

University Students' Intention to Use the Chaoxing Smart Learning Platform at Zhanjiang University of Science and Technology

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Abstract

Purpose: This study examines the effects of performance expectancy, effort expectancy, social influence, task-technology fit, and reputation on undergraduate students' behavioral intention to use the Chaoxing Smart Learning Platform, and the relationship between behavioral intention and use behavior. **Research design, data and methodology:** Using stratified random sampling, 450 valid questionnaires were collected. Data were analyzed through CFA and SEM. **Results:** The analysis revealed that effort expectancy ($\beta = 0.169$) had a significant influence on behavioral intention, while task-technology fit ($\beta = 0.265$) and reputation ($\beta = 0.464$) also significantly influenced behavioral intention, with reputation having the strongest effect. In contrast, performance expectancy ($\beta = 0.034$) and social influence ($\beta = 0.004$) did not exhibit statistically significant effects on behavioral intention. **Conclusions:** During the initial promotion phase of the platform at Zhanjiang University of Science and Technology, students' continued usage of the Platform is primarily driven by reputation, TTF, and EE, while SI plays no significant role, and PE does not show a notable promoting effect. It is recommended that platform operators and university administrators prioritize strengthening platform reputation, enhancing the alignment between platform functionalities and learning tasks, and continuously optimizing the user experience to effectively foster students' sustained usage intention and actual behavior.

JEL Classification Code: O33, I23, D83, M15

Keywords: Chaoxing Smart Learning Platform, Behavioral Intention, UTAUT, TTF, Structural Equation Model

1. Introduction

The development of global educational informatization has become a significant force driving the transformation of contemporary teaching and learning models. Educational informatization originated from computer-assisted instruction in the 1960s and has deepened continuously with the advancement of the internet and digital technologies (Fedorenko et al., 2023). Entering the 21st century, digital learning (E-Learning) and online education have experienced explosive growth. The rapid proliferation of information and communication technology (ICT) has ignited a global wave of educational digitalization (Abdovakhidov et al., 2021). Within this trend, the global educational technology (EdTech) market continues to expand, projected to reach USD 404 billion by 2025, with an average annual compound growth rate of approximately

16.3% (Holoniq, 2020).

As a key participant in global educational informatization, China has undergone a developmental process from pilot computer education initiatives to comprehensive smart education (Zuo et al., 2014). Policies such as the "Education Informatization 2.0 Action Plan" and "China's Education Modernization 2035" emphasize "empowering the reconstruction of learning experiences through technology" (Yan & Yang, 2021), promoting the in-depth development of educational informatization towards intelligence and personalization. In 2023, the market size of digital education in China reached 413.3 billion yuan, with a user base of 349 million, demonstrating strong growth momentum (NetEconomy.cn, 2024).

Among the widely adopted educational informatization platforms, the Chaoxing Smart Learning Platform (CSLP) has become one of the representative platforms by covering

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over 95% of higher education institutions in mainland China (Ying, 2020; Zou et al., 2021). The platform has been extensively integrated into university teaching practices, such as in flipped classrooms and blended learning, significantly enhancing students' learning interest and effectiveness (Yang, 2018; Zhao et al., 2019). However, the successful implementation of technology depends not only on its functional advantages but, more critically, on students' acceptance and willingness to use it (Ali et al., 2018), a point particularly evident during the COVID-19 pandemic (Li & Zhu, 2022).

In September 2023, Zhanjiang University of Science and Technology (ZUST) implemented the "One Platform, Three Terminals" smart teaching system across the university, fully introducing the Chaoxing Smart Learning Platform (CSLP). Although existing research confirms the platform's teaching effectiveness, there remains a lack of in-depth exploration into the usage intentions and acceptance mechanisms of students in newly partnered institutions. Therefore, this study takes ZUST as a case, integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), the Task-Technology Fit (TTF) model, and the Initial Trust Model, to systematically investigate the key factors influencing students' intention to use the CSLP and their underlying mechanisms.

This study aims to fill the research gap on educational technology acceptance in the context of newly partnered higher education institutions, providing theoretical and empirical support for platform optimization, teaching integration, and digital transformation in universities. It also offers reference for theoretical expansion and methodological innovation in the field of educational technology adoption.

2. Literature Review

2.1 Theoretical Background

Integrating multiple theories can build a more explanatory analytical framework than a single model (Al-Rahmi et al., 2021), providing a comprehensive explanation for students' willingness to adopt the CSLP.

The UTAUT proposed by Venkatesh et al. (2003), integrates eight original theories and is widely used to analyze key factors influencing users' adoption of various innovative technologies, including educational management systems (Al-Mamary et al., 2023; Samsudeen & Mohamed, 2019). VanDerSchaaf's (2020) research found that effort expectancy and social influence play key roles in undergraduates' behavioral intention to adopt learning platforms. Twum et al. (2022) applied the UTAUT model and added other variables to assess students' intention to use

e-learning, with results showing that performance expectancy, hedonic motivation, and social influence had significant effects on the dependent variable. In the context of learning management systems, students' level of adoption depends on their perceived degree of system usefulness within the educational environment (Al-Mamary et al., 2023).

The Task-Technology Fit (TTF) model posits that users' performance and willingness to continue using a technology depend on the degree of fit between the platform's functional characteristics and users' daily task requirements (Al-Rahmi et al., 2020; Spies et al., 2020; VanDerSchaaf, 2020). The model consists of four constructs: task characteristics, technology characteristics, task-technology fit, and usage behavior. The first two jointly determine the level of fit, which subsequently influences adoption and use (Ahmed et al., 2017; Wu & Chen, 2017). TTF is often combined with other theories to enhance its explanatory power. For instance, Wu and Chen (2017) integrated TTF with the Technology Acceptance Model (TAM) to predict users' willingness to continue using MOOCs. Similarly, Ahmed et al. (2017) combined TTF with UTAUT to study factors influencing users' adoption of mobile banking systems.

The Initial Trust Model (ITM) focuses on the level of trust between users and service providers at the beginning of their relationship. It is often used to assess users' trust levels when adopting new services (Farooq et al., 2021). Factors influencing initial trust are diverse and include user characteristics (such as prior experience), institutional characteristics (such as corporate reputation), and structural safeguards (such as security and privacy policies) (Lin et al., 2022; Ooge et al., 2022). For example, Ooge et al. (2022) explored key factors influencing adolescents' initial trust in an e-learning platform, while Saha et al. (2022) proposed strategies for fostering mobile payment adoption by building initial user trust.

In summary, UTAUT, TTF, and ITM provide complementary theoretical perspectives for understanding new technology adoption behaviors from three key dimensions: usage motivation, functional fit, and trust establishment. This paper will use these three as the core framework to construct a conceptual model for exploring ZUST students' willingness to use the CSLP.

2.2 Variable Definition and Research Hypotheses

2.2.1 Performance Expectancy (PE)

Performance Expectancy (PE) refers to "the degree to which an individual believes that using the system will help them attain gains in job performance" (Venkatesh et al., 2003). It reflects an individual's belief that the system can improve their overall performance in specific tasks or activities and provide advantages (Mahande & Malagoan,

2019). In the e-learning context, performance expectancy specifically refers to learners' belief that using an e-learning system will enhance their educational skills and academic performance, enabling them to complete learning activities more efficiently and conveniently (Twum et al., 2022).

Extensive research confirms that performance expectancy is a key factor in predicting individuals' behavioral intention to adopt new technologies (Twum et al., 2022). In the field of educational technology, it is often regarded as a core variable influencing users' perceptions and adoption decisions (Al-Mamary et al., 2023). For example, Rudhumbu's (2022) study indicated that university students are more likely to accept a blended learning technology system if they believe it can improve their academic performance. Al-Mamary et al. (2023) further explained that performance expectancy reflects the extent to which users trust that a new technology can effectively meet their needs and aspirations across various scenarios, including work, study, and life. Additionally, Yee and Abdullah (2021) found that performance expectancy is the most prominent factor influencing educators' behavioral intention to adopt information and communication technology in teaching practice.

Based on the above theoretical and empirical evidence, this study proposes the following hypothesis:

H1: Performance Expectancy has a significant influence on Behavioral Intention.

2.2.2 Effort Expectancy (EE)

Effort Expectancy refers to "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). It reflects users' perception of whether using the system is difficult or inconvenient (Al-Mamary et al., 2023). In specific contexts, effort expectancy refers to the level of simplification and convenience users perceive when adopting and using an e-learning system (Twum et al., 2022). It involves the physiological and psychological skills and capabilities required for users to interact with the system (Lan et al., 2022).

Relevant studies indicate that effort expectancy is a key antecedent influencing users' technology adoption behavior. Huang (2021) pointed out that effort expectancy is a decisive factor in determining whether students will continue using a technology. Almaiah and Alyoussef (2019) also confirmed that effort expectancy, as a core construct of the UTAUT model, is widely used to study the influence of new technologies on classroom teaching. Moreover, the perceived convenience and simplicity of technology serve as important quality benchmarks for users' future acceptance and usage behavior (Al-Mamary et al., 2023). Specifically, in educational contexts, the ease of use of technology is highly valued by students, prompting educators to select more user-friendly technologies for students (Li & Zhao, 2021). Mouli et al. (2023) further

elaborated that the less effort users perceive in using a technology, the clearer their behavioral intention to adopt it becomes.

Based on the above research review, this study proposes the following hypothesis:

H2: Effort Expectancy has a significant influence on Behavioral Intention.

2.2.3 Social Influence (SI)

Social Influence refers to the extent to which an individual's decision to adopt a new technology is influenced by the attitudes and opinions of important reference groups (Rudhumbu, 2022; Twum et al., 2022). This definition emphasizes that an individual's acceptance of technology is closely linked to the support of their social network (Mouli et al., 2023). In the UTAUT model, this construct encompasses multiple dimensions, including subjective norms, social factors, and public image, reflecting the social pressure or support individuals perceive when using a technological system (Udang, 2021).

Related studies further reveal the mechanisms and boundaries of social influence. Samsudeen and Mohamed (2019) noted that the role of social influence is far more significant in mandatory usage contexts than in voluntary ones. Hamdan et al. (2021) also proposed that this concept is similar to subjective norms and emphasized that its influence is particularly pronounced among women and individuals with experience in mandatory usage contexts. In the educational technology context, social influence has been confirmed as a key sociopsychological factor affecting students' technology adoption behavior. Jou et al. (2023) regarded it as a critical indicator for assessing how significant others influence an individual's technology acceptance. Maisha and Shetu's (2023) research further demonstrated that social influence is one of the key factors predicting students' continued use of e-learning systems, with its effect moderated by the voluntariness of use.

Based on the above discussion, this study proposes the following hypothesis:

H3: Social Influence has a significant influence on Behavioral Intention.

2.2.4 Task-Technology Fit (TTF)

Task-Technology Fit (TTF) refers to the degree to which a specific technology aligns with and supports an individual in completing a series of specific work tasks (Al-Maatouk et al., 2020; Spies et al., 2020). This construct emphasizes that the actual utility of a technology depends on the fit between its functional characteristics and users' daily task requirements (Alyoussef, 2021). In educational contexts, students' acceptance of new technologies depends not only on their technological expectations but also closely relates to the applicability of the technology in authentic learning activities (Alyoussef, 2021).

Relevant literature indicates that TTF is a key variable

for assessing and predicting technology adoption, continued use, and work (learning) performance. Kurniawan et al. (2021) investigated factors influencing users' intention to continue using MOOCs by integrating the TAM and TTF models. Al-Rahmi et al. (2021) and Zaremohzzabieh et al. (2022) pointed out that the recognition and utility of new technologies highly depend on the alignment between technological functionalities and actual task requirements. At the practical application level, Chen et al. (2022) research in the context of learning systems found that actual use and user satisfaction significantly influence TTF.

Based on the above theoretical and empirical evidence, this study proposes the following hypothesis:

H4: Task-Technology Fit has a significant influence on Behavioral Intention.

2.2.5 Reputation (RT)

Reputation (RT) refers to the overall perception formed by users based on a comprehensive evaluation of an organization's value creation capability, particularly reflected in the company's ability to provide high-quality services and the resulting level of customer trust (Al Hassani & Wilkins, 2022; Jang & Lee, 2018). In the field of educational technology, platform reputation stems from the academic prestige of its partner institutions, course quality, and the platform's own credibility, serving as a critical factor influencing users' choices and willingness to adopt (Khurana et al., 2019). When users lack direct experience, reputation, as an important external signal, helps users assess the organization's strength, values, and reliability, thereby establishing initial confidence (Farooq et al., 2021; Lin et al., 2022).

Relevant research confirms that reputation is a key antecedent influencing users' technology adoption behavior. Lin et al. (2022) indicated that reputation is crucial for building users' confidence and willingness to use information services. Saravanos et al.'s (2022) study integrating the UTAUT model also found that reputation has a significant positive influence on users' behavioral intention. However, some research suggests that in educational service contexts, the relationship between reputation and students' behavioral intention may be more complex (Ngan & Khoi, 2020).

Based on the above theoretical and empirical evidence, this study proposes the following hypothesis:

H5: Reputation has a significant influence on Behavioral Intention.

2.2.6 Behavioral Intention (BI) and Use Behavior (UB)

Behavioral Intention refers to an individual's internal motivation to plan and be willing to use a particular technology to perform tasks under specific conditions in the future (Huang, 2021). In technology acceptance research, it is regarded as a key antecedent variable for predicting actual behavior, influenced by a combination of internal and

external factors such as performance expectancy and social influence (Al-Mamary et al., 2023). Existing research confirms that behavioral intention has a significant direct influence on e-learning acceptance (Mahande & Malagoan, 2019) and serves as a key indicator in predicting users' continued use of online learning systems (Maisha & Shetu, 2023).

Use Behavior refers to the actual application of technology by users after forming the intention to use it, specifically including the frequency, duration, depth, and purposeful operation of usage (Mouli et al., 2023; Strzelecki, 2024). In the educational technology context, it specifically refers to students' concrete practices of integrating specific platforms or tools into their learning processes (Ali et al., 2018).

Extensive research indicates that behavioral intention is the most direct and strong predictor of use behavior. Yee and Abdullah's (2021) systematic review found that, whether for teachers or students, their use behavior of new technologies (such as Google Classroom) is directly driven by behavioral intention. Thongsri et al. (2019) empirical study also confirmed that behavioral intention explains up to 41% of actual use behavior, making it the strongest predictor.

Based on the above theoretical and empirical foundations, this study proposes the following hypothesis:

H6: Behavioral Intention has a significant influence on Use Behavior.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework aims to systematically present the core constructs, variables, and hypothesized relationships of the study (Miles & Shevlin, 2007). In exploring user acceptance and behavioral intention toward emerging educational technology services, such as the CSLP, this study notes that the UTAUT and the TTF model have been widely adopted. Meanwhile, the Initial Trust Model (ITM) demonstrates critical explanatory power in technology adoption studies involving financial risks (Farooq et al., 2021; Lin et al., 2022; Oliveira et al., 2014; Saravanos et al., 2022; Windasari et al., 2022).

Given the unique context of the first-time collaboration between ZUST and the CSLP, examining the influence of reputation on students' usage intention and behavior from an ITM perspective holds distinct value. This not only reveals the trust-building pathways during the initial phase of technology promotion but also provides insights for similar "platform-institution" collaboration models in other universities (Lin et al., 2022; Saravanos et al., 2022). Therefore, this study innovatively integrates the core

variables and causal relationships of three models—UTAUT (technology cognition evaluation), TTF (task-adaptation mechanism), and ITM (initial trust formation)—to construct the theoretical framework.

The framework includes seven core variables. Independent variables: Performance Expectancy, Effort Expectancy, Social Influence, Task-Technology Fit, and Firm Reputation. Dependent variables: Behavioral Intention and Actual Use Behavior.

This integrated framework aims to more comprehensively and deeply reveal the key factors and mechanisms influencing students' behavioral intention to adopt and use the CSLP in the context of newly collaborating universities.

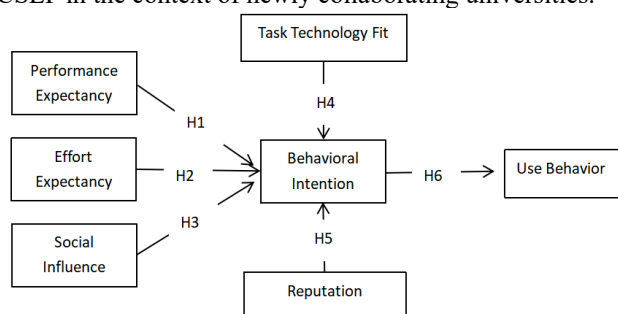


Figure 1: Research Conceptual Framework

3.2 Research Methods

This study adopts a quantitative research design, using questionnaire surveys to investigate the mechanisms influencing undergraduate students' intention to use the CSLP at ZUST. Based on an integrated theoretical framework combining UTAUT, TTF, and ITM, the study examines the structural relationships among seven latent variables: performance expectancy, effort expectancy, social influence, task-technology fit, reputation, behavioral intention, and use behavior.

Data were collected through self-administered questionnaires. The questionnaire comprises three sections: screening questions to confirm usage experience, demographic information, and a measurement system for the seven latent variables based on the theoretical framework (totaling 26 Likert five-point scale items). A combination of judgmental sampling and stratified random sampling was employed. Stratification was conducted by grade level, and questionnaires were distributed through the Wenjuanxing platform. A total of 450 valid questionnaires were ultimately collected.

Before the formal survey, a pilot test was conducted to assess questionnaire quality. Fifty students were invited to participate in the pilot survey, based on which reliability and validity were evaluated. Content validity was ensured through expert review (all items had an Item-Objective Congruence Index ≥ 0.5), and internal consistency reliability

was tested using Cronbach's Alpha coefficient (Cronbach's $\alpha > 0.7$ for all variables), both meeting measurement requirements.

Data analysis was performed using Jamovi for descriptive statistics and AMOS for confirmatory factor analysis (CFA) and structural equation modeling (SEM). The measurement model's fit and validity were first evaluated through CFA, followed by SEM to test research hypotheses and path relationships among variables.

The study adhered to academic ethics by stating the research purpose, anonymity, and voluntary participation principles in the questionnaire, and informed consent was obtained. All data were used solely for academic research and anonymized.

3.3 Population and Sample Size

This study focuses on undergraduate students at ZUST, specifically targeting full-time sophomores to seniors who have continuously used the CSLP for at least one semester. This group possesses sufficient knowledge and practical experience with the platform, providing in-depth usage feedback for the study.

To ensure scientific rigor in sample size determination, Daniel Soper's sample size calculator was used. Based on the structural equation modeling design with seven latent variables and 26 observed variables, the calculation indicated a minimum required sample size of 425 under a significance level of $\alpha = 0.05$. To enhance data stability and statistical power, the study aimed to collect 500 valid questionnaires. Stratified sampling was conducted according to the proportional distribution of students across grades (detailed in Table 1), ensuring the sample structure accurately reflected the actual population distribution of the university.

In terms of sampling methods, this study employed a combination of judgmental sampling and stratified random sampling. First, the undergraduate student population at ZUST was identified as meeting the research criteria based on the study's objectives. Subsequently, stratified random sampling by grade was implemented, distributing questionnaires to students across grade levels via the Wenjuanxing platform to ensure both representativeness and randomness of the sample.

Table 1: Sample Size of Students

Grades	Population Size	Proportional Sample Size
Sophomores	9,000	163
Juniors	11,000	199
Seniors	7,600	138
Total	27,600	500

4. Results and Discussion

4.1 Demographic Profile

In digital education platform research, systematically collecting demographic information such as gender, grade level, and disciplinary background provides critical dimensions for analyzing platform usage behaviors across different student groups (Hawi & Samaha, 2017). This information not only aids in understanding user characteristics but also offers empirical evidence for platform optimization (Yusifov & Akhundova, 2022).

A total of 450 valid questionnaires were collected in this study, with the basic sample characteristics presented in Table 2. Regarding gender distribution, the proportion of female respondents slightly exceeded that of males. The overall gender distribution was relatively balanced, facilitating comparisons of behavioral patterns across gender groups in subsequent analyses. In terms of grade composition, third-year students accounted for the highest proportion, followed by second-year students and fourth-year students. This distribution structure reflects the actual proportions of students from different academic years participating in online learning surveys, enabling an examination of usage characteristics and continuance intention regarding the learning platform across various stages of study.

Overall, the sample demonstrates good representativeness in both gender and grade dimensions, providing a reliable statistical foundation for subsequent analyses of differences in learning platform usage behaviors.

Table 2: Demographic Information

Demographic and General Data (N=450)		Frequency	Percentage
Gender	Male	189	42
	Female	261	58
Year of Study	Year 2	147	32.6
	Year 3	179	39.7
	Year 4	124	27.7

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a critical step in the structural equation modeling process, systematically assessing the validity and fit of the measurement model. As a vital link between theoretical frameworks and empirical data, its primary function is to examine whether the relationships between observed variables and their corresponding latent variables align with theoretical assumptions, thereby ensuring the scientific rigor and reliability of subsequent structural analyses (Goretzko et al., 2024; Hair et al., 2021).

Specifically, this study employs Confirmatory Factor Analysis to evaluate the quality of the measurement model, utilizing AMOS software to assess convergent validity and discriminant validity, thereby ensuring the reliability and validity of latent variable measurements (Gao et al., 2022). During the analysis, effective items are screened based on standardized factor loadings. Convergent validity is assessed using composite reliability and average variance extracted (AVE), while discriminant validity is validated by comparing the correlations among latent variables with the square roots of their respective AVEs (Baharum et al., 2023; Wang & Phongsatha, 2023). This analytical process provides the necessary measurement foundation for the subsequent construction of the structural model and hypothesis testing.

The overall fit indices of the measurement model in this study are presented in Table 4. The CMIN/DF value is 2.938, meeting the criterion of being less than 5.00. Regarding absolute fit indices, both the GFI (0.872) and AGFI (0.839) meet the recommended thresholds (≥ 0.85 and ≥ 0.80 , respectively), and the RMSEA value of 0.068 is below the critical threshold of 0.08. For incremental fit indices, the NFI (0.934), CFI (0.955), and TLI (0.948) all significantly exceed the recommended standard of 0.90.

The comprehensive evaluation indicates that the measurement model demonstrates good overall fit, with all indices meeting statistical requirements, thereby establishing a reliable measurement foundation for subsequent research.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Performance Expectancy (PE)	Rudhumbu (2022)	3	0.932	0.902-0.912	0.933	0.822
Effort Expectancy (EE)	Rudhumbu (2022)	3	0.929	0.869-0.935	0.930	0.816
Social Influence (SI)	Kurniawan et al. (2021), Samsudeen and Mohamed (2019)	4	0.911	0.823-0.871	0.911	0.720
Task-technology Fit (TTF)	Kurniawan et al. (2021), Wu and Chen (2017)	4	0.935	0.868-0.915	0.936	0.787
Reputation (RT)	Farooq et al. (2021), Windasari et al. (2022)	4	0.960	0.915-0.945	0.961	0.859
Behavioural Intentions (BI)	Samsudeen and Mohamed (2019)	4	0.932	0.850-0.902	0.932	0.775

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Use Behavior (UB)	Samsudeen and Mohamed (2019), Rudhumbu (2022)	4	0.894	0.665-0.898	0.898	0.691

Note: CR = Composite Reliability, AVE = Average Variance Extracted

4.2.1 Convergent Validity Analysis

This study evaluated the convergent validity of the measurement model using standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). The evaluation criteria were as follows: standardized factor loadings should ideally be ≥ 0.70 (Hair et al., 2010), composite reliability (CR) should be ≥ 0.70 , and average variance extracted (AVE) should be ≥ 0.50 (Fornell & Larcker, 1981).

According to the confirmatory factor analysis results presented in Table 3, all measurement indicators demonstrated good convergent validity.

Specifically, the standardized factor loadings for all latent variables (PE, EE, SI, TTF, RT, BI, UB) ranged from 0.665 to 0.945, with most indicators meeting or approaching the ideal threshold of 0.7. At the same time, the composite reliability (CR) values for all latent variables fell within the range of 0.898 to 0.961, all significantly exceeding the recommended threshold of 0.7, indicating excellent internal consistency reliability for each construct. Furthermore, the average variance extracted (AVE) values for the latent variables ranged from 0.691 to 0.859, all meeting the requirement of being greater than 0.5. In summary, all evaluation metrics met or exceeded the recommended standards, demonstrating that the measurement model in this study possesses sufficient convergent validity.

Table 4: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (West et al., 2023)	2.938
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.872
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.839
RMSEA	< 0.08 (Kumari, 2021)	0.068
CFI	≥ 0.90 (Hair et al., 2013)	0.955
NFI	≥ 0.90 (Hair et al., 2013)	0.934
TLI	≥ 0.90 (Huang & Duangekanong, 2022)	0.948

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.2.2 Discriminant Validity Analysis

To examine discriminant validity among variables, this study applied the Fornell-Larcker criterion for evaluation. This criterion requires that the square root of the AVE of any

latent variable must be strictly greater than the absolute value of its correlation with all other latent variables.

The discriminant validity test results are presented in Table 5. The bolded values on the diagonal represent the square roots of the AVE for each latent variable. These values are all greater than the absolute values of the correlations in their respective rows and columns (e.g., the square root of the AVE for the latent variable PE is 0.907, which is greater than its correlation with EE at 0.718 and its correlation with SI at 0.613, among others). This result indicates that the shared variance between each latent variable and its own measurement indicators is greater than the shared variance with other distinct latent variables. Therefore, the measurement model in this study satisfies the Fornell-Larcker criterion, demonstrating good discriminant validity among the latent variables.

Table 5: Discriminant Validity

Variable	Factor Correlations						
	EE	SI	TTF	RT	BI	UB	PE
EE	0.903						
SI	0.721	0.849					
TTF	0.751	0.805	0.887				
RT	0.638	0.665	0.827	0.927			
BI	0.681	0.663	0.783	0.806	0.880		
UB	0.658	0.620	0.788	0.754	0.875	0.881	
PE	0.718	0.613	0.674	0.633	0.607	0.654	0.907

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is a core component of structural equation analysis, primarily used to examine theoretical relationships and causal pathways among latent variables and to test the validity of research hypotheses (Hair et al., 2021). Unlike traditional measurement models, structural models focus more on quantifying the internal mechanisms of influence among variables and their significance through path coefficients (Kline, 2023). Therefore, after confirming that the measurement model demonstrates good fit, the structural model must be further evaluated. Model evaluation involves systematically examining the significance of path coefficients and comprehensively assessing overall fit and explanatory power (Mardia et al., 2024). Typically, tools such as AMOS are employed, combined with indicators like

χ^2 , CFI, and RMSEA to evaluate model fit (Hu & Bentler, 1999). The Bootstrap method is used to test path significance ($p < 0.05$), verifying whether research hypotheses receive statistical support (Chen et al., 2022; Li et al., 2025).

The fit test results of the structural model in this study are presented in Table 6. In terms of overall fit indices, the CMIN/DF value is 3.029, which is below the recommended threshold of 5.00, indicating a good level of model fit. The RMSEA value is 0.069, meeting the criterion of being less than 0.08, suggesting that model error is within an acceptable range. Regarding incremental fit indices, the NFI (0.931), CFI (0.952), and TLI (0.945) all significantly exceed the recommended standard of 0.90, reflecting the model's strong comparative fit. Among the absolute fit indices, the GFI (0.866) and AGFI (0.834), although slightly below the ideal thresholds, remain within an acceptable range, indicating that the overall fit of the model generally meets requirements.

Based on the evaluation of all indicators, this structural equation model performs well on the majority of fit indices, demonstrating reasonable overall fit. It is therefore suitable for subsequent hypothesis testing and path analysis.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (West et al., 2023)	3.029
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.866
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.834
RMSEA	< 0.08 (Kumari, 2021)	0.069
CFI	≥ 0.90 (Hair et al., 2013)	0.952
NFI	≥ 0.90 (Hair et al., 2013)	0.931
TLI	≥ 0.90 (Huang & Duangekanong, 2022)	0.945

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

This study employed structural equation modeling to conduct path analysis and significance testing for the six research hypotheses (H1-H6) in the theoretical framework. Hypothesis testing was based on standardized path coefficients (β) and their corresponding t-values, with a significance level set at $*p < 0.05$. The analysis results, summarized in Table 7, indicate that four of the six hypotheses (H2, H4, H5, H6) received statistical support, demonstrating that effort expectancy, task-technology fit, reputation, and behavioral intention have significant effects on use behavior. In contrast, the roles of performance expectancy and social influence were not validated in this sample, possibly reflecting that users in this technology adoption context place greater emphasis on practical functional fit and system reputation rather than external

social pressure or mere performance expectations.

H1: Performance Expectancy has a significant influence on Behavioral Intention. The analysis results show that the standardized path coefficient from performance expectancy to behavioral intention is 0.034, with a t-value of 0.704, which does not reach the significance level ($*p > 0.05$). Therefore, H1 is not supported, indicating that performance expectancy is not a key factor influencing users' behavioral intention in the context of this study.

H2: Effort Expectancy has a significant influence on Behavioral Intention. The path coefficient from effort expectancy to behavioral intention is 0.169, with a t-value of 3.012 ($*p < 0.01$), showing a significant positive effect. H2 is supported, indicating that system ease of use and convenience effectively promote users' willingness to use.

H3: Social Influence has a significant influence on Behavioral Intention. The path coefficient from social influence to behavioral intention is 0.004, with a t-value of 0.072, which does not reach statistical significance ($*p > 0.05$). Therefore, H3 is not supported, reflecting that peer or social normative opinions did not significantly influence behavioral intention in this study.

H4: Task-Technology Fit has a significant influence on Behavioral Intention. The path coefficient from task-technology fit to behavioral intention is 0.265, with a t-value of 3.230 ($*p < 0.001$), showing a highly significant positive effect. H4 is supported, indicating that the alignment between system functionalities and user tasks is a key motivator for users to develop usage intention.

H5: Reputation has a significant influence on Behavioral Intention. The influence of reputation on behavioral intention is the most prominent, with a path coefficient of 0.464 and a t-value of 7.725 ($*p < 0.001$), demonstrating strong statistical significance and a positive direction. H5 is supported, indicating that the reputation of the platform or system is a critical consideration in users' adoption decisions.

H6: Behavioral Intention has a significant influence on Use Behavior. The path coefficient from behavioral intention to use behavior is 0.891, with a t-value of 19.962 ($*p < 0.001$), reaching an extremely significant level with a positive effect. H6 is strongly supported, consistent with conclusions from classical models such as the Unified Theory of Acceptance and Use of Technology, indicating that behavioral intention is a direct and powerful antecedent of actual use behavior.

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: PE \rightarrow BI	0.034	0.704	Not Supported
H2: EE \rightarrow BI	0.169	3.012**	Supported
H3: SI \rightarrow BI	0.004	0.072	Not Supported
H4: TTF \rightarrow BI	0.265	3.230***	Supported

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H5: RT \rightarrow BI	0.464	7.725***	Supported
H6: BI \rightarrow UB	0.891	19.962***	Supported

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

5. Conclusions and Recommendation

5.1 Conclusions

This study integrates UTAUT, TTF, and reputation to examine CSLP adoption among students at ZUST. Based on 450 valid questionnaires, the analysis yields the following results.

EE ($\beta = 0.169$, $p < 0.01$) has a significant influence on BI, which is consistent with Strzelecki's (2024) findings on how system ease of use promotes users' willingness to adopt. TTF ($\beta = 0.265$, $p < 0.001$) also exhibits a significant influence, supporting Khan et al.'s (2018) perspective on the importance of alignment between system functionalities and user tasks. Notably, RT ($\beta = 0.464$, $p < 0.001$) emerges as the strongest predictor of behavioral intention, highlighting the critical role of platform credibility in students' adoption decisions. The strong predictive power of BI on UB ($\beta = 0.891$, $p < 0.001$) further validates the classic technology adoption pathway proposed by Venkatesh et al. (2003).

In contrast, PE ($\beta = 0.034$, $p > 0.05$) and SI ($\beta = 0.004$, $p > 0.05$) did not pass the significance test, indicating that during the initial promotion phase of the platform, students are more concerned with actual user experience and platform reliability rather than anticipated performance improvements or external social pressures. This finding echoes Li's (2024) view on the importance of perceived usefulness and self-confidence in technology use among students in the post-pandemic era, while also revealing the uniqueness of technology acceptance mechanisms in new contexts.

In summary, this study confirms that, during the initial promotion of educational technology in newly collaborating universities, effort expectancy, task-technology fit, and firm reputation are the core factors driving students' adoption intentions. Specifically, this study contributes two new insights: (1) it reveals that reputation is the strongest predictor of behavioral intention in the initial adoption phase, surpassing traditional UTAUT constructs; (2) it demonstrates that performance expectancy and social influence may not be significant in voluntary, early-stage contexts. These findings provide targeted theoretical and practical guidance for educational technology promotion in newly partnered institutions.

5.2 Recommendations

Based on the above research conclusions, the following practical recommendations are proposed for school administrators, platform providers, and teachers to promote the in-depth application and sustained use of the CSLP at ZUST.

For school administrators, systematic training on platform operations should be conducted, with a focus on strengthening guidance on platform ease of use. The platform's market reputation and success stories should be highlighted during freshman orientation and related promotional activities. Teachers should be encouraged and supported in optimizing course design and teaching tasks based on platform functionalities to improve task-technology fit. Additionally, incorporating platform usage into the teaching evaluation system can create institutional incentives.

For the platform provider (Chaoxing Group), it is recommended to continuously optimize the user interface and operational processes, particularly the mobile user experience. Customized teaching templates and resource libraries should be developed according to the disciplinary characteristics of ZUST. Establishing a responsive local technical support team is also essential to address technical issues promptly during use.

For teachers, it is important to actively integrate platform functionalities into daily teaching activities, designing learning activities and assessment tasks that must be completed through the platform. Demonstrating and exemplifying effective platform usage in the classroom is also crucial. Additionally, fostering positive teacher-student interactions and peer learning environments through the platform is highly encouraged.

Through these multi-stakeholder collaborative measures, key obstacles in the platform adoption process can be systematically addressed, transforming students' willingness to use into stable usage behaviors and ultimately achieving the expected goal of technology-enhanced teaching and learning.

5.3 Limitation and Further Study

This study has three main limitations: First, the sample is drawn solely from ZUST, and the research was conducted during the initial promotion phase of the platform. Therefore, generalizing the findings to other types of universities or different stages of application requires caution. Second, the cross-sectional research design, while capable of revealing relationships among variables, cannot track the dynamic evolution of technology adoption intentions as users gain experience. Third, the theoretical framework primarily focuses on individual student-level perceptual factors, with insufficient exploration of contextual factors such as teachers'

usage behaviors and institutional support policies, which may affect the model's comprehensiveness and explanatory power.

Based on these limitations, future research could be expanded in the following directions. First, comparative studies across multiple universities could be conducted to examine differences in technology adoption mechanisms across different types of institutions and geographical regions. Longitudinal designs could also be employed to track students' entire journey from initial exposure to proficient use. Second, the theoretical model could be enriched by incorporating contextual variables such as teachers' instructional practices and institutional support policies. Additionally, efforts could be made to validate self-reported data by combining it with backend platform usage data. Finally, intervention experiments could be designed based on empirical findings to test the practical effectiveness of specific strategies, such as ease-of-use training, task integration design, and reputation-building initiatives, providing more targeted guidance for educational technology promotion.

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