating role of translating system performance experience into behavioral intention^[10]. Grounded in human-computer interaction and information systems research, which maintains that the objective performance characteristics of a technological platform serve as the material basis for shaping users' ease-of-use perceptions, GenAI's responsiveness, operational stability, interactional logic, and fault tolerance constitute the foundational elements of students' perceived operational convenience^[8]. This intuitive experience of technological performance is further internalized as a belief in the tool's ease of use, that is, effort expectancy.

In the process of translating system quality into behavioral intention, effort expectancy plays a significant mediating role. Superior system performance does not directly drive usage intention; rather, it first provides a smooth, effortless, and low-frustration user experience, thereby strengthening students' recognition of the technology as easy to master and use, converting external technical performance advantages into internal psychological acceptance, and subsequently lowering usage barriers and psychological resistance, which in turn drives the formation of behavioral intention. System quality influences the experiential judgment of whether the tool is convenient and reliable to operate, while effort expectancy influences the belief transformation of whether such convenience can translate into motivation for use. Together, they form a transformation chain from system input to experiential perception and then to motivation formation. Based on this reasoning, the following hypotheses are proposed:

H8: System quality positively affects effort expectancy.

H10: Effort expectancy mediates the relationship between system quality and behavioral intention.

In accordance with the variables and their relationship, the following research model and hypotheses are presented (Figure 1).

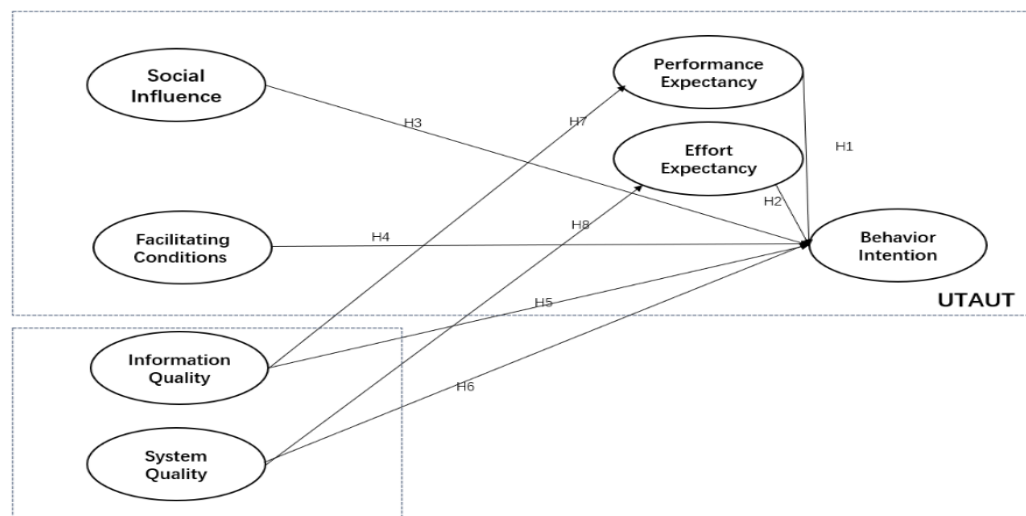


Fig 1. Research model and hypotheses.

4. Research Design

4.1. Research Participants

This study targeted English-major students at Panzhuhua University. Following the principle of convenience random sampling, a total of 600 questionnaires were distributed to the participants via the online survey platform Wenjuanxing. After screening out responses with abnormal completion times, patterned or regular answering, and invalid data, 521 valid questionnaires were retained, yielding an effective response rate of 86.83%.

4.2. Research Instruments

This study aimed to investigate the factors influencing university students' continuous use intention

of generative artificial intelligence (GenAI) to enhance their English expression ability regarding Chinese culture. To ensure the reliability and validity of the research data, the main body of the questionnaire was designed using structured scales. All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The scale design in this study primarily integrated constructs from classical technology acceptance theories and the information system success model. Specifically, the five core variables including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI), were adapted from the classic UTAUT model scale developed by Venkatesh et al. (2003) and were further informed by the subsequent research of Venkatesh and Xu (2012)^{[8][21]}. These scales have been extensively validated in the field of information technology adoption, demonstrating high authority and generalizability. Furthermore, considering the characteristics of GenAI as an information system and drawing on established authoritative studies, this research introduced two additional key variables: Information Quality (IQ) and System Quality (SQ). The measurement items for these variables were primarily derived from the scales employed by Kim et al. (2010) and Zhou (2013)^{[22][23]} in their studies on continuance intention in information systems. The specific items and their corresponding sources are presented in Table 1.

The questionnaire consisted of two sections. The first section gathered basic demographic information of the sample, including their major and grade. The second section investigated the influencing factors, comprising 23 items distributed across seven variables: Performance Expectancy (4 items), Effort Expectancy (3 items), Social Influence (3 items), Facilitating Conditions (4 items), Behavioral Intention (3 items), Information Quality (3 items), and System Quality (3 items).

Table 1. Measurement Items and Sources.

Construct	Item Code(s)	Source(s)
Performance Expectancy (PE)	PE1–PE4	Venkatesh et al. (2003); Venkatesh & Xu (2012) ^{[8][21]}
Effort Expectancy (EE)	EE1–EE3	Venkatesh et al. (2003); Venkatesh & Xu (2012) ^{[8][21]}
Social Influence (SI)	SI1–SI3	Venkatesh et al. (2003); Venkatesh & Xu (2012) ^{[8][21]}
Facilitating Conditions (FC)	FC1–FC4	Venkatesh et al. (2003); Venkatesh & Xu (2012) ^{[8][21]}
Behavioral Intention (BI)	BI1–BI3	Venkatesh et al. (2003); Venkatesh & Xu (2012) ^{[8][21]}
Information Quality (IQ)	IQ1–IQ3	Kim et al. (2010); Zhou (2013) ^{[22][23]}
System Quality (SQ)	SQ1–SQ3	Kim et al. (2010); Zhou (2013) ^{[22][23]}

4.3. Data Analysis Methods

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 software to examine the quality of the measurement model, test the path relationships among variables, and further verify the mediating effects. In the measurement model assessment, convergent validity was evaluated through composite reliability (CR), average variance extracted (AVE), and standardized factor loadings. Discriminant validity was examined using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlations. The structural model was assessed by examining the significance of path coefficients, the coefficient of determination (R^2), and the effect size (f^2) to evaluate the direct effects among variables. Mediation effects were tested using the bootstrap method with 5,000 resamples, and the significance of indirect paths was determined using bias-corrected 95% confidence intervals.

5. Research Results

5.1. Reliability Analysis

Reliability analysis was conducted to examine the internal consistency of the scale indicators. As shown in Table 2, the Cronbach's Alpha coefficients for all latent variables ranged from 0.841 to 0.939, exceeding the recommended threshold of 0.70^[24]. To further validate the reliability, composite reliability values were also reported, which ranged from 0.904 to 0.956, well above the suggested criterion of 0.70. These results consistently indicate that the measurement model possesses a high degree of internal consistency and reliability.

Table 2. Results of Reliability and Convergent Validity.

Construct	Cronbach's Alpha	Composite Reliability (rho _a)	Composite Reliability (rho _c)	AVE
Behavioral Intention	0.898	0.898	0.936	0.831
Effort Expectancy	0.841	0.848	0.904	0.760
Facilitating Conditions	0.908	0.911	0.935	0.783
Information Quality	0.907	0.908	0.942	0.844
Performance Expectancy	0.939	0.939	0.956	0.844
Social Influence	0.920	0.922	0.949	0.862
System Quality	0.902	0.902	0.938	0.836

5.2. Validity Analysis

Validity analysis included both convergent validity and discriminant validity. As presented in Table 2, the Average Variance Extracted (AVE) values for all latent variables ranged from 0.759 to 0.862, all exceeding the threshold of 0.50^[25]. This indicates that each latent variable can explain more than half of the variance in its corresponding indicators, confirming that the measurement model demonstrates satisfactory convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of the AVE for each construct be greater than its correlations with all other constructs^[25]. As shown in Table 3, the square roots of the AVEs (presented in bold on the diagonal) were substantially greater than the off-diagonal elements (correlation coefficients) in their corresponding rows and columns, providing strong evidence for the discriminant validity of the measurement model^[25].

Table 3. Discriminant Validity Assessment: Fornell-Larcker Matrix.

Construct	BI	EE	FC	IQ	PE	SI	SQ
Behavioral Intention (BI)	0.911						
Effort Expectancy (EE)	0.545	0.872					
Facilitating Conditions (FC)	0.705	0.754	0.885				
Information Quality (IQ)	0.785	0.571	0.698	0.919			
Performance Expectancy (PE)	0.680	0.540	0.594	0.673	0.919		
Social Influence (SI)	0.655	0.658	0.725	0.665	0.605	0.928	
System Quality (SQ)	0.770	0.636	0.756	0.802	0.645	0.670	0.914

Note: Bold values on the diagonal represent the square roots of the AVE for each latent variable.

5.3. Structural Model and Hypothesis Testing

After confirming that the measurement model possessed adequate reliability and validity, this study further evaluated the structural model to test the proposed research hypotheses. The bootstrap resampling method (with 5,000 subsamples) was employed to examine the statistical significance of the path coefficients.

5.3.1 Direct Effects and Hypothesis Testing

The hypothesis test results for the direct paths are summarized in Table 4. Path coefficients were considered statistically significant when the t-statistic exceeded 1.96 (two-tailed test, significance level $\alpha = 0.05$).

The direct path analysis revealed that Information Quality ($\beta = 0.323$, $p < 0.001$) was the primary predictor of Behavioral Intention, surpassing the influence of System Quality ($\beta = 0.251$, $p < 0.001$), Performance Expectancy ($\beta = 0.190$, $p < 0.001$), and Facilitating Conditions ($\beta = 0.193$, $p < 0.01$). A critical finding was that Effort Expectancy exerted a significant negative effect on Behavioral Intention ($\beta = -0.103$, $p < 0.05$), while the effect of Social Influence ($\beta = 0.085$, $p > 0.05$) was not significant. Furthermore, Information Quality and System Quality were confirmed to be key drivers shaping Performance Expectancy ($\beta = 0.673$, $p < 0.001$) and Effort Expectancy ($\beta = 0.636$, $p < 0.001$), respectively.

Table 4. Direct Path Hypothesis Testing Results.

Hypothesis	Path	Path Coefficient (β)	t-value	p-value	Conclusion
H1	PE $\rightarrow$ BI	0.190	4.303	< 0.001	Supported
H2	EE $\rightarrow$ BI	-0.103	2.488	0.013	Not Supported (opposite direction)
H3	SI $\rightarrow$ BI	0.085	1.753	0.080	Not Supported
H4	FC $\rightarrow$ BI	0.193	3.195	0.001	Supported
H5	IQ $\rightarrow$ BI	0.323	4.821	< 0.001	Supported
H6	SQ $\rightarrow$ BI	0.251	3.990	< 0.001	Supported
H7	IQ $\rightarrow$ PE	0.673	22.524	< 0.001	Supported
H8	SQ $\rightarrow$ EE	0.636	19.448	< 0.001	Supported

5.3.2 Mediation Effect Analysis

This study further examined the indirect paths through which Information Quality and System Quality influence Behavioral Intention via mediating variables. The results are presented in Table 5. The mediation analysis tested the mediating roles of Performance Expectancy and Effort Expectancy in the relationship between external technological attributes and Behavioral Intention. The results indicated that Performance Expectancy played a significant partial mediating role between Information Quality and Behavioral Intention (indirect effect = 0.128, VAF = 28.0%), thus supporting Hypothesis H9. Meanwhile, Effort Expectancy also played a significant partial mediating role between System Quality and Behavioral Intention (indirect effect = -0.065, VAF = 34.9%), supporting Hypothesis H10.

Table 5. Mediation Effect Testing Results.

Mediation Path	Indirect Effect	t-value	p-value	VAF	Conclusion
IQ $\rightarrow$ PE $\rightarrow$ BI	0.128	4.131	< 0.001	28.00%	Partial Mediation
SQ $\rightarrow$ EE $\rightarrow$ BI	-0.065	2.458	0.014	34.90%	Partial Mediation

5.3.3 Model Predictive Power and Effect Sizes

This study evaluated the predictive power of the structural model and the effect sizes of the predictors using R^2 and f^2 (Table 6). The model demonstrated strong explanatory power for the core dependent variable, Behavioral Intention, with an R^2 value of 0.711, indicating that the model explains 71.1% of the variance in Behavioral Intention. The R^2 values for Performance Expectancy and Effort Expectancy were also at acceptable to good levels. The effect size (f^2) analysis revealed that System Quality on Effort Expectancy ($f^2 = 0.679$) and Information Quality on Performance Expectancy ($f^2 = 0.829$) both exhibited large effect sizes.

Table 6. Predictive Power (R^2) and Effect Sizes (f^2).

Endogenous Variable	R^2	Adjusted R^2	Predictor	f^2
Behavioral Intention	0.711	0.708	Information Quality	0.108
			System Quality	0.059
			Facilitating Conditions	0.035
			Performance Expectancy	0.060
			Effort Expectancy	0.015
			Social Influence	0.010
Performance Expectancy	0.453	0.452	Information Quality	0.829
Effort Expectancy	0.404	0.403	System Quality	0.679

5.3.4 Overall Model Fit

Finally, the overall model fit was assessed to determine the degree of alignment between the theoretical model and the empirical data. The results are presented in Table 7. The Standardized Root Mean Square Residual (SRMR) was 0.088, which fell below the acceptable threshold of 0.10 indicating a good fit between the model and the data^[26].

Table 7. Overall Model Fit Indices.

Fit Index	Saturated Model	Estimated Model
SRMR	0.038	0.088
d ULS	0.401	2.142
d G	0.394	0.507
NFI	0.893	0.873

The model's explanatory power for Behavioral Intention reached 71.1% ($R^2 = 0.711$), demonstrating strong predictive accuracy. In empirical research, model explanatory power is often considered to have greater theoretical and practical value than absolute fit indices^[27]. Taking into account both the model's predictive capacity and fit indices, this study concludes that the theoretical model adequately fits the empirical data and that the findings are robust.

6. Discussion and Implications

6.1. Discussion

The extended UTAUT model developed in this study demonstrated strong explanatory power for behavioral intention ($R^2 = 0.711$), effectively addressing the research questions. The findings reveal the complex interplay between technological attributes and user cognition in the context of utilizing GenAI to achieve the specialized learning objective of enhancing English expression ability regarding Chinese culture. These findings are discussed below in relation to existing theoretical frameworks.

Information quality and system quality emerged as the strongest predictors of behavioral intention. This finding extends the DeLone & McLean (2003) Information Systems Success Model to the GenAI-assisted learning domain and is consistent with the findings of Qiu et al.^{[9][10]}. It suggests that in high-stakes learning contexts such as cross-cultural expression, users' decision-making is characterized by pronounced instrumental rationality. The underlying question in students' minds is not whether it is easy to use, but rather whether they can trust its output and rely on its performance. The accuracy, completeness, and cultural appropriateness of generated content, along with system reliability and responsiveness, constitute non-negotiable prerequisites for adoption. Deficiencies in any of these aspects may undermine cognitive trust and disrupt the immersive learning process, thereby weakening students' usage intentions. This indicates that for complex GenAI applications, technological credibility and substantive utility carry greater weight than mere ease of use in users' decision-making calculus.

Performance expectancy and facilitating conditions exerted significant positive direct effects, consistent with the UTAUT framework. The mediation analysis revealed the psychological mechanisms through which external attributes influence intention. Performance expectancy partially mediated the relationship between information quality and behavioral intention, establishing a clear transmission pathway: cognition, belief, and intention. This implies that high-quality information first shapes users' firm belief that the tool is useful, and this value belief subsequently serves as the primary psychological driver of usage intention. This pathway aligns with cognitive appraisal theory, which posits that individuals' rational evaluation of external stimuli (information quality) forms the basis for subsequent attitudes and behavioral intentions^{[28][29]}. The significance of facilitating conditions underscores that GenAI integration is not merely a tool issue but also an ecosystem issue. A supportive infrastructure encompassing knowledge, resources, and accessible assistance is critical for lowering adoption barriers.

A theoretically challenging finding was the significant negative effect of effort expectancy on behavioral intention, which challenges the core tenets of most technology acceptance models. Drawing on signaling theory and cognitive load theory, we offer a theoretical interpretation. In the high-cognitive-demand professional learning context of enhancing English expression ability regarding Chinese culture, student users hold high expectations regarding the functional depth and professional capacity of the tool. A GenAI interface perceived as overly simple or extremely easy to use may signal to users that the system has limited functionality and insufficient capacity to handle complex cultural concepts. Users may infer that the tool cannot meet their nuanced needs for expressive accuracy, depth of cultural connotation, and semantic subtlety. Conversely, an interface exhibiting "moderate complexity" or offering advanced customization options may convey a positive signal that the system is powerful, professional, and capable of sophisticated manipulation, thereby earning greater trust from professional learners and enhancing their usage intention^[29]. From the perspective of cognitive load theory, tasks requiring high-quality cultural output inherently consume substantial germane cognitive load for knowledge schema construction. A system that sacrifices powerful, fine-grained control functions in pursuit of extreme

simplicity may paradoxically increase extraneous cognitive load by failing to meet users' need for precise control, leading to frustration^[30]. This finding points to a boundary condition in the relationship between Effort expectancy and Behavioral intention, that is, in highly specialized and high-cognitive-demand learning contexts, this relationship may be nonlinear or even negative.

6.2. Implications

Based on the theoretical extensions and empirical mechanistic pathways identified in this study, and in consideration of the unique context of GenAI-assisted Chinese culture English expression learning, the following targeted recommendations are proposed to promote the deep integration of GenAI into foreign language teaching, enhance students' cross-cultural expression abilities and technological application literacy, and facilitate the high-quality digital transformation of foreign language education.

Enhancing technological quality entails building a GenAI tool ecosystem adapted to teaching scenarios. This study confirms that information quality and system quality are core prerequisites influencing students' technology adoption intentions. At the levels of technology development and educational application, efforts should focus on the dual core of cultural accuracy and functional professionalism to achieve precise alignment between GenAI tools and foreign language teaching scenarios. On the one hand, the cultural adaptability of information quality should be strengthened by integrating authoritative cross-cultural corpora and introducing cultural semantic verification mechanisms to ensure the reliability of generated content in terms of terminological accuracy, cultural connotation transmission, and pragmatic appropriateness, thereby avoiding cultural misinterpretation and expressive deviations. On the other hand, the stratified adaptability of system quality should be optimized by adhering to the principle of basic usability and advanced controllability, providing simple and intuitive interfaces for novice users while developing professional functions such as cultural style adjustment and semantic precision control for advanced users, in response to the nonlinear influence mechanism of effort expectancy. Meanwhile, technology iteration feedback channels should be established to incorporate the actual teaching needs of teachers and students, promoting the dynamic optimization of tool functions and teaching scenarios.

Cognitive reshaping is essential for cultivating scientific and proactive technology adoption attitudes. The empirical results illuminate the complex psychological mechanisms underlying students' technology adoption, specifically by revealing the mediating role of performance expectancy and the negative influence of effort expectancy. At the pedagogical level, efforts should extend beyond mere tool-use training to establish a guided pathway from value perception to belief internalization and then to practice transfer, thereby enhancing students' deep identification with GenAI and their scientific usage competence. First, the concrete perception of performance expectancy should be strengthened by developing an exemplary teaching case database and organizing theme-based hands-on activities, such as AI-assisted cultural expression exercises, to vividly demonstrate GenAI's practical value in precise vocabulary matching, sentence optimization, and cultural contextual adaptation. This approach enables students to tangibly perceive the technology's learning enhancement effects. Second, scientific perceptions of effort expectancy should be cultivated by challenging the oversimplified assumption that simpler is always better. Through thematic lectures and group seminars, students should be guided to recognize the professional functional value embedded in moderate complexity, to learn to employ advanced functions for addressing complex cultural expression challenges, and to transform cognitive load into momentum for capability enhancement. Third, peer learning communities should be established to encourage students to share technology use experiences and collaboratively tackle cross-cultural expression challenges. Such communities can compensate for the non-significant effect of social influence and foster a technology-use atmosphere characterized by active exploration and mutual progress.

Ecological empowerment entails improving multi-faceted institutional support mechanisms^[30]. The significant positive effect of facilitating conditions indicates that a comprehensive support system is the key underpinning for technology implementation. Educational administrative departments and universities should collaboratively construct a three-in-one guarantee system encompassing resources, practice, and institutions, to achieve the goal of enabling students to effectively use tools for improvement. In terms of resource support, the provision of facilitating conditions should be optimized to ensure that students have stable technology access and sufficient learning time, and that online-offline integrated technical guidance platforms are established to promptly address operational questions and functional demands arising during student use. In terms of practical support, the systematic integration of GenAI into foreign language teaching curricula should be promoted, with technology application embedded in instructional design, classroom practice, and assessment and evaluation. Project-based tasks grounded in

authentic teaching scenarios should be developed to facilitate students' internalization of technological tools as learning strategies. In terms of institutional support, ethical norms and data security standards for GenAI use should be established, clarifying students' rights and responsibilities in information use and content creation. Simultaneously, innovation incentive mechanisms should be established to encourage teachers and students to explore new models of integrating technology with cross-cultural teaching, thereby constructing a safe, orderly, and efficient technology application ecosystem.

7. Limitations and Future Research

This study has several limitations that merit attention in future research. First, the sample was drawn exclusively from English-major students at a single university. While this ensured the specificity of the research context, the representativeness of the sample and the generalizability of the findings require further verification. Future research could expand the scope to include students from different regions, different types of institutions, and different academic backgrounds, thereby enhancing the external validity of the results. Second, this study employed a cross-sectional design, which could not capture the dynamic evolution of relationships among variables. The cognitive changes and behavioral adjustments that may result from GenAI technological iterations and the accumulation of student usage experience warrant further investigation through longitudinal tracking studies. Third, the variables examined in this study were confined to technological attributes and user cognition, without fully considering the potential moderating effects of learning motivation, cultural identity, and teacher guidance. Future research could construct more complex theoretical models to deepen the understanding of multi-factor interaction mechanisms. Fourth, this study relied primarily on quantitative analysis and lacked in-depth exploration of students' usage experiences, cognitive confusions, and needs. Subsequent research could incorporate qualitative methods such as semi-structured interviews and classroom observations to achieve complementarity between quantitative and qualitative approaches, thereby enhancing the comprehensiveness and practical guidance of the conclusions.

Future research may be extended in several directions. First, the differential mechanisms of various types of GenAI tools in cross-cultural language learning could be explored, including conversational AI and generative writing assistants. Second, the heterogeneous characteristics of technology adoption among students at different educational stages and with different language proficiency levels could be examined to provide a basis for stratified teaching support. Third, teaching intervention experiments could be conducted to verify the actual effects of instructional strategies and technology optimization plans based on the conclusions of this study, thereby promoting the translation of theoretical research into teaching practice.

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