DETERMINANTS OF STUDENTS' ACCEPTANCE AND USE OF DIGITAL CHINESE LEARNING APPLICATIONS: A UTAUT-BASED ANALYSIS AT A THAI PRIVATE UNIVERSITY

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Abstract

Purpose: This study examines the determinants of students' acceptance and use of digital Chinese learning applications in higher education. Despite growing adoption, evidence on technology acceptance among Thai university students remains limited, and prior studies report inconsistent effects of key UTAUT constructs. This study investigates how technological and social perceptions shape students' behavioral intention and actual use of these learning applications.

Study Design/Methodology/Approach: A quantitative survey was conducted with 243 undergraduate students at a private university in Thailand who had experience using digital Chinese learning applications. The questionnaire measured UTAUT constructs, and structural equation modeling examined direct and indirect relationships, including the mediating role of Behavioral Intention.

Findings: Effort Expectancy and Social Influence significantly and positively influence Behavioral Intention ($\beta = 0.4434$, $p < .001$; $\beta = 0.6599$, $p < .001$, respectively), with Social Influence exerting the strongest effect. In contrast, Performance Expectancy has a significant negative effect on Behavioral Intention. Behavioral Intention is the strongest predictor of Actual Use ($\beta = 0.9665$, $p < .001$), whereas Facilitating Conditions has no significant effect. Mediation analysis confirms that Behavioral Intention mediates the effects of Effort Expectancy and Social Influence on Actual Use. The indirect effect of Performance Expectancy is significant but negative.

Originality/Value: This study provides empirical evidence on Thai university students' acceptance of digital Chinese learning applications, a context that has received limited scholarly attention. The findings extend the UTAUT framework for mobile-assisted language learning by highlighting the dominant roles of social influence, usability, and intention formation over perceived usefulness, and offer practical implications for enhancing student engagement and optimizing the integration of digital language learning tools in higher education.

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Introduction

The rapid expansion of Chinese language learning worldwide has highlighted the growing importance of digital tools in supporting effective language acquisition. As China's global economic and cultural presence grows, Mandarin Chinese has become one of the most widely studied foreign languages globally, with demand increasing across many countries, including Thailand. Digital applications such as Duolingo, HelloChinese, HelloTalk, and WeChat-based tools are now commonly used to supplement classroom learning by providing varied practice in pronunciation, vocabulary, and sentence structures through interactive and self-paced activities. Gamified applications like Duolingo and HelloChinese provide structured lessons, pronunciation practice, and immediate feedback on interactive tasks (Li & O'Rourke, 2022; Puri et al., 2025). Communication-oriented platforms, such as HelloTalk and WeChat, enable authentic interaction with native speakers through text, voice, and multimedia messaging (Puri et al., 2025). These features allow learners to practice pronunciation, vocabulary, and syntax structures through both guided and self-paced activities.

Existing research provides strong evidence that digital learning applications can enhance a range of Chinese language skills. Ma (2024) reported that Quizlet significantly improved vocabulary retention and learner motivation through structured digital flashcards and spaced-repetition techniques. Likewise, Cheng (2024) demonstrated that WeChat-supported learning activities enhance students' speaking and reading proficiency by facilitating authentic communication and social interaction. A systematic review by Cao et al. (2025) confirmed that WeChat also contributes to reduced anxiety, stronger learner confidence, and richer multimodal learning experiences through its multimedia, messaging, and collaborative features. These findings collectively suggest that Mobile-Assisted Language Learning (MALL) environments offer meaningful opportunities for Chinese learners to engage in continuous and interactive practice beyond the traditional classroom.

In addition to pedagogical advantages, research on digital language learning increasingly draws on the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain students' adoption behavior. Chen and Zhao (2022) found that while mobile vocabulary applications were perceived as useful, ease of use and motivational design elements played a stronger role in shaping behavioral intention among Chinese learners. Meanwhile, Ke et al. (2025) further emphasized the importance of digital and AI literacy in strengthening university students' acceptance of educational technologies. Yet despite these insights, prior studies have reported inconsistent effects of Performance Expectancy and Facilitating Conditions across cultural and institutional settings, suggesting the need for additional context-specific research.

However, despite the growing international literature on MALL and UTAUT, empirical studies from Thailand—especially those focusing on Chinese language learning in private universities—remain limited.

Most regional studies instead examine English-language learning applications or general digital literacy, leaving a gap in understanding how Thai learners adopt digital Chinese learning applications. Additionally, the mediating role of Behavioral Intention, although theoretically central in UTAUT, has been insufficiently tested in mobile Chinese-learning environments. Emerging research also shows that Facilitating Conditions can have unexpected negative effects on Actual Use when excessive support undermines learner autonomy, as seen in studies of MALL engagement (Hwang et al., 2024) —a phenomenon not yet explored with Thai university students.

Given these gaps, the present study investigates the determinants of students' acceptance and actual use of digital Chinese learning applications at a Thai private university. Applying the UTAUT framework, the study examines both direct effects among key constructs—Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, and Actual Use—and indirect effects mediated by Behavioral Intention. The findings aim to extend empirical evidence on MALL adoption and support the development of more effective digital Chinese language-learning strategies within Thai higher education.

Objectives

The objectives of this study are as follows:

1. To examine the levels of acceptance and actual use of digital Chinese learning applications among students at a private university in Thailand.
2. To investigate the effects of Performance Expectancy, Effort Expectancy, and Social Influence on Behavioral Intention to use digital Chinese learning applications.
3. To determine the effects of Behavioral Intention and Facilitating Conditions on the Actual Use of digital Chinese learning applications.
4. To assess the mediating role of Behavioral Intention in the relationships among the UTAUT constructs and the actual use of the applications.

Literature Review

Digital Chinese Learning Applications in Thai Learners

Thai, which uses an abugida writing system, differs fundamentally from Chinese in several linguistic aspects. Although Thai is also a tonal language with five tones, Thai learners of Mandarin often experience persistent difficulties in perceiving and producing Mandarin tones, which may contribute to increased communicative anxiety. In addition, learning and processing Chinese characters pose substantial challenges for second-language learners due to the logographic writing system and the complex semantic structure of Chinese words, particularly in compound character forms (Jiang, 2018). Several studies have further reported that Thai students perceive writing Chinese characters as more difficult than writing English words (Guo & Lertlit, 2021; Xinyan & Kongjit, 2020).

Digital learning applications have demonstrated their effectiveness in supporting Chinese language learning. Interactive features such as speech recognition and gamified tasks in the Hong En literacy application have been shown to enhance Thai learners' listening proficiency (Wu et al., 2025). Quizlet has been found to improve vocabulary retention and learner motivation through spaced repetition and interactive flashcards (Ma, 2024). Similarly, the web-based tool stroke order has been shown to increase learners' writing speed, thereby supporting improvements in writing accuracy and learning motivation (Sun et al., 2026). Overall, the evidence indicates that digital applications play an important role in assisting Thai learners of Chinese.

Research trends also emphasize the psychological dimension of Digital learning applications. Hu et al. (2023) showed that flow experience and collaboration significantly increase continuance intention, suggesting motivation is a key component of sustained engagement with digital applications. Ye et al. (2025) reported that short video viewing and interaction stimulate the intrinsic motivation and self-efficacy of Thai students. These studies collectively demonstrate that digital Chinese learning tools provide pedagogical value across various skills and learning settings.

The varied features of these Chinese learning applications may influence learners' acceptance of technology. Functions such as stroke-order animation, voice recognition, and structured vocabulary exercises reduce the complexity of learning tones and characters, thereby enhancing perceived ease of use (Sun et al., 2026). This suggests that Effort Expectancy may play an important role in learning Chinese, a linguistically complex language that is different from Thai, a phonetic language. In addition, communication features in applications such as WeChat and HelloTalk may strengthen Social Influence (Wang & Jiang, 2025), while mobile accessibility and feedback functions contribute to Facilitating Conditions and Performance Expectancy. These relationships indicate that particular features of digital applications may shape learners' acceptance across the UTAUT framework.

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT proposes four determinants of technology acceptance: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Venkatesh et al., 2003). The model has been widely applied in educational technology, including mobile language learning. Findings related to Performance Expectancy remain mixed. Chen and Zhao (2022) found that usefulness was less influential than motivational and ease-of-use factors in gamified Chinese vocabulary learning. Effort Expectancy has consistently been identified as a strong predictor of behavioral intention, implying that ease of use reduces cognitive load and enhances willingness to adopt digital tools (Venkatesh et al., 2003; Hoi, 2020). Social Influence is particularly influential in collectivist cultures. Cheng (2024) found that teacher guidance and peer support significantly shape participation in WeChat-based learning. Similarly, Ke et al. (2025) emphasized that social expectations strongly predict adoption of digital learning platforms.

Facilitating Conditions traditionally predict system use, but recent studies suggest more complex outcomes. Hwang et al. (2024) observed that excessive external support in MALL may reduce autonomous

use when learners depend too heavily on institutional resources. This signals a need to revisit UTAUT assumptions in different learning contexts.

This study adopts the original UTAUT model (Venkatesh et al., 2003) rather than UTAUT2, as the additional constructs in UTAUT2 (e.g., hedonic motivation, price value, and habit) are more relevant to consumer behavior contexts. The original model is considered more appropriate for examining technology acceptance in educational settings (Venkatesh et al., 2012).

Empirical Studies on Acceptance of Digital Language Learning Tools

Numerous studies examine MALL. Burston (2015) reviewed MALL advances and highlighted its potential in improving language skills. Hoi (2020) found that perceived usefulness and ease of use strongly predicted mobile language learning acceptance among higher education learners.

Collaboration and communication via WeChat also emerge as key factors in digital Chinese learning success. Dimov and Mutti (2023) described how WeChat supports language interaction and strengthens vocabulary retention through peer engagement. Li (2023) demonstrated that WeChat-based vocabulary modules promote long-term retention. These findings underscore the necessity of evaluating both technological and social determinants in examining learners' acceptance of digital tools.

Research Gap

While numerous studies confirm the pedagogical benefits of digital Chinese learning tools, very few investigations focus on Thai learners' acceptance of these applications. Existing research insufficiently covers how technological perceptions, social contexts, and support environments jointly affect acceptance of Chinese learning applications.

Additionally, inconsistent findings regarding Performance Expectancy and Facilitating Conditions indicate the need to reassess these constructs in different cultural settings. Although Behavioral Intention is theorized to mediate relationships in UTAUT, empirical evidence in mobile Chinese learning remains limited. Therefore, this study fills the gap by applying UTAUT to examine both direct and indirect effects among technological and social determinants influencing acceptance and actual use of digital Chinese learning applications among Thai university students.

The conceptual framework of this study is based on the UTAUT model, in which Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions influence Behavioral Intention and Actual Use. Behavioral Intention is also proposed as a mediating variable between the independent variables and Actual Use.

Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and prior literature on technology acceptance and mobile-assisted language learning, the following hypotheses are proposed:

H1: Performance Expectancy positively affects Behavioral Intention.

H2: Effort Expectancy positively affects Behavioral Intention.

H3: Social Influence positively affects Behavioral Intention.

H4: Behavioral Intention positively affects Actual Use.

H5: Facilitating Conditions positively affect Actual Use.

Methodology

This study employed a quantitative survey design to investigate the determinants of students' acceptance and actual use of digital Chinese learning applications. The participants consisted of 243 students at a private university in Thailand who reported using digital Chinese learning applications. Convenience sampling was used due to easy accessibility to the target population. Convenience sampling is widely adopted in exploratory technology-acceptance research because of its practicality and efficiency in obtaining participants from accessible groups (Fowler Jr, 2009; Leedy & Ormrod, 2019).

Sample Size Justification

The adequacy of the sample size was supported by SEM guidelines. According to Hair et al. (2006), covariance-based SEM generally requires a minimum of 200 participants and 10-20 respondents per observed indicator to ensure sufficient statistical power and model stability. With 19 observed indicators in the UTAUT-based measurement model, the recommended sample size ranges from 190 to 380 participants. Therefore, the sample of 243 respondents meets these requirements. In addition, prior methodological literature suggests that CB-SEM typically requires at least 200 cases for models involving multiple constructs and structural relationships (Hair et al., 2006). The sample size used in this study exceeds this threshold, supporting the adequacy of the data for SEM analysis.

Research Instrument

The questionnaire consisted of 19 items across six constructs: Performance expectancy (3 items), Effort expectancy (3 items), Social influence (4 items), Facilitating conditions (3 items), Behavioral intention (3 items), and Actual use (3 items). Representative items include "Using digital applications helps me learn Chinese more effectively" and "I plan to use these applications for learning Chinese in the future". All items were adapted from Venkatesh et al. (2003) and reworded to reflect the context of digital Chinese learning applications among Thai university students. Responses were measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Measurement Model

The measurement model was assessed using Confirmatory Factor Analysis (CFA), and the results indicated an acceptable model fit (CFI = 0.950, TLI = 0.940, SRMR = 0.039, RMSEA = 0.084). Reliability was confirmed using Cronbach's alpha, with all constructs exceeding the recommended threshold of 0.70 (Hair et al., 2006). Construct validity was supported by standardized factor loadings ranging from 0.746 to 0.933, exceeding the recommended minimum of 0.70 and indicating adequate indicator reliability. Convergent validity was further supported by Average Variance Extracted (AVE) values above 0.50 for all constructs, while discriminant validity was assessed using the HTMT criterion.

Data Collection Procedures

Data was collected online through course communication channels. Students were informed of the study purpose and provided voluntary participation and confidentiality assurances. Responses were screened for completeness before analysis. Missing data were examined prior to analysis and found to be minimal; therefore, listwise deletion was applied.

Ethical considerations were carefully addressed in this study. Participation was voluntary, and all respondents were informed of the purpose of the research prior to data collection. No personally identifiable information was collected, and responses were analyzed in aggregate to ensure anonymity and confidentiality. Participants were free to withdraw from the study at any time without any consequences. The study involved minimal risk and adhered to standard ethical principles for survey-based research involving human participants.

Data Analysis

Data analysis was conducted using Jamovi. Descriptive statistics were used to summarize demographic characteristics and construct-level mean scores. The analysis followed a two-step approach. First, CFA was conducted to evaluate the measurement model, including factor loadings, internal consistency reliability, convergent validity, and discriminant validity. Second, Structural Equation Modeling (SEM) was applied to examine the relationships among constructs, as it enables the simultaneous estimation of measurement and structural models and is widely used in technology-acceptance research (Hair et al., 2006).

Model fit was assessed using standard indices, including CFI, TLI, RMSEA, and SRMR. Factor loadings, internal consistency reliability, and overall model fit were evaluated in accordance with accepted covariance-based SEM assessment guidelines (Hair et al., 2006; Kline, 2023). Behavioral Intention was further analyzed as a mediator of the effects of Performance Expectancy, Effort Expectancy, and Social Influence on Actual Use.

Common method bias was assessed using Harman's single-factor test. The first factor accounted for 63.6% of the total variance, which exceeds the recommended threshold of 50%, indicating the possible presence of common method bias. Therefore, the results should be interpreted with caution. However, additional evidence from confirmatory factor analysis showed that the measurement model demonstrated acceptable validity and model fit, suggesting that the observed relationships remain meaningful within the context of the study. In addition, respondents were assured of anonymity and confidentiality, and the questionnaire used previously validated constructs adapted to the study context.

Results

This section presents the findings of the descriptive analysis, measurement model evaluation, and hypothesis testing. The results are organized to address the research objectives and the proposed UTAUT relationships.

Descriptive Statistics

Descriptive analysis was conducted to examine students' perceptions of the UTAUT constructs. As shown in Table 1, students reported consistently high levels across all constructs. Facilitating Conditions (FC) had the highest mean score ($\bar{x}$ = 4.185, SD = 0.906), indicating that students perceived strong technological and resource support. Behavioral Intention (BI) ($\bar{x}$ = 4.095, SD = 0.870), Performance Expectancy (PE) ($\bar{x}$ = 4.054, SD = 0.920), and Effort Expectancy (EE) ($\bar{x}$ = 4.011, SD = 0.916) also received high ratings. Social Influence (SI) ($\bar{x}$ = 3.931, SD = 0.917) and Actual Use (AU) ($\bar{x}$ = 3.948, SD = 0.992) recorded slightly lower means but remained above the scale midpoint.

Table 1 Mean and Standard Deviation of UTAUT Constructs

Construct	Mean	SD
Performance Expectancy (PE)	4.054	0.920
Effort Expectancy (EE)	4.011	0.916
Social Influence (SI)	3.931	0.917
Facilitating Conditions (FC)	4.185	0.906
Behavioral Intention (BI)	4.095	0.870
Actual Use (AU)	3.948	0.992

Measurement Model Assessment

Construct validity and reliability were evaluated before testing the structural model. All items demonstrated strong standardized factor loadings ranging from 0.746 to 0.933, exceeding the recommended threshold of 0.70. Reliability analysis showed excellent internal consistency, with Cronbach's alpha values above 0.70 for all constructs.

Table 2 AVE and Square Root of AVE

Construct	AVE	√AVE
PE	0.817	0.904
EE	0.772	0.879
SI	0.732	0.856
FC	0.744	0.863
BI	0.796	0.892
AU	0.814	0.902

Convergent validity was further supported by AVE values ranging from 0.732 to 0.817, all of which exceeded the recommended threshold of 0.50. These results confirm that the measurement model adequately represents the underlying UTAUT variables and demonstrates satisfactory reliability and validity.

Table 3 Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	PE	EE	SI	FC	BI	AU
PE	**0.904**	0.848	0.830	0.758	0.690	0.694
EE		**0.879**	0.829	0.902	0.788	0.735
SI			**0.854**	0.789	0.820	0.834
FC				**0.862**	0.791	0.669
BI					**0.892**	0.891
AU						**0.903**

Remarks: Diagonal values represent √AVE; off-diagonal values represent inter-construct correlations.

Discriminant validity was initially assessed using the Fornell–Larcker criterion, which indicated potential concerns as several inter-construct correlations exceeded the square root of AVE. To address this limitation, the Heterotrait–Monotrait (HTMT) ratio was employed as a more robust assessment. As shown in Table 4, most HTMT values were below the recommended threshold of 0.90, although the value between EE and FC slightly exceeded the threshold (0.906), suggesting a potential overlap between these constructs. However, given that the majority of construct pairs met the HTMT criterion and the theoretical distinction between constructs is well established in the UTAUT framework, discriminant validity was considered acceptable for the purposes of this study.

Table 4 Heterotrait–Monotrait Ratio of Correlations (HTMT)

Construct	PE	EE	SI	FC	BI	AU
PE	-	0.852	0.835	0.769	0.697	0.694
EE	0.852	-	0.830	0.906	0.792	0.739
SI	0.835	0.830	-	0.784	0.824	0.838
FC	0.769	0.906	0.784	-	0.799	0.673
BI	0.697	0.792	0.824	0.799	-	0.887
AU	0.694	0.739	0.838	0.673	0.887	-

Remarks: HTMT values below 0.90 indicate acceptable discriminant validity.

Discriminant validity was further assessed using the HTMT criterion. As shown in Table 4, most HTMT values were below the recommended threshold of 0.90, although the value between EE and FC slightly exceeded the threshold (0.906), indicating potential overlap between these constructs.

Structural Model Evaluation

The structural model demonstrated an acceptable fit, with key fit indices within acceptable ranges (CFI = 0.950, TLI = 0.940, SRMR = 0.039, RMSEA = 0.084). These results indicate that the model provides an adequate representation of the data and is suitable for examining the hypothesized relationships among the constructs.

Direct Effects

Table 5 presents the results of hypothesis testing for direct effects. SI and EE emerged as significant predictors of BI. SI had the strongest positive effect ($\beta = 0.6599$, $p < .001$), followed by EE ($\beta = 0.4434$, $p < .001$). In contrast, PE showed a significant negative effect on BI ($\beta = -0.2134$, $p = 0.030$).

BI was the strongest determinant of AU ($\beta = 0.9665$, $p < .001$). FC did not have a significant effect on AU ($\beta = -0.0735$, $p = 0.265$), indicating that perceived support does not significantly influence students' actual usage of digital Chinese learning applications.

Table 5 Direct Effects Among UTAUT Constructs

Path	*β*	*p*-value	Result
PE → BI	-0.2134	0.030	Not supported (negative relationship observed)
EE → BI	0.4434	< .001	Supported
SI → BI	0.6599	< .001	Supported
BI → AU	0.9665	< .001	Supported
FC → AU	-0.0735	0.265	Not supported

Indirect Effects

The mediation analysis examined whether BI mediated the effects of PE, EE, and SI on AU. As shown in Table 6, BI significantly mediated the relationships between EE and AU ($\beta = 0.4286$, $p < .001$) and between SI and AU ($\beta = 0.6378$, $p < .001$). In contrast, the indirect effect of PE on AU through BI was significant but negative ($\beta = -0.2063$, $p = 0.032$), indicating that higher perceived usefulness may reduce intention and, consequently, actual usage in this context.

Table 6 Indirect Effects via BI

Indirect Path	*β*	*p*-value	Result
PE → BI → AU	-0.2063	0.032	Not supported (negative relationship observed)
EE → BI → AU	0.4286	< .001	Supported
SI → BI → AU	0.6378	< .001	Supported

Overall, the findings highlight the central role of Behavioral Intention in shaping students' actual use of digital Chinese learning applications. Social Influence and Effort Expectancy were the strongest predictors of Behavioral Intention, with Social Influence exerting the greatest influence. In contrast, Performance Expectancy showed a significant negative effect on Behavioral Intention, indicating that perceived usefulness may not necessarily encourage intention to use in this context.

Behavioral Intention emerged as the strongest determinant of Actual Use, confirming its key role in driving actual behavior. Facilitating Conditions did not have a significant direct effect on Actual Use, suggesting that perceived support does not play a decisive role in influencing students' usage of digital Chinese learning applications.

Furthermore, Behavioral Intention significantly mediated the effects of Effort Expectancy and Social Influence on Actual Use. The indirect effect of Performance Expectancy on Actual Use through Behavioral Intention was also significant but negative, reflecting the negative relationship between Performance Expectancy and Behavioral Intention.

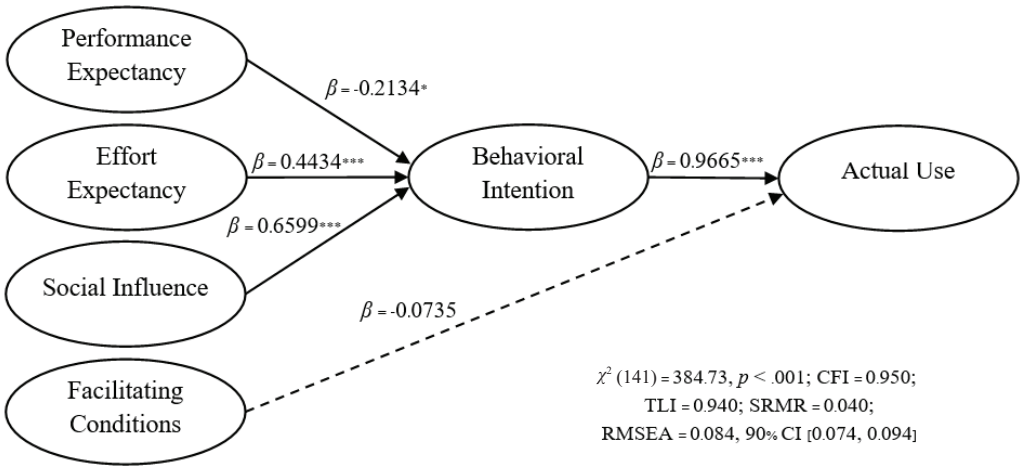


Figure 1 Structural Model with Standardized Path Coefficients

Remarks: Standardized coefficients shown; * $p < .05$, ** $p < .01$, *** $p < .001$.

Discussion

The findings of this study provide important insights into the determinants of students' acceptance and use of digital Chinese learning applications within the UTAUT framework (Venkatesh et al., 2003). Overall, the results both support and extend existing literature in technology acceptance and mobile-assisted language learning contexts.

The results indicate that both Social Influence and Effort Expectancy significantly and positively influence Behavioral Intention. This is consistent with the UTAUT model, which highlights the importance of social factors and perceived ease of use in shaping users' intention to adopt technology (Venkatesh et al., 2003). Similarly, Effort Expectancy has been widely recognized as a key determinant of Behavioral Intention in both UTAUT and TAM, where ease of use reduces cognitive effort and increases willingness to engage with technology (Davis, 1993). Empirical evidence from mobile-assisted language learning contexts also supports this relationship, indicating that user-friendly systems enhance learners' intention to use digital applications (Hwang et al., 2024).

In contrast to most prior studies, Performance Expectancy was found to have a significant negative effect on Behavioral Intention. This finding challenges the traditional assumption that perceived usefulness positively influences technology adoption (Davis, 1993; Venkatesh et al., 2003). Also, this finding may reflect unmet expectations or a mismatch between perceived usefulness and actual learning experience. This interpretation is consistent with studies suggesting that perceived usefulness alone may not be sufficient to sustain engagement if it does not align with actual user experience (Li, 2023).

The analysis further shows that Behavioral Intention was the strongest predictor of Actual Use, as indicated by the largest standardized path coefficient, which is consistent with both UTAUT and TAM. These frameworks emphasize that intention is the most direct determinant of behavior (Davis, 1993; Venkatesh et al., 2003). This finding is also supported by research in mobile-assisted language learning, which demonstrates that higher levels of intention lead to greater engagement and sustained usage of learning applications (Hwang et al., 2024).

However, Facilitating Conditions were found to have no significant effect on Actual Use. This result suggests that facilitating conditions may not directly influence usage behavior in contexts where access to technology and infrastructure is already widespread. As students already possess sufficient access to devices and internet connectivity, external support systems may not play a decisive role in determining whether they use digital learning applications. This finding is consistent with recent research indicating that the importance of facilitating conditions may diminish in highly digitalized environments where technological access is no longer a major barrier (Hwang et al., 2024). This finding may also be interpreted through the lens of self-determination theory, which suggests that excessive external support can undermine learners' sense of autonomy, thereby reducing intrinsic motivation to engage in self-directed learning activities.

In addition, the mediation analysis confirms that Behavioral Intention plays a crucial role in translating Effort Expectancy and Social Influence into Actual Use. This supports the theoretical assumption of UTAUT that intention functions as a key mediating mechanism between external factors and user behavior (Venkatesh et al., 2003). Meanwhile, the indirect effect of Performance Expectancy was also significant but negative, reflecting the same pattern observed in the direct relationship and reinforcing the complexity of users' perception of usefulness in this context.

In summary, this study confirms the importance of Social Influence, Effort Expectancy, and Behavioral Intention in explaining technology adoption in digital language learning. At the same time, it provides new evidence that challenges traditional assumptions regarding Performance Expectancy and Facilitating Conditions. These findings highlight that technology acceptance is context-dependent and influenced by users' expectations, experiences, and learning environments. The strong relationship between Behavioral Intention and Actual Use may also reflect a high degree of conceptual proximity between the constructs and should be interpreted with caution.

Conclusions

This study explored the factors influencing students' acceptance and actual use of digital Chinese learning applications in a private university in Thailand, using the UTAUT framework as the theoretical foundation. The findings clearly highlight the central role of Behavioral Intention, which emerged as the strongest predictor of Actual Use. In particular, Social Influence and Effort Expectancy were found to significantly shape students' intention to use the applications, with Social Influence showing the strongest

effect. This suggests that peer and social environments, together with ease of use, play a crucial role in encouraging students to engage with digital language learning tools.

On the other hand, Performance Expectancy was found to have a significant but negative effect on Behavioral Intention. This indicates that perceived usefulness alone may not always encourage adoption, especially when users' expectations do not align with their actual experience. In addition, Facilitating Conditions did not significantly influence Actual Use. These findings challenge traditional assumptions within the UTAUT framework and suggest that, in highly accessible technological environments, external support may no longer be a decisive factor in driving usage behavior.

The mediation analysis further reinforces the importance of Behavioral Intention, showing that it acts as a key mechanism through which Effort Expectancy and Social Influence translate into Actual Use. At the same time, the indirect effect of Performance Expectancy was significant but negative, reflecting the same pattern observed in the direct relationship. This highlights the complexity of user perceptions in digital learning contexts.

Overall, this study contributes empirical evidence to the growing literature on technology acceptance and digital language learning, particularly in the context of Asian higher education. The findings suggest that social influence, usability, and intention formation are more influential than perceived usefulness in shaping students' behavior. These insights offer practical implications for educators, curriculum designers, and application developers, emphasizing the need to design user-friendly systems, create supportive social learning environments, and focus on enhancing students' intention to engage with digital learning tools.

Limitations

This study has several limitations that should be considered when interpreting the findings. First, the use of convenience sampling and data collection from a single private university may limit the generalizability of the results to other educational contexts. Second, the study relied on self-reported data, including the measurement of Actual Use, which may be subject to response bias. Third, the cross-sectional design does not allow for causal inferences over time. In addition, although common method bias was assessed and procedural remedies were applied, the relatively high variance explained by a single factor suggests that potential bias cannot be entirely ruled out. Finally, some constructs exhibited high inter-correlations, indicating possible conceptual overlap, which should be interpreted with caution. Future studies may employ longitudinal designs and multi-source data to further validate the causal relationships identified in this study.

Recommendations

Recommendations for Educators

1. Strengthen social influence within the learning environment: As Social Influence was the strongest predictor of Behavioral Intention, instructors should actively promote the use of digital Chinese learning applications during classroom activities. Peer-based approaches—such as group tasks, collaborative

exercises, or shared learning progress—can help build a supportive learning environment and motivate students to engage more consistently with the applications.

2. Provide structured app-based learning activities: Since Behavioral Intention strongly predicted Actual Use, integrating app-based tasks into the curriculum (e.g., weekly vocabulary assignments, tone practice logs, or character recognition exercises) can help reinforce intention and convert it into actual behavior. Applications with structured learning paths, progress tracking, and assignment-friendly features may better support such integration.

3. Support ease of use through initial guidance: Given the significant effect of Effort Expectancy, educators should ensure that students feel comfortable using the applications. Short demonstrations, onboarding sessions, or guided practice at the beginning can reduce uncertainty and help students use digital tools more confidently. Instructors should also select applications with clear instructions, simple navigation, and built-in tutorials to further reduce perceived effort.

Recommendations for Application Developers

1. Prioritize usability and simplicity: Developers should focus on creating intuitive and user-friendly interfaces to enhance Effort Expectancy. Clear navigation, simple layouts, and guided features such as tutorials or step-by-step instructions can improve the overall learning experience.

2. Incorporate social learning features: Given the importance of Social Influence, integrating social components—such as collaborative tasks, leaderboards, message boards, or peer challenges—may increase learners' motivation and help sustain long-term application use.

3. Make learning outcomes more visible: Since performance expectancy showed a negative effect on Behavioral Intention, applications should better communicate their value to users. Features such as progress tracking, immediate feedback, and visible learning achievements can help users clearly see the benefits of using the application.

Recommendations for Institutions

1. Encourage autonomous learning: As facilitating conditions were not found to significantly influence Actual Use, institutions should avoid over-reliance on external support systems. Instead, they should promote self-directed learning while providing support only when necessary.

2. Promote digital learning engagement: Institutions can foster stronger engagement by encouraging the use of digital learning tools as part of the learning culture. This may include integrating digital applications into courses or recognizing students who actively engage with them.

3. Provide reliable but non-intrusive support: Rather than expanding technical support beyond necessity, institutions should focus on ensuring stable internet access, up-to-date devices, and accessible help desks-all of which support learning without diminishing students' reliance on the applications themselves.

Recommendations for Future Implementation

1. Integrate applications into course planning: Digital Chinese language courses should be designed

to include application-based practice as a standard component, ensuring alignment between classroom instruction and digital learning tasks.

2. Monitor usage to improve learning outcomes: Educators and institutions can review students' usage patterns to better understand engagement levels and identify areas for improvement. This can help refine teaching strategies and enhance the effectiveness of digital learning over time.

Appendix A: Measurement Items

All measurement items were derived and adapted from the original UTAUT instrument and modified to fit the context of digital Chinese learning applications. Responses were measured using a five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree).

Table 7 Measurement Items of UTAUT Constructs

Construct	Code	Measurement Item
Performance Expectancy (PE)	PE1	Using digital applications helps me learn Chinese more effectively
	PE2	Digital applications help me achieve my Chinese learning goals more quickly
	PE3	Using applications helps me understand Chinese lessons better than traditional learning methods
Effort Expectancy (EE)	EE1	Learning Chinese through digital applications is easy for me
	EE2	I find these applications uncomplicated and easy to understand
	EE3	I can learn how to use the applications for learning Chinese by myself
Social Influence (SI)	SI1	Important people in my life (such as teachers, friends, or family) think that I should use applications to learn Chinese
	SI2	My classmates often use digital applications to learn Chinese
	SI3	I feel encouraged by people around me to use technology to improve my Chinese skills
	SI4	The popularity of other users influences my decision to use Chinese learning applications
Facilitating Conditions (FC)	FC1	I have devices (such as a smartphone or tablet) that allow me to conveniently use applications for learning Chinese
	FC2	I have sufficient internet access to use applications for learning Chinese
	FC3	If I encounter problems while using the applications, I can find help or guidance
Behavioral Intention (BI)	BI2	I plan to use these applications for learning Chinese in the future
	BI3	If there are new applications related to learning Chinese, I am willing to try them
	BI4	Overall, I intend to make digital technology a part of my Chinese language learning
Actual Use (AU)	AU2	I use Chinese learning applications to review vocabulary or previous lessons regularly
	AU3	I often use applications to improve my Chinese listening, speaking, reading, and writing skills
	AU4	Using digital applications has become a part of my routine for learning Chinese

Remarks: All measurement items were derived and adapted from Venkatesh et al. (2003) and modified to reflect the context of digital Chinese learning applications.

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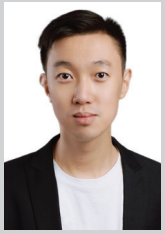
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