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# Understanding the Drivers of Digital Library Use: Evidence from College Students in Chengdu, China

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## Abstract

**Purpose:** This study aims to explore the factors influencing students' attitudes and behavioral intentions toward using digital libraries in universities and colleges in Sichuan Province, China. **Research design, data and methodology:** Quantitative methods and structured questionnaires were used to collect sample data. Prior to distribution, the alignment between research objectives and survey items was assessed, and a pilot test ensured content validity and reliability. Confirmatory factor analysis and structural equation modeling were applied to assess the model fit and examine causal relationships among variables. **Results:** The conceptual framework has been shown to effectively predict college students' behavioral intentions (BI) regarding digital library usage. Notably, Effort Expectancy (EE) and Social Influence (SI) are the most influential factors driving this intention. **Conclusions:** Effort Expectancy is the strongest predictor of students' intention to use digital libraries, followed by Social Influence and User Attitude. These findings suggest that simplifying system interfaces, offering user training, and encouraging peer recommendations can significantly boost adoption rates. Universities should also strengthen digital literacy and invest in intuitive IT infrastructure. By prioritizing ease of use, enhancing service quality, and maintaining strong data security, institutions can improve student engagement and support the broader, sustainable integration of digital libraries into higher education.

**Keywords:** Digital Library, Attitude, Behavioral Intention

**JEL Classification Code:** A22, I23, L86, O30

## 1. Introduction

The rapid advancement of science and technology is transforming various industries, including libraries, which are embracing digital solutions and facing new challenges (Bosque & Lampert, 2009). The internet has significantly changed how users search for information, leading libraries to rely on advanced databases and software for mobile access and convenient digital services (Iglesias & Meesangnil, 2011). A digital library's core feature is the complete digitization of resources, including text, images, audio, and video. These resources are efficiently stored and managed through computer networks, allowing users to access information anytime, anywhere, using devices like computers, mobile phones, or tablets (Gan & Song, 2015). This flexibility supports independent learning and enhances information retrieval efficiency (Liu et al., 2010). Digital libraries also offer advanced search options, such as keyword, topic, and author searches, integrating full-text search and intelligent recommendations to improve user experience. Additionally, they facilitate global resource sharing, accelerating knowledge dissemination and collaboration.

As digital transformation reshapes knowledge access and delivery, understanding user interaction with digital libraries has become a core concern in the field of Library and Information Science (LIS). The benefits of digital libraries are clear: they remove time and space limitations,

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provide extensive digital resources across disciplines, and promote academic exchange and innovation (Wang et al., 2009). Their efficient search systems help users quickly find relevant information, enhancing learning and research productivity. Looking ahead, digital libraries will focus on improving user experience with intelligent search, personalized recommendations, and voice interaction. With the rise of mobile devices, they will expand mobile applications for seamless access (Chang, 2013b). Big data will be used to analyze user behavior, optimizing library services and acquisitions. Furthermore, digital libraries will integrate with education, research, and culture to create a comprehensive knowledge service platform, supporting knowledge growth and societal development (Calhoun, 2014).

Despite rapid growth, user engagement with digital libraries remains inconsistent. A recent survey by the China Internet Network Information Center (CNNIC, 2023) reported that while over 94% of Chinese university students have internet access, less than 60% regularly use digital library platforms. In Sichuan Province, usage rates vary widely across institutions, with some reporting active usage by fewer than 45% of their student population.

This reveals a critical research gap in understanding the psychological and contextual factors that influence students' willingness to adopt and continuously use digital libraries. While technical development has advanced rapidly, there is limited empirical research focusing on students' behavioral intentions, a key predictor of actual system use behavior according to the Theory of Planned Behavior and the Unified Theory of Acceptance and Use of Technology (Ajzen, 1991; Venkatesh et al., 2003). Behavioral intention reflects a user's motivation and readiness to use a system, and it is essential for predicting long-term adoption and return on investment in digital library systems.

China's Ministry of Education prioritizes digital library development, aligning with the 14th Five-Year Plan's digital education strategy to meet the needs of students and teachers. Digital libraries play a crucial role in university education, especially for open education students relying on e-learning resources (Oseghale, 2023). In Chengdu, Sichuan Province, university digital libraries have made significant progress in resource development, technology, and service optimization. However, practical challenges remain: low participation rates, limited student engagement, and varied levels of digital literacy. To better meet users' expectations, efforts should focus on increasing student engagement, improving information literacy training, and upgrading technical facilities. As digital educational resources grow, there is an urgent need to understand the determinants of usage behavior to optimize resource allocation and student support.

This study addresses this gap by systematically investigating the factors influencing college students' attitudes and behavioral intentions toward digital library use, using a validated structural equation model (SEM). By focusing on undergraduate students with at least one year of digital library experience across eight universities in Chengdu, this research offers practical and theoretical insights into user behavior. It contributes to the LIS field by identifying key psychological and social determinants—such as effort expectancy and social influence—that can inform more user-centric digital library strategies and policy decisions.

## 2. Literature Review

### 2.1 Information Technology

According to existing studies, the assessment of individual attitude change is essentially a cognitive restructuring mechanism (Sun & Chen, 2016), which is a psychological process that can effectively reveal the agent's positive or negative emotional orientation towards certain things (Oliver, 2006). It is worth noting that studies in information technology adoption show that compared with other psychological variables, user attitude has a stronger predictive effect on the intention of continuous use of information technology, which has been verified by empirical studies (Franque et al., 2021). Empirical evidence suggests that favorable user evaluations significantly correlate with increased technology acceptance likelihood and continued system engagement (Thong et al., 2006). Yoon (2016) interprets attitude as the positive feelings experienced by users when using digital libraries, and this theory provides a research basis for understanding how users' subjective feelings affect actual usage behaviors.

Recent research systematically examines the affective dimension in technology adoption, with empirical findings demonstrating emotional states' critical role in shaping initial and sustained usage intentions (Dinger et al., 2010). This aligns with established evidence that affective responses mediate users' technological evaluations, ultimately determining adoption behaviors across different usage stages (Beaudry & Pinsonneault, 2010). This study builds upon prior work by empirically validating the influence of information technology on both user attitude and behavioral intention in the specific context of Chinese university students' digital library use—an underexplored demographic in existing literature. Based on these supporting studies, the following hypotheses are proposed:

**H1:** Information technology has a significant impact on user attitude.

**H2:** Information technology has a significant impact on behavior intention.

## 2.2 User Attitude

The predictive effect of user attitude on behavioral intention has been verified in many technical application scenarios. Studies have shown that individuals' acceptance of technological systems is not only related to their long-term technological attitudes (Struckmann & Karnowski, 2016) but also significantly related to the functional quality of the system (Huang et al., 2015). Technical quality in information systems such as mobile libraries indirectly affects usage behavior by influencing user satisfaction (Park et al., 2014). It is worth noting that this attitude-behavior relationship model is stable across scenarios and shows significant predictive power in both online and offline environments (Liu & Shih, 2021).

Scholars emphasize the need to consider multi-dimensional influencing factors in research design. Bodur et al. (2000) suggest including variables such as time dimension, specific goals, and operating environment to improve research validity. In particular, the decision to use emerging technology devices reflects the interaction between users' existing technology attitudes and current situational elements (Li et al., 2008). This deep correlation between attitude and behavioral intention is essentially rooted in the dynamic matching process between individual cognitive systems and external technical features (Park et al., 2014). This study extends this research by incorporating user attitude as a mediating variable in a broader model of behavioral intention, supported by structural equation modeling in a digital library context. According to the support of research, the following hypothesis has been formulated:

**H3:** User attitude has a significant impact on behavior intention.

## 2.3 Performance Expectancy

In digital technology adoption studies, performance expectation as a core predictor of behavioral intention has been validated in multiple dimensions (Shivdas & Ilavarasan, 2018). This mechanism is particularly significant in the field of mobile services. When the matching degree between technical functions and user performance requirements increases, the behavioral intention shows an exponential growth trend (Zhou, 2008). The research thread shows that Moorthy et al. (2019) verified the robustness of the explanatory power of this variable through longitudinal data. Their conclusions extended Chang's (2015) original model on the expected transmission path of technology and became methodologically complementary to El-Masri and Tarhini's (2017) research on revising the technology adoption framework.

Focusing on the application scenario of digital libraries, the perception of technical effectiveness directly affects the optimization degree of users' work performance, and the realization of such instrumental value will significantly improve the intention of continuous use (Chang, 2013a). This dynamic relationship essentially reflects the collaborative evolution of technology maturity and user cognition with the iterative upgrading of mobile digital technology (Zhou, 2008), its performance improvement enhances users' performance expectations, thus forming a stronger driving force for technology adoption decisions (Shivdas & Ilavarasan, 2018). This study confirms and contextualizes these findings by evaluating how performance expectancy influences behavioral intention in university digital libraries, contributing new empirical evidence from a Chinese educational environment. The hypothesis is formulated:

**H4:** Performance expectancy has a significant impact on behavior intention.

## 2.4 Effort Expectancy

In the study of technology adoption, the positive correlation between effort expectation and behavior intention has formed a cross-domain evidence chain. From mobile payment systems (Al-Saedi et al., 2020) to Internet of Things applications, the perception of operational convenience has been shown to increase user retention significantly, and this mechanism has also been validated early in health information technology scenarios (Habibi et al., 2022). Especially in digital libraries, the cross-cultural research of El-Masri and Tarhini (2017) shows that the explanatory power of this variable is particularly prominent in the Qatari user group.

From a theoretical perspective, effort expectations map users' cognitive assessment of the system's ease of use, which directly influences their continuous use decisions (Wu & Wu, 2018). A systematic study by Sharma and Sharma (2019) further quantified the driving coefficient of this variable on positive behavioral intention and confirmed that its explanatory power could reach a significant level. The extension of the research framework also suggests that social groups' collective perception of technological value may synergize with individual effort expectations through normative pressure mechanisms (Wei & Zhang, 2021). This study adds to this literature by identifying effort expectancy as the most influential factor driving digital library usage among Chinese university students, offering targeted insight for improving user experience and engagement strategies. The studies have then led to the following hypothesis:

**H5:** Effort expectancy has a significant impact on behavior intention.

### 2.5 Social Influence

Basic research shows that social influence continues to affect the formation process of technology use intention by changing individuals' cognitive framework and value judgment (Tarhini et al., 2017). This mechanism shows stable explanatory power in multiple scenarios, such as digital libraries (Ayaz & Yanartas, 2020) and social media (Dhiman et al., 2020), and its strength is significantly positively correlated with the level of organizational support (Sultan & Wong, 2019).

It is worth noting that demographic variables constitute the key moderators. With the accumulation of users' technical experience, the influence of external social factors such as peer pressure decreases, and decision-making dominance gradually shifts to individual cognition (Brown & Venkatesh, 2010). This dynamic balance relationship is particularly prominent in accounting information systems. When technology adoption involves organizational hierarchy, the institutional pressure from management and the operational demonstration effect of peers will have a superimposed impact (Cokins, 2010). Research further reveals that the close correlation between social norms and technology usage intentions is due to group cognition's standardized reshaping of individual behavioral scripts (Sultan & Wong, 2019). This study builds upon prior research by measuring social influence alongside other psychological and technical variables to examine its comparative weight in shaping behavioral intentions toward digital library usage in higher education settings. Hence, the following research hypothesis is constructed:

**H6:** Social influence has a significant impact on behavior intention.

### 2.6 Self-efficacy

In technology adoption research, self-efficacy has become a core dimension of research that explains individual behavioral differences (Kavandi & Jaana, 2020). This concept is the subject's belief assessment of his technical operation ability, and its mechanism of action is independent of the basic skill level (Ding & Jiang, 2023). Specifically, smartphone use efficacy is defined as users' confidence in their ability to complete specific mobile tasks (Nand et al., 2020), while academic self-efficacy is represented by learners' self-efficacy belief in achieving educational goals and confidence in the use of resources (Hayat et al., 2020).

Studies have shown that this variable has a significant positive correlation with behavioral attitude, entrepreneurial inclination, achievement motivation, and other psychological dimensions (Chen, 2018) and a negative regulatory relationship with operational anxiety (Alam et al., 2020). In digital learning scenarios, a high level of self-efficacy has been proven to significantly improve learning effectiveness, which explains the necessity of multidimensional efficacy assessment (Shen et al., 2013). Its deep mechanism of action lies in the fact that this kind of spiritual self-cognition ultimately shapes the behavioral pattern of technology use through such mediating paths as stimulating operation interest and optimizing experience satisfaction (Hu & Zhang, 2016). This study extends prior research by examining self-efficacy as a direct predictor of behavioral intention in a digital library context, providing localized insights for improving student confidence in using academic digital platforms. Survey of the conclusion of the following hypothesis:

**H7:** Self-efficacy has a significant impact on behavior intention.

### 2.7 Behavioral Intention

In the technology acceptance model (TAM) theoretical perspective, behavioral intention is quantified as the strength of users' willingness to adopt technological behavior (Davis, 1989; Sripalawat et al., 2011). This concept can be traced back to behavioral decision theory, which Ajzen (1991) defined as the cognitive preparation state of an individual before implementing a target behavior. Empirical research reveals a significant causal relationship between consumers' subjective attitudes and behavioral tendencies, which has been widely verified in behavioral science (Ajzen & Fishbein, 1980). This study contributes to the behavioral intention literature by offering a validated conceptual model grounded in TAM and UTAUT frameworks, specifically tailored to the higher education digital library environment in Sichuan Province. It also empirically tests multiple interacting predictors of behavioral intention, enhancing the model's practical relevance.

## 3. Research Methods and Materials

### 3.1 Research Framework

This study integrates two classical theoretical models to construct a new theoretical analysis framework: Davis' (1989) technology acceptance model (TAM) explained the predictive mechanism of perceived technology usability and usefulness on adoption decisions, while Venkatesh et al. 's (2003) integrated technology acceptance theory (UTAUT) integrated system performance expectation, effort expectation, and other core variables. A theoretical analysis framework with explanatory power is formed through the critical integration of the existing literature.

TAM and UTAUT were selected due to their consistent empirical success in explaining user acceptance of technology across various domains, including digital services. In the context of digital libraries, these models provide a robust lens to capture both cognitive appraisals (e.g., performance and effort expectancy) and social-psychological influences (e.g., social influence and self-efficacy) that shape usage behavior.

This theoretical framework integrates three key research findings: Wang et al. (2018) analyzed the driving mechanism of mobile library user behavior from the perspective of information ecology; Zhang and Xi (2021) focused on the construction of a scene-oriented behavioral intention model for university WeChat libraries; Hu and Zhang (2016) revealed the key decision-making factors of mobile service adoption through the analysis of user perception factors. Together, the three studies build a multi-dimensional analysis path. The research conceptual framework is proposed as shown in Figure 1.

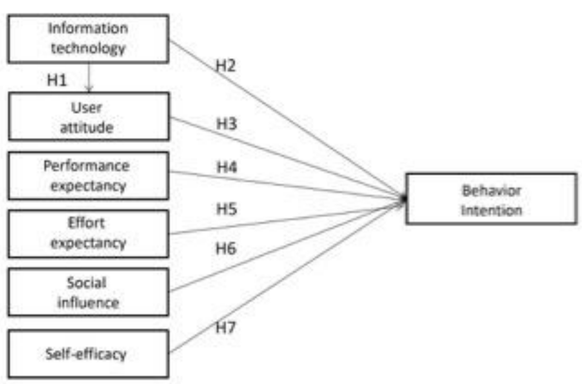


**Figure 1:** Conceptual Framework

This study aims to identify key factors influencing college students' attitudes and behavioral intentions toward digital library use in Chengdu, China. It empirically examines how cognitive and social variables shape technology acceptance and explores the causal relationships among these factors using quantitative methods.

Within the framework, performance expectancy captures students' perceptions of how digital libraries improve academic efficiency; effort expectancy reflects the ease of system use; social influence measures the impact of peers and institutional support; and self-efficacy represents users' confidence in navigating digital library tools. These constructs are measured through validated questionnaire items tailored to the university digital library context.

### 3.2 Research Methodology

This study employs a combination of empirical and quantitative analysis methods, using a questionnaire as the primary data collection tool to gather sample data from targeted groups. The questionnaire items were adapted from established measurement scales in prior theoretical studies related to TAM and UTAUT constructs, ensuring content alignment with the conceptual framework. To ensure quality before large-scale data collection, an Item-Objective Congruence (IOC) test was conducted with three academic experts to assess item relevance and clarity. Items with IOC scores below the accepted threshold of 0.67 (Turner & Carlson, 2003) were revised or removed. A pilot test was then carried out with a small group of students to identify potential issues in clarity, structure, and response time. Cronbach's Alpha coefficients were calculated to verify internal consistency, with a minimum acceptable reliability threshold of 0.70 (Nunnally & Bernstein, 1994). After finalizing the questionnaire, the study targeted undergraduate students with prior digital library experience. The questionnaire was distributed online to sophomore, junior, and senior students from eight higher education institutions in Chengdu, Sichuan Province, China, all of whom had at least one year of digital library usage.

SEM proposed by Anderson and Gerbing (1988), was used to analyze the sample data. In the first stage, confirmatory factor analysis (CFA) was conducted using SPSS and AMOS to ensure convergent validity, verifying that measurement indicators accurately reflect latent variables and establishing a foundation for further analysis. In the second stage, structural equation modeling (SEM) was applied to examine causal relationships within the conceptual model, determining the significance of each factor and validating theoretical assumptions. SEM's ability to analyze complex interactions, including direct and indirect effects (Hair et al., 2010), enhances the accuracy and depth of the findings.

Ethical considerations were addressed by ensuring participant anonymity, voluntary participation, and informed consent. The study complied with institutional ethical standards and data protection principles throughout the research process.

### 3.3 Population and Sample Size

The survey objects of this study are undergraduate students from eight universities in Chengdu, Sichuan Province, China, who have more than one year's experience using digital libraries. This group was chosen to ensure that participants are familiar with the operational processes and functions of the digital library so that they can provide effective feedback based on their experience. According to the structural equation model (SEM) A-prior sample size calculation method proposed by Soper (2006), at the significance level of 0.05, the recommended minimum sample size is 425 for a model containing seven potential variables and 30 observed variables. Therefore, this study decided to issue and collect 500 questionnaires for data analysis after screening.

In this study, sampling techniques of judgment sampling, stratified random sampling, and convenient sampling, were comprehensively used to ensure sample representative and scientific selection. First, through judgment sampling, eight universities in Chengdu, Sichuan, China, are selected as research objects. Then, the stratified random sampling method is used to determine the number of samples that should be taken from each university according to each university's characteristics or classification standards, as shown in Table 1.

**Table 1:** Population and Sample Size

| University Name | Population Size | Proportional Sample Size |
|---|---|---|
| Sichuan University | 42,036 | 80 |
| University of Electronic Science and Technology of China | 23,304 | 45 |
| Southwest Jiaotong University | 29,476 | 57 |
| Sichuan Agricultural University | 37,244 | 71 |
| Sichuan Normal University | 37,182 | 71 |
| Chengdu University of Technology | 36,388 | 70 |
| Southwest Minzu University | 32,133 | 61 |
| Sichuan University of Media and Communications | 23,350 | 45 |
| **Total** | **261,113** | **500** |

**Source:** Constructed by author

To ensure efficient and accurate data collection, the questionnaire was distributed online via a professional WeChat mini program. A convenience sampling method was used, sharing the questionnaire link with respondents willing to participate. To enhance the scientific rigor and validity of the survey, a series of screening questions was carefully designed at the beginning of the questionnaire. These questions ensured that only undergraduate students with at least one year of digital library experience could proceed and complete the survey. This approach maximized sample relevance and data reliability.

# 4. Results and Discussion

## 4.1 Demographic Profile

Among 500 individuals, 214 (42.8%) were males and 286 (57.2%) were females. Regarding education, 106 students, or 21.2 percent, are in their second year of college. The third-year students were 185, accounting for 37.0 percent; in the fourth year, there were 209 students or 41.8 percent. These statistics are presented in detail in Table 2.

**Table 2:** Demographic Information

| Demographic and General Data (N=500) | | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 214 | 42.8 |
| | Female | 286 | 57.2 |
| Year of Study | Sophomore | 106 | 21.2 |
| | Junior | 185 | 37.0 |
| | Senior | 209 | 41.8 |

## 4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is essential in Structural Equation Modeling (SEM) and serves as the foundation for constructing reliable models (Hair et al., 2010). It evaluates not only the reliability of variables but also their validity (Byrne, 2010). Statistical methods such as Cronbach's Alpha, factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) are commonly employed to assess convergent validity (Fornell & Larcker, 1981).

Research indicates significant factor loadings above 0.50 (Hair et al., 1998). In this study, all factor loadings surpassed 0.50, with most exceeding 0.70, ranging between 0.531 and 0.843, as shown in Table 3. Furthermore, CR values of 0.70 or higher and AVE values greater than 0.40 are recommended (Fornell & Larcker, 1981; Hair et al., 1998). Table 3 reveals that all variables in this study achieved CR values exceeding 0.70 and AVE values above 0.40, confirming the significance of these estimates.

Cronbach's Alpha is widely used to measure internal consistency (Kline, 2016), and values of 0.70 or higher are considered acceptable (George & Mallery, 2003; Hair et al., 2010). As reported, Cronbach's Alpha values for all variables in this study exceeded 0.70

**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 |
|---|---|---|---|---|---|---|
| Information technology (IT) | Wang et al. (2018) | 5 | 0.821 | 0.531-0.793 | 0.826 | 0.490 |
| User attitude (UA) | Wang et al. (2018) | 3 | 0.808 | 0.721-0.823 | 0.811 | 0.589 |
| Performance expectancy (PE) | Zhang and Xi (2021) | 3 | 0.812 | 0.743-0.824 | 0.816 | 0.596 |
| Effort expectancy (EE) | Zhang and Xi (2021) | 3 | 0.853 | 0.787-0.843 | 0.853 | 0.659 |
| Social influence (SI) | Zhang and Xi (2021) | 4 | 0.822 | 0.650-0.766 | 0.823 | 0.539 |
| Self-efficacy (SE) | Hu and Zhang (2016) | 3 | 0.774 | 0.692-0.767 | 0.774 | 0.533 |
| Behavior intention (BI) | Hu and Zhang (2016) | 3 | 0.804 | 0.750-0.766 | 0.804 | 0.577 |

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

Additionally, Table 4 shows satisfactory results for discriminant validity, with the square root of AVE for each variable surpassing the corresponding factor correlations, indicating a high degree of differentiation among latent variables.

**Table 4:** Discriminant Validity

| Variable | Factor Correlations | | | | | | |
|---|---|---|---|---|---|---|---|
| | IT | UA | PE | EE | SI | SE | BI |
| **IT** | **0.700** | | | | | | |
| **UA** | 0.218 | **0.767** | | | | | |
| **PE** | 0.264 | 0.520 | **0.772** | | | | |
| **EE** | 0.238 | 0.729 | 0.501 | **0.812** | | | |
| **SI** | 0.055 | 0.057 | 0.054 | 0.105 | **0.734** | | |
| **SE** | 0.265 | 0.382 | 0.381 | 0.388 | 0.145 | **0.730** | |
| **BI** | 0.105 | 0.278 | 0.240 | 0.295 | 0.174 | 0.228 | **0.760** |

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

## 4.3 Structural Equation Model (SEM)

This study used a structural equation model (SEM) to process and analyze the collected data. SEM is unique in many dimensions. First and foremost, it can reveal dependencies between variables (Hair et al., 2010). Secondly, SEM can analyze the causal relationship between potential and observed variables. Thirdly, it incorporates random error in observed variables to yield more precise measurement outcomes. Fourthly, it utilizes multiple indicators to evaluate latent variables. Lastly, it allows for hypothesis testing at the construct level beyond the item level (Hoyle, 2011).

The structural model's goodness of fit was evaluated and presented in Table 5. The statistical metrics were as follows: CMIN/DF = 3.714, GFI = 0.851, AGFI = 0.811, NFI = 0.832, CFI = 0.871, TLI = 0.849, and RMSEA = 0.074. All fit indices exceeded the acceptable thresholds, confirming the model's adequacy.

**Table 5:** Goodness of Fit for Structural Model

| Index | Criterion | Statistical Value |
|---|---|---|
| CMIN/DF | < 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012) | 3.714 |
| GFI | ≥ 0.85 (Sica & Ghisi, 2007) | 0.851 |
| AGFI | ≥ 0.80 (Sica & Ghisi, 2007) | 0.811 |
| NFI | ≥ 0.80 (Wu & Wang, 2006) | 0.832 |
| CFI | ≥ 0.80 (Bentler, 1990) | 0.871 |
| TLI | ≥ 0.80 (Sharma et al., 2005) | 0.849 |
| RMSEA | < 0.08 (Pedroso et al., 2016) | 0.074 |

**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

The standardized path coefficient or regression coefficient measures the independent variable and the dependent variable in the hypothesis. These are important tools for quantifying the relationship between the independent and dependent variables.

**Table 6:** Hypothesis Testing Result

| Hypothesis | Standardized path coefficients (β) | t-value | Test Result |
|---|---|---|---|
| H1: IT → UA | 0.194 | 3.516* | Supported |
| H2: IT → BI | -0.003 | -0.048 | Not Supported |
| H3: UA → BI | 0.128 | 2.294* | Supported |
| H4: PE → BI | 0.112 | 2.065* | Supported |
| H5: EE → BI | 0.186 | 3.416* | Supported |
| H6: SI → BI | 0.180 | 3.275* | Supported |
| H7: SE → BI | 0.117 | 2.086* | Supported |

**Note:** *=p-value<0.05

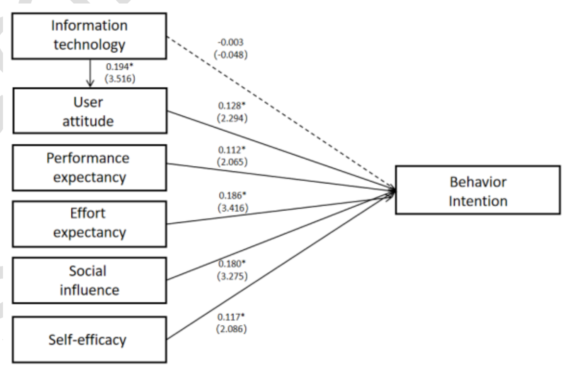


**Figure 2:** Path Diagram Result
**Note:** Solid line reports the Standardized Coefficient with * as p<0.05, and t-value in Parentheses

**H1:** The analysis confirms that information technology has a significant positive influence on user attitude (β=0.194, t=3.516), consistent with findings from Oliver (2006), Beaudry and Pinsonneault (2010), and Franque et al. (2021). In the context of digital libraries, this suggests that students' perceptions of system responsiveness, interface quality, and platform reliability shape their emotional and cognitive stance toward usage. Continued improvement in system performance and accessibility is likely to foster a more welcoming and positive user attitude, especially among frequent academic users.

**H2:** Unexpectedly, no significant link was found between information technology and behavioral intention β=-0.003, t=-0.048), diverging from earlier work such as Thong et al. (2006). One explanation may be that for digital-native users, fundamental technological functions are already normalized and no longer actively drive decision-making. As digital systems become baseline expectations, users may instead rely more on experiential or social cues when deciding whether to engage. This shift calls for greater focus on features that enrich interaction and personalization rather than merely upgrading core infrastructure.

**H3:** User attitude exerts a significant effect on behavioral intention (($\beta$=0.128, t=2.294), reaffirming models established by Park et al. (2014), Huang et al. (2015), and Struckmann and Karnowski (2016). A favorable attitude likely reflects users' overall satisfaction, sense of benefit, and emotional engagement. To encourage ongoing use, digital library services may benefit from regularly assessing user satisfaction and making iterative improvements based on real feedback to sustain positive attitudes over time.

**H4:** Performance expectancy shows a moderate but significant effect (($\beta$=0.112, t=2.065), aligned with the findings of El-Masri and Tarhini (2017), Moorthy et al. (2019), and Shivdas and Ilavarasan (2018). When students perceive that using digital libraries supports their academic tasks effectively—such as accessing references, saving time, or improving research outcomes—they are more inclined to use them consistently. Strengthening academic-oriented features like citation tools, full-text access, and intelligent recommendations can further reinforce this perception.

**H5:** Effort expectancy emerged as the most influential predictor of behavioral intention ($\beta$=0.186, t=3.416), echoing recent studies by Habibi et al. (2022) and Al-Saedi et al. (2020). Students are more willing to use platforms that are intuitive, easy to navigate, and require minimal learning time. This emphasizes the importance of user-centered design in digital libraries. Simplified interfaces, clear navigation pathways, and onboarding features can significantly increase user willingness to engage, especially for those balancing study schedules with independent research.

**H6:** Social influence demonstrated a strong and consistent effect ($\beta$=0.180, t=3.275), supported by findings from Tarhini et al. (2017), Ayaz and Yanartas (2020), and Sultan and Wong (2019). In academic communities, students are often guided by peer behavior and institutional cues. Recommendations from instructors or integration of digital library tools into coursework can increase awareness and perceived value. Within collectivist cultures such as China, the group norm and shared academic expectations can be a powerful motivator for adoption.

**H7:** Self-efficacy was found to significantly influence behavioral intention ($\beta$=0.117, t=2.086), in line with the work of Kavandi and Jaana (2020), Hayat et al. (2020), and Ding and Jiang (2023). When students feel confident in their ability to navigate digital library tools independently, they are more likely to engage voluntarily. To strengthen this effect, universities can support students through workshops, digital literacy training, and responsive help systems that increase user confidence and reduce perceived barriers.

Effort expectancy and social influence emerged as the most decisive factors in shaping behavioral intention toward digital library use. User attitude, performance expectancy, and self-efficacy also play significant roles. The lack of a direct link between IT and behavioral intention suggests a shift in student expectations, where functionality alone no longer drives usage decisions. Instead, the experience—ease of use, peer influence, and confidence—becomes central. These insights underscore the need for digital library systems to evolve from being technically functional to being user-responsive, socially endorsed, and psychologically empowering.

## 5. Conclusions and Recommendation

### 5.1 Conclusions

This study systematically examined the factors influencing college students' attitudes and behavioral intentions toward digital library use in Chengdu, Sichuan Province. Grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), a conceptual framework was developed and tested using structural equation modeling (SEM). Data were collected from undergraduate students with at least one year of digital library experience across eight universities. Confirmatory factor analysis (CFA) confirmed the reliability and validity of the measurement model. Of the seven proposed hypotheses, six were statistically supported, validating the key constructs influencing user engagement.

Effort expectancy emerged as the most influential factor in shaping behavioral intention, reaffirming the principle that systems perceived as easy to use are more likely to be adopted (Habibi et al., 2022). Students who encounter minimal cognitive load and intuitive system interfaces are significantly more inclined to use digital libraries for independent learning. This reinforces the priority of usability in educational technology design.

Following effort expectancy, social influence, user attitude, self-efficacy, and performance expectancy all demonstrated significant effects on behavioral intention. These results align with earlier studies by Venkatesh et al. (2003) and Ajzen (1991), affirming the importance of peer endorsement, perceived capability, and system utility in technology adoption decisions. Interestingly, information technology did not directly affect behavioral intention, a finding that deviates from traditional models but reflects recent shifts among digital-native students who view basic IT capabilities as an expected baseline rather than a motivator. This suggests that psychological and social factors now play a more prominent role than technological novelty in influencing use.

## 5.2 Recommendations

Based on the findings, several actionable strategies can guide the development and promotion of digital library systems in higher education institutions:

First, the study highlights the need to prioritize ease of use through thoughtful interface design, clear navigation, and streamlined user flows. As effort expectancy is the strongest driver of behavioral intention, simplifying the user experience is essential for boosting adoption.

Second, fostering social influence—through peer-driven awareness, faculty advocacy, and integration with academic tasks—can substantially enhance engagement. Digital library usage tends to increase when it is embedded in learning communities and reinforced by institutional messaging.

Although the direct impact of information technology on behavioral intention was not significant, its indirect effect through user attitude was validated. This implies that improvements in system performance, responsiveness, and integration with mobile platforms still matter—but primarily as a foundation for shaping user perceptions.

To amplify this effect, digital libraries should incorporate intelligent features such as personalized recommendations, AI-driven search, and adaptive learning tools to meet diverse academic needs. Trust and satisfaction can also be improved through enhanced privacy protection, faster response speeds, and consistent service quality.

Ultimately, digital library development must go beyond technical upgrades. It should involve cultivating user confidence, enhancing perceived value, and integrating into students' learning habits. This holistic approach will support sustainable adoption in the digital education ecosystem.

## 5.3 Limitation and Further Study

This study has several limitations, suggesting directions for future research. First, the sample was restricted to students from eight universities in Sichuan Province. Although this allows for a focused regional analysis, it limits the generalizability of findings to broader populations across China or internationally. Cultural, institutional, or technological differences in other regions may yield different usage patterns.

Second, the study primarily relied on self-reported quantitative data through structured questionnaires. While this approach is effective for testing theoretical models, it may not fully capture the depth and nuance of students' motivations or contextual influences. Behavioral intention, in particular, may not always align with actual system usage, especially in environments with mandatory or externally driven use.

Third, the rapid evolution of digital resources, including the proliferation of open-access databases and AI tools may alter students' reliance on institutional digital libraries. This dynamic technological landscape could influence the perceived value and usage intention over time, introducing potential bias in interpreting longer-term trends.

To address these limitations, future research should consider a mixed-methods approach, incorporating in-depth interviews, usage analytics, or longitudinal tracking to capture behavior more comprehensively. Expanding the sample scope across diverse academic and regional contexts would also enhance external validity. Additionally, studies should examine how new technologies like generative AI, blockchain for academic integrity, or immersive search tools reshape student engagement with digital libraries.

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