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Determinants of Students' Behavioral intention to use Chaoxing Learning Management System (LMS) in Ideological and Political Classroom by Structural Equation Modeling approach: an integration of TAM, UTAUT and TPB

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Abstract

Purpose: This study examines factors shaping students' behavioral intention to use the Chaoxing LMS in ideological and political classes at Zhanjiang University of Science and Technology.It integrates TAM, UTAUT, and TPB to build the conceptual framework. A total of 500 undergraduate students completed the questionnaire. Reliability analysis showed that the internal consistency coefficients of the scales ranged from 0.815 to 0.882, all above the 0.70 threshold. The average variance extracted (AVE) values ranged from 0.525 to 0.688, exceeding the recommended minimum for most constructs. The AVE for Facilitating Conditions was 0.525, slightly above the 0.50 threshold. **Research design, data and methodology:** This was a quantitative study that employs Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) for data analysis. **Results:** The results show that attitude toward Chaoxing LMS (ATCL) has the strongest effect on behavioral intention to use (BITU) ($\beta = 0.595$, $t = 11.79$). This is followed by perceived behavioral control (PBC), social influence (SI), and facilitating conditions (FC). Perceived ease of use (PEOU) affects BITU indirectly through perceived usefulness (PU).PEOU has a strong positive effect on PU ($\beta = 0.801$, $t = 14.502$), both positively correlating with ATCL.

Keywords: Behavioral intention to use, Chaoxing LMS, Higher Education

JEL Classification Codes: I21; I23; M15; C83

1. Introduction

With rapid global technological development, the digital revolution has significantly influenced education worldwide (Latchem, 2017).This change is largely driven by long-term progress in information and communication technology and shifts in human interaction.As a result, teaching practices have gradually changed, and educational digital platforms have been increasingly adopted (UNESCO, 2019, as cited in Sangwan et al., 2021). In line with this global trend, China has systematically advanced educational informatization. From 1979 to 2000, development focused on audio-visual education. Between 2000 and 2010, reforms emphasized infrastructure construction. The period from 2010 to 2016 was characterized by application-driven implementation. Since 2017, educational informatization has entered an innovation-driven stage, marked by intelligent, socially embedded reforms that differ fundamentally from earlier phases. Chaoxing LMS emerged during the late application-driven stage of China's educational informatization.

During the COVID-19 pandemic in 2020, many higher education institutions shifted from face-to-face instruction to online learning. As a result, the use of Chaoxing LMS increased markedly, reflects in higher platform engagement rates (Cheong et al., 2021). Virtual learning platforms are widely adopted to support online instruction and interaction

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(Bahasoan et al., 2020).This rapid transition introduce new challenges for teachers. Previous studies indicate that many teachers hold low or negative attitudes toward the integration of technology into teaching (Farjon et al., 2019; Sundqvist et al., 2020). Researchers often link these attitudes to insufficient digital competencies developed during initial teacher education, which highlights the need for targeted professional development for in-service teachers (Gibson et al., 2014).Teachers commonly report concerns related to online instructional methods, activity design, platform operation, assessment practices, and student interaction. In addition, structural and individual barriers may limit LMS use, including inadequate network infrastructure, low teacher engagement, limited technology satisfaction, insufficient student digital skills, and resistance to instructional change (Kim & Park, 2017).

1.1 Chaoxing Leaening Management System (LMS)

Chaoxing was founded in 1993 as a Chinese provider of digital library and online educational resources.The company developed the integrated “Chaoxing System,” which includes Xuexitong, Erya, Discovery, and an electronic library (Beijing Century Chaoxing Information Technology Development Co., Ltd.). Between 1993 and 2003, Chaoxing focused on building electronic libraries by digitizing print resources into databases accessible through local and internet networks. This stage supported the early informatization of university libraries in China (Xiang et al., 2022).From 2003 to 2013, Chaoxing expanded into online learning services, with the Erya platform widely used in university general education courses (Chaoxing Learning, 2024).Since 2014, the Chaoxing System has shifted toward mobile and intelligent learning environments. In 2016, the launch of Xuexitong(The Chaoxing Learning App) marked its adoption as a comprehensive LMS for students, integrating course delivery, library services, teaching management, assignments, attendance, and examinations (Chaoxing Learning, 2024).

By 2025, the Chaoxing System—covering most university teaching, research, and reading scenarios, serving over 1800 institutions—has become one of China’s key academic platforms and widely used LMS (Hengyang Normal University, 2025).The Chaoxing system includes three main components(Yang, 2021): Chaoxing Live, Fanya, and the Chaoxing Learning App. Chaoxing Live is a PC-based tool used primarily for teachers’ live lectures. Fanya is a MOOC-style platform that supports course creation and resource sharing. The Chaoxing Learning App integrates the core functions of Chaoxing Live and Fanya, including live streaming, recording content, and teacher-student communication. PC-based platforms are mainly used by teachers for lesson preparation and instruction. Mobile applications are more commonly used by students for attendance tracking and learning activities.

Institutional reports and preliminary course records indicate that, despite the official adoption of the Chaoxing LMS, overall student engagement remains limited. Only 8.9% of students report an average weekly usage duration exceeding 30 minutes, while 8.4% show no recorded usage. Among the 714 users, the attendance-check function demonstrates a notably high utilization rate (89.2%); However, the use of other instructional and interactive functions remains limited. These functions include in-class assignments, access to learning videos and materials, responses to in-class questions, and participation in group discussions. (Chen & Chen, 2020).In addition, limitations in supporting infrastructure restrict effective platform use. Survey results show that 14.7% of respondents report inconvenience caused by weak network signals in teaching buildings. Another frequently cited issue is excessive mobile device storage consumption. Users also report several operational difficulties. These include the need for manual updates of information, complex procedures for revising instructional materials, and reliance on manual service processes for routine operations.(Chen & Chen, 2020).

A pilot survey conducted before the main study shows relatively low levels of perceived usefulness and attitude toward using the Chaoxing LMS. The mean score for perceived usefulness falls below the midpoint of the five-point Likert scale (PU < 3.50). These findings indicate limited perceived value of the system. Such perceptions may reduce students’ willingness to continue using the platform.

Importantly, these issues are interrelated rather than independent. Lower perceived ease of use may reduce perceived usefulness. Changes in perceived usefulness can further influence students’ attitudes and Behavioral intention to use. Such relationships are difficult to examine using single-variable or bivariate analyses.Therefore, this study adopts structural equation modeling to evaluate both the measurement properties and the structural relationships among the theoretical constructs.

1.2 Ideological and Political Theory Course

Ideological and Political Theory courses are compulsory for all university students and are often delivered in large, combined classes. In this context, the Chaoxing Learning App is commonly used as an auxiliary instructional tool. The platform improves the efficiency of managing attendance, continuous assessment, and final grades compared with traditional classroom practices.

Attendance can be completed within a short time through functions such as dynamic QR codes, which helps reduce proxy sign-ins and improve data accuracy. Teachers use the PC-based system to create courses and organize instructional content. The platform supports teaching management across different stages of instruction.

Before class, teachers can select and upload learning resources. During class, interactive activities are conducted and participation data are recorded as part of continuous assessment. After class, homework and online discussions are assigned and managed through the system. At the end of the semester, teachers can review students' grades, participation records, and learning progress.

2. Literature Review

2.1 Theoretical background

The conceptual framework integrates TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), TPB (Ajzen, 1985), and evidence from prior empirical studies. These models identify key factors underlying technology adoption and use. Previous research has applied them to explain usage behavior, extend existing constructs, or combine models for empirical analysis (Taherdoost, 2018).

Previous TAM-based studies typically report standardized factor loadings between 0.60 and 0.90, reflecting acceptable to strong construct validity (Davis, 1989; Venkatesh et al., 2003). The factor loadings in this study fall within this range, indicating consistency with prior research.

Previous studies on LMS adoption have reported moderate to high scores for constructs such as PEOU SI, FC, and PBC, typically ranging from 3.8 to 4.2 (Davis, 1989; Venkatesh et al., 2003). In this study, students report relatively high scores on these constructs. This indicates generally positive perceptions and a supportive attitude toward using Chaoxing LMS.PU (M = 3.46, SD = 0.46) and ATCL (M = 3.24, SD = 0.44) are lower than typical values reported in previous studies, which usually range from 3.8 to 4.2. This indicates that, although students find the system easy to use and perceive strong social and structural support, their perceived benefits and overall attitudes are less positive. BITU also shows a relatively low mean of 3.14 (SD = 0.77). This suggests that positive perceptions of ease and support do not fully translate into strong intention to use.

2.1.1 The Technology Acceptance Model (TAM)

TAM is derived from the Theory of Reasoned Action (Fishbein & Ajzen, 1977) and further developed by Davis (1989). TAM explains technology adoption through key constructs, including PU, PEOU, attitude (ATT), BITU, and actual use(AU) (Scherer et al., 2019).The model assumes that BITU directly predicts AU. BITU is influenced by users' AT T and PU. Attitude toward using(ATU) is shaped by both P U and PEOU. PEOU also affects PU, with the former referring to the effort required to use a system and the latter to its contribution to performance (Riyath et al., 2022).In this study, TAM is used to examine students' attitudes and Behavioral intention toward the Chaoxing LMS.

2.1.2 Unified Theory of Acceptance and Use of Tech nology model (UTAUT)

Venkatesh et al. (2003) proposed the UTAUT, which integrates key elements from TAM, TRA, TPB, and IDT to explain technology adoption. UTAUT identifies four core determinants: Performance Expectancy (PE),Effort Expectancy(EE), SI, and FC. As an extension of TAM, the model consolidates multiple antecedents into a unified explanatory framework. Researchers have widely applied the UTAUT in higher education research, including studies of LMS use during the COVID-19 pandemic (Hsu, 2012). However, previous research has noted limited empirical evidence from China validating the combined explanatory power of TAM and UTAUT for students' intention to use the Chaoxing LMS.

2.1.3 Theory of Planned Behavior(TPB)

Ajzen (1985) proposed TPB as an extension of the Theory of Reasoned Action (Fishbein & Ajzen, 1977). TPB introduces perceived behavioral control to account for behaviors that are not entirely under volitional control (Ajzen, 1991). The model explains BITU as a function of ATT, Soci al Norm(SN), and PBC. Stronger levels of these constructs are expected to lead to stronger BITU, which are key predictors of actual behavior (Abbad, 2021). Researchers have widely applied the TPB to explain technology-related behaviors, including both short- and long-term LMS adoption (Ngafeeson & Gautam, 2021). In this study, resear cher apply the TPB to examine Chinese university students' behavioral intention to use the Chaoxing LMS.

2.2 Hypotheses development

2.2.1 Perceived Ease Of Use and Perceived Usefulness

According to the TAM, BITU is influenced by PEOU and PU. PEOU is expected to have a positive effect on PU. Users who find a system easy to use are more likely to perceive it as useful and to engage with it (Ngafeeson et al., 2024).

Previous studies have consistently supported the positive relationship between PEOU and PU across different contexts (e.g., Bakirtas & Akkas, 2020; Chuenyindee et al., 2022). User-friendly systems are more likely to be adopted, whereas complex systems tend to discourage use. These findings highlight the role of PEOU in shaping PU and technology use intention.Based on this rationale, the following hypothesis is proposed:

H1a: PEOU has a significant positive effect on PU of the Chaoxing LMS.

2.2.2 Perceived Usefulness and Attitude Toward Chaoxing LMS

Prior research shows that PU and PEOU contribute to positive attitudes toward online learning among both students and teachers. Among these factors, PU has been found to exert a stronger influence on attitude than PEOU (Martinez Lopez et al., 2020; Sinha & Bag, 2023). PU is a key determinant of attitudes toward technology use and subsequent behavioral intention. Studies in higher education indicate that students are more likely to adopt learning technologies when they perceive clear learning benefits (Harper et al., 2024; Kim & Kim, 2021). Evidence from teacher-focused research also confirms the central role of perceived usefulness in shaping positive attitudes toward online teaching and learning (Dorji, 2021; Rahayu & Wirza, 2020). These findings suggest that PU plays a critical role in forming favorable attitudes toward LMSs. Based on this rationale, the following hypothesis is proposed:

H2a: Perceived usefulness has a significant positive effect on students' attitude toward Chaoxing LMS.

2.2.3 Perceived Ease of Use and Attitude Toward Chaoxing LMS

Users who perceive a system as easy to use are more likely to develop positive attitudes toward it. According to the TAM, PEOU and PU directly influence attitude, which in turn affects BITU and actual system use (Bag et al., 2020; Choi & Park, 2020). Empirical studies in higher education consistently show that PEOU significantly shapes students' attitudes toward e-learning platforms. User-friendly systems tend to foster positive attitudes, whereas complex systems may discourage adoption (Masumo Gwebente & Phiri, 2022; Natcher et al., 2021). Based on this evidence, the following hypothesis is proposed:

H3a: Perceived ease of use has a significant positive effect on students' attitude toward Chaoxing LMS.

2.2.4 Social Influence and Behavioral intention to use

Prior studies in mobile-assisted and online learning contexts show that social influence from peers, teachers, and family positively affects technology adoption and continued use (Marandu et al., 2023; Harper et al., 2024; Hoi, 2020). According to the UTAUT, SI plays a significant role in shaping individuals' intention to use technology, particularly when adoption is common within their social environment (Singh & Tewari, 2021). Although mandatory LMS use may reduce the strength of this effect in some settings (Hu & Lai, 2019), SI and FC often exert a direct impact on BITU. These factors may also indirectly affect attitudes through PU (Schmitz et al., 2022; Teo et al., 2019). Based on this evidence, the following hypothesis is proposed:

H4a: Social influence has a significant positive effect on students' Behavioral intention to use the Chaoxing LMS.

2.2.5 Attitude Toward Chaoxing LMS and Behavioral intention to use

Prior research indicates that attitude toward technology positively influences Behavioral intention to use learning systems (Choi & Park, 2020). Studies based on the TAM show that attitude and social influence significantly affect BITU, whereas FC may have weaker effects (Buabeng-Andoh & Baah, 2020).Attitude has also been shown to mediate the relationships between PU, PEOU, and BITU. This mediating role has been observed across various e-learning platforms, including video conferencing tools, social media, and LMSs (Harper et al., 2024; Ramdhony et al., 2021). Most studies report a positive association between attitude and intention in online and mobile learning contexts (Azhari & Usman, 2021; Shao, 2020), although some studies report inconsistent findings in certain settings (Siswanto et al., 2018). These mixed results indicate the need for further empirical examination. Based on this rationale, the following hypothesis is proposed:

H5a: Attitude toward Chaoxing LMS has a significant positive effect on students' Behavioral intention to use Chaoxing LMS.

2.2.6 Facilitating Conditions and Behavioral intention to use

FC refer to the availability of technical support, training, infrastructure, and system access. Prior studies show that FC positively influence Behavioral intention to use learning technologies, including e-learning systems and LMSs (Hoi, 2020; Riyath et al., 2022). Adequate facilitating conditions support teacher engagement, student participation, and technology adoption, whereas insufficient support may hinder system use (Kulal & Nayak, 2020; Salloum et al., 2019). According to the UTAUT, FC contribute to learners' BITU, particularly in institutional learning contexts (Abbad, 2021).Although some studies report non-significant relationships between FC and BITU(Siswanto et al., 2018), FC remain important for sustaining LMS use in higher education (Cavus et al., 2021). These mixed findings justify further empirical examination. Based on this rationale, the following hypothesis is proposed:

H6a: Facilitating conditions have a significant positive effect on students' Behavioral intention to use the Chaoxing LMS.

2.2.7 Perceived Behavioral Control and Behavioral intention To Use

In the TPB, PBC reflects individuals' confidence in their ability to perform a behavior. Higher levels of PBC are associated with stronger BITU and greater effort (Cai et al., 2019).Empirical studies show that PBC is a strong predictor of students' intention to use online learning systems, including LMSs and MOOCs (Al-Mamary, 2023; Pan et al., 2021; Wang et al., 2022).Factors such as information quality, enjoyment, accessibility, and satisfaction may enhance PBC, whereas technology-related anxiety may reduce it (Fernandez Batanero et al., 2021; Salloum et al., 2019).Based on this evidence, the following hypothesis is proposed:

H7a: Perceived behavioral control has a significant positive effect on students' Behavioral intention to use the Chaoxing LMS.

2.3 The Conceptual Framework

This study empirically tested the conceptual framework and hypothesized relationships between variables, as illustrated in Figure 1.

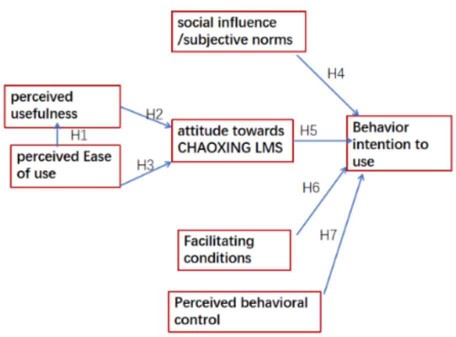

Figure 1: The Conceptual Framework of factors affecting intention to use Chaoxing LMS
Source: Created by author

3. Research methodology

This study used a mixed sampling strategy, combining probability and non-probability methods. For the probability component, four colleges were selected through stratified random sampling based on institutional type, such as comprehensive universities and technical colleges. This ensured representativeness across different college categories. For the non-probability component, students with prior experience using the Chaoxing LMS were recruited through quota sampling. Quotas reflected the distribution of students by year level (second to fourth year) and major within the selected colleges. A total of 500 valid questionnaires were collected from undergraduates across these strata.

Content validity was established through expert review by three specialists in educational technology and LMSs. Item-Objective Congruence (IOC) values ranged from 0.67 to 1.00, exceeding the accepted threshold of 0.50 and indicating satisfactory content validity. In addition, A pilot study involving 30 undergraduate students, excluded from the final sample, was conducted to assess reliability. Cronbach's alpha values ranged from 0.80 to 0.89, exceeding the recommended threshold of 0.70 and indicating satisfactory internal consistency. Foremore, common method bias was examined using Harman's single-factor test. The first unrotated factor explained 32.36% of the total variance, below the 50% threshold, indicating that common method bias is unlikely to be a significant concern.

3.1 Questionnaire development

This study used a quantitative questionnaire survey to collect data from undergraduates in four colleges.The questionnaire were distributed online ,including screening questions, measurements of all variables, 5-point Likert-scale items, and demographic questions. The questionnaire used a five-point Likert scale (Likert, 1932) and was translated into Chinese. The 27-item survey covered: PU (items 1-5), PUOU (6-10), PBC (11-13), SI (14-17), ATCL (18-20), FC (21-24), and BITU (25-27), adapted mainly from Al-Mamary (2023) and Tarhini et al. (2017), As was showed in Table 1.

3.2 Demographics

The study surveyed 500 respondents who provided demographic and behavioral information. As was shown Table 2.

Table 2: Demographic Information Characteristics of Respondents Sample Size (n=500)

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	147	29.4%
	Female	353	70.6%
OFFEN	One to two years	319	63.8%
	More than two years	181	36.2%
COLLEGE	College of Music and Dance	148	29.6%
	College of Education	129	25.8%
	College of Economics and Finance	124	24.8%
	College of Management	99	19.8%

Source: Created by author

4. Results and Discussion

4.1 Descriptive Analysis of Measurement Scales

Table3 presents descriptive statistics for all constructs and items.Skewness and kurtosis values suggest approximately normal distributions, supporting the suitability of the data for further analyses.

4.2 Confirmatory Factor Analysis (CFA)

4.2.1 Cronbach's Alpha Reliability (CA)

Table 3 presents the internal consistency reliability of the study constructs. All variables demonstrate strong reliability, with Cronbach's alpha values ranging from 0.815 to 0.882. All constructs meet the recommended reliability threshold ($\alpha \geq 0.70$), indicating that the measurement scales are reliable for subsequent analysis.

4.2.2 Measurement Model Assessment

Table 4 reports the factor loadings derived from the Confirmatory Factor Analysis results. The results indicate a clear two-factor structure. Component 1 shows high loadings for PEOU, PU, ATCL, and BITU. This component reflects students' perceptions and attitudinal evaluations of the system.Component 2 is characterized by strong loadings for SI, FC, and PBC. This component represents social and contextual influences on system use.

Table 4: Summary of Factor Loading

Variables	Factors Loading	
	Component1	Component2
Perceived Ease of Use	0.8372	0.2
Social Influence	0.117	0.705
Facilitating Conditions	0.1599	0.598
Perceived Behavioral Control	0.0267	0.738
Perceived Usefulness	0.8727	0.113
Attitude Towards Chaoxing LMS	0.8484	0.138
Behavior Intention to use	0.5087	0.628

Source: Created by author

4.3 The Results of Confirmatory Factor Analysis

Fitness indexes present the model fit indices for the structural equation model.These results indicate that the proposed model fits the data well.

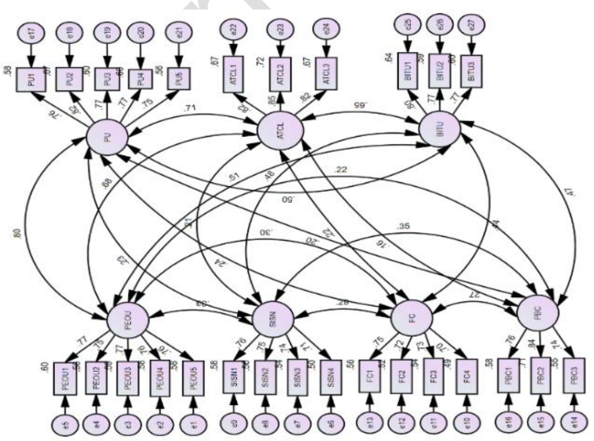

Figure 2: Measurement Model

Fitness indexes 1.X2/df (CMIN/df) = 1.145 2.GFI = 0.952 3. AGFI = 0.940 4. NFI = 0.950 5.IFI = 0.993 6.CFI = 0.993 7.RMR = 0.009 8. RMSEA = 0.017

Source: Created by author

Table 3 reports the results of the confirmatory factor analysis for all latent constructs. All observed indicators load significantly on their corresponding latent constructs.All t-values are statistically significant ($p < 0.001$), supporting the validity of the measurement model.The standardized factor loadings range from 0.697 to 0.852. Although two items under FC load slightly below 0.70, all values exceed the acceptable minimum of 0.60, which is considered adequate in SEM when composite reliability and AVE meet recommended criteria (Hair et al., 2019).The average variance extracted for BITU is 0.558, which exceeds the recommended threshold of 0.50. This result indicates acceptable convergent validity for the construct.The R^2 values represent the proportion of variance in each observed variable accounted for by its corresponding latent construct. Most R^2 values exceed 0.50, indicating that the latent variables provided adequate explanatory power for their indicators.

4.4 Discriminant Validity

Table 5 present the correlation matrix and the square roots of the AVE for all constructs. The diagonal AVE values range from 0.724 to 0.829, exceeding the recommended 0.70 threshold and surpassing inter-construct correlations, supporting both convergent and discriminant validity.

Correlations among constructs are generally moderate. PEOU is strongly correlated with PU and ATCL. BITU shows moderate correlations with all key predictors.These results confirm the reliability and validity of the measurement model.

Discriminant validity is assessed using the heterotrait-monotrait ratio (HTMT). As shown in Table 6, all HTMT values are below the conservative cutoff of 0.85, providing evidence of satisfactory discriminant validity among the constructs (Henseler et al., 2015).

Table 5: Inter-Construct Correlations and the Square Root of AVE

Variables	1	2	3	4	5	6	7
PEOU	0.764						
SI	0.283	0.74					
FC	0.256	0.241	0.724				
PBC	0.19	0.294	0.219	0.782			
PU	0.703	0.195	0.205	0.176	0.774		
ATCL	0.597	0.178	0.192	0.144	0.624	0.829	
BITU	0.433	0.399	0.364	0.394	0.425	0.554	0.747

Source: Created by author

Table 6: Heterotrait-Monotrait Ratio (HTMT)

Construct	PEOU	SI	PU	ATU	BITUTU
PEOU		0.332	0.801	0.686	0.511
SI	0.332		0.23	0.21	0.484
PU	0.801	0.23		0.713	0.499
ATCL	0.686	0.21	0.713		0.654
BITU	0.511	0.484	0.499	0.654	

Source: Created by author

4.5 Structural Equation Modeling (SEM)

Fitness indexes presents the model fit indices for the structural model,supporting that the structural model fits the data well.

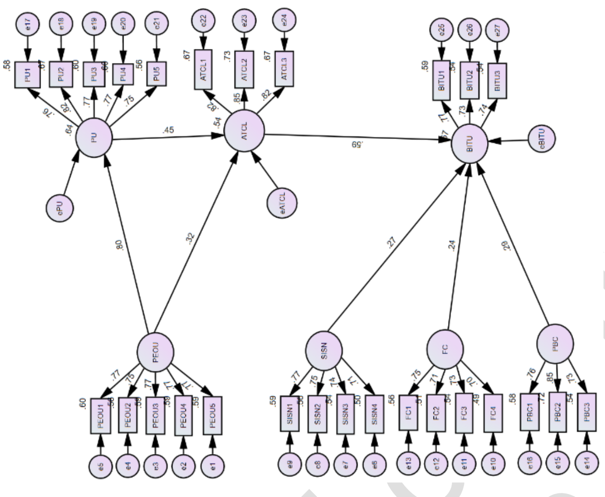

Figure 3: Structural Equation Model
Fitness Indexes
1.X2/df (CMIN/df) = 1.585 2.GFI = 0.929 3.AGFI = 0.915 4.NFI = 0.928
5.IFI = 0.972 6.CFI = 0.972 7.RMR = 0.034 8.RMSEA = 0.034
Source: Constructed by author

4.6 Research Hypothesis Testing Result

Table 7 presents the results of hypothesis testing for the structural model. All hypothesized paths are statistically significant. These results empirically support all proposed relationships in the structural model.

Table 7: Hypothesis Result of the Structural Model

Hypo theses	Paths	Standardized Path Coefficients (β)	S.E.	T-Value	Tests Result
H1	PU<---PEOU	0.801	0.056	14.502*	Supported
H2	ATCL<---PU	0.453	0.071	5.699*	Supported
H3	ATCL<---PEOU	0.318	0.07	4.075*	Supported
H4	BITU<---SI	0.273	0.086	5.985*	Supported
H5	BITU<---ATCL	0.595	0.085	11.79*	Supported
H6	BITU<---FC	0.235	0.091	5.172*	Supported
H7	BITU<---PBC	0.295	0.088	6.427*	Supported

Source: Created by author

4.7 Discussion

This study investigates factors influencing undergraduate students' Behavioral intention to use the Chaoxing LMS.The conceptual framework was developed through a systematic literature review and the integration of three core theories: the TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and TPB(Ajzen, 1985).Key constructs from TAM—PU, AT CL, and PEOU—and from TPB/UTAUT—BITU, SI, FC, and PBC—formed the basis of the proposed model.

This study uses a quantitative research approach.The results validated the proposed theoretical framework. BITU was found to be directly influenced by ATCL, SI,FC, and PB C.PU and PEOU exerted indirect effects on BITU.

In the research, H1 is supported, showing that PEOU has a strong positive effect on PU (β = 0.801, t = 14.502, p < 0.001). The strong effect of PEOU on PU (β = 0.801) indicates that usability is a key determinant of students' perceptions of the Chaoxing LMS. This result is consistent with the core premise of TAM that PEOU enhances PU.Compared with prior studies reporting coefficients of approximately 0.40-0.60, the larger effect observed here suggests that interface simplicity may be particularly salient in the LMS context.

Regarding ATCL, H2 is supported. PU positively influences ATCL (β = 0.453, t = 5.699, p < 0.001). PU exerts a moderate effect on students' ATCL.This finding aligns with the TAM, which identifies PU as a key antecedent of attitude.The observed coefficient (0.30-0.50) is consistent with prior TAM-based studies, supporting the theoretical validity and empirical robustness of this relationship.

In addition, H3 is also supported, PEOU also exerts a significant positive effect on ATCL (β = 0.318, t = 4.075, p < 0.001). These results indicate that PEOU has a moderate effect on ATCL, consistent with TAM's view that ease of interaction positively shapes users' evaluations of a system. Although weaker than the effect of PU, the coefficient falls within the range commonly reported in prior studies (0.20-0.40).

SI positively affects BITU (β = 0.273, t = 5.985, p < 0.001; H4). SI has a moderate effect on BITU, consistent with TAM extensions and the TPB, which emphasizes the role of SI.

The effect size aligns with prior findings (typically 0.20-0.35), indicating a meaningful but secondary influence on LMS adoption.

ATCL has the strongest effect on BITU ($\beta = 0.595$, $t = 11.79$, $p < 0.001$; H5).The substantial effect of ATCL on BIT U ($\beta = 0.595$) indicates that students' overall evaluations of the LMS strongly influence their Behavioral intention to use it. This finding is consistent with both TAM and TPB, which identify attitude as a key mediator between beliefs and Behavioral intention to use.

FC have a weak to moderate effect on BITU ($\beta = 0.235$, $t = 5.172$, $p < 0.001$; H6).This finding is consistent with TPB and related models, which emphasize the role of external support and resources.Although slightly lower than coefficients reported in prior studies (approximately 0.25-0.40), the result suggests that FC exert a supportive rather than primary influence on BITU.

PBC significantly influences BITU ($\beta = 0.295$, $t = 6.427$, $p < 0.001$; H7). PBC has a moderate effect on BITU.This finding aligns with TPB, which identifies PBC as a direct antecedent of BITU.The coefficient (0.25-0.45) falls within the range reported in prior studies, indicating a stable and theoretically consistent relationship.

5. Conclusions

This study examines factors influencing undergraduate students' use of the Chaoxing LMS in ideological and political theory courses. The study developed and validated a conceptual model integrating TAM, TPB, and UTAUT. Results indicate that PEOU positively affects PU and ATCL.ATCL,SI, FC, and PBC positively influence BITU.

The mean score for ATCL is 3.24, placing it in the moderate range on the five-point Likert scale (2.50-3.49). This indicates a neutral to cautious evaluation rather than a negative attitude. The mean score for PU is 3.46, near the upper bound of the moderate range, indicating that usefulness is not perceived as low. This suggests that students recognize the LMS's benefits, though further improvement is possible.The results indicate that users perceive the Chaoxing LMS as easy to use and adequately supported, while their evaluations of its usefulness, attitude, and Behavioral intention to use remained moderate. This study finds that PEOU strongly influenced PU ($\beta = 0.801$), while ATCL exerted a substantial effect on BITU ($\beta = 0.595$).

5.1 Limitations and Future Research

This study has several limitations.First, relying solely on quantitative methods limits insight into the psychological processes underlying the observed relationships.Second, the sample was drawn from a single institution, which may restrict the generalizabituility of the findings.Third, the model includes a limited set of variables, potentially constraining its explanatory power.Future research could use mixed-methods approaches, recruit more diverse samples, and incorporate additional relevant factors to enhance robustness and generalizability.

5.2 Implications

5.2.1 Implications for Theory

This study extends the TAM by integrating key constructs from the TPB, including SI(SN), FC, and PBC.Attitude is positioned as a central mediating variable, capturing both direct and indirect effects on BITU.This approach strengthens TAM's explanatory power in the LMS context.The inclusion of resource- and control-related factors emphasizes the roles of technical support and user autonomy in digital learning. Overall, the model provides a more integrated framework for understanding platform-based learning behavior.

5.2.2 Implications for Practice

The findings show that users perceive the Chaoxing LMS as easy to use and well supported.However, evaluations of its perceived usefulness, overall attitude, and Behavioral intention to use to continue using it remain limited.To enhance adoption, developers and institutions should improve instructional value, interactive functions, and curriculum integration. Strengthening teacher involvement and technical support can reinforce social influence.These measures may foster more positive attitudes and sustained use, thereby improving the effectiveness of Chaoxing LMS implementation in instructional settings.

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Table 8: Operationalization Table of Questionnaire

Variables	Operationalization	Source	Scale
Perceived Usefulness	1. Chaoxing LMS can help students fulfill their needs quickly and effectively. 2.The use of Chaoxing LMS can create a more equitable learning environment for all students. 3.Implementing Chaoxing LMS could lead to time savings for students. 4.Incorporating Chaoxing LMS into education can enhance the quality of the learning experience. 5.I am satisfied with the performance of the Chaoxing LMS.	Adapted from Al-Mamary (2023).	5 point Likert Scale (Agreement) 1-Strongly disagree 2-Disagree 3-Neutral 4-Agree 5-Strongly agree
Perceived Ease of Use	1.My interaction with Chaoxing LMS is clear and understandable. 2. Chaoxing LMS is easy to learn. 3.I find Chaoxing LMS to be easy to use. 4.I find it easy to get Chaoxing LMS to do what I want it to do. 5.I find it simple to become proficient in using Chaoxing LMS.	Adapted from Al-Mamary (2023).	
Social Influence	1.My teachers think that I should use Chaoxing LMS. 2.My classmates think that I should use Chaoxing LMS. 3.The opinion of non-academic groups (e.g. friends and family) suggests that I should use Chaoxing LMS. 4.People whose opinions matter to me suggest that I use Chaoxing LMS.	Adapted from Tarhini et a l. (2017).	
Attitude Towards Chaoxing LMS	1.Using Chaoxing LMS is advantageous. 2.I personally favor using Chaoxing LMS. 3.I would recommend Chaoxing LMS to my peers for their education.	Adapted from Al-Mamary (2023).	
Facilitating Conditions	1.When I need help to use Chaoxing LMS, guidance is available to me. 2.A specific person/group is available for assistance with any difficulties related with Chaoxing LMS use. 3.Specialized instruction concerning Chaoxing LMS use is available to me. 4. I possess sufficient knowledge to effectively use Chaoxing LMS.	Adapted from Al-Mamary (2023).	
Perceived Behavioral Control	1. I had full autonomy in using Chaoxing LMS. 2. I had access to the necessary resources and skills to proficiently use Chaoxin g LMS. 3. I am self-assured in my aBITUTUlity to effectively use Chaoxing LMS for the learning process.	Adapted from Al-Mamary (2023).	
Behavioral Intention to use	1. I will use the Chaoxing LMS on a regular basis in the Future. 2.I will continue using Chaoxing LMS in order to fulfil my future needs. 3.I will strongly recommend others to use Chaoxing LMS.	Adapted from Al-Mamary (2023).	

Source: Created by author