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Abstract

This research examines the key factors that shape vocational college students' continued use of Learnmaster E-Learning Technology (LELT) in Wuhu, Anhui Province, China. Drawing upon an integrated framework that merges the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Social Cognitive Theory (SCT), this study incorporates self-efficacy, effort expectancy, facilitating conditions, and performance expectancy as additional constructs to strengthen its explanatory capacity. This approach effectively addresses domain-specific challenges within vocational education contexts, including technological instability and limited interactive capabilities in digital learning platforms. A structured survey was distributed to 500 students across eight departments of Anhui Mechanical and Electrical Vocational College, all of whom had previous exposure to LELT. This investigation is particularly necessary for the focal institution, as it is currently seeking to modernize its teaching models, enhance digital learning engagement, and improve student outcomes by leveraging e-learning platforms. Confirmatory Factor Analysis (CFA) was utilized to verify both convergent and discriminant validity, after which Structural Equation Modeling (SEM) was conducted to assess the overall model fit and examine seven proposed paths. The findings provided support for all proposed hypotheses, highlighting self-efficacy as the strongest determinant of behavioral intention, while facilitating conditions and performance expectancy also exhibited significant positive impacts. Based on these findings, the study proposes three strategic recommendations: integrating LELT performance metrics into institutional evaluation and scholarship systems; enhancing technical support infrastructure through micro-service architecture optimization; and implementing phased training programs designed to build user confidence and reduce cognitive load. The proposed recommendations are intended to promote a more comprehensive incorporation of e-learning tools within vocational education contexts. Moreover, the study confirms the applicability of the extended TAM-UTAUT-SCT framework in interpreting technology adoption behaviors in Chinese vocational colleges, thereby offering both conceptual contributions and actionable implications for educators, system designers, and policymakers working toward digital education advancement.

Keywords: Learnmaster E-Learning Technology, Vocational Education, TAM, UTAUT, SCT, Behavioral Intention

Introduction

The widespread coverage of digital infrastructure and the deep penetration of the mobile Internet are driving a paradigm shift in the teaching model of global higher education (Rodero, 2023). In China, the online education market has experienced continuous growth in recent years, reaching a considerable transaction volume. (iResearch, 2023). A significant driver of this change is LELT. Developed independently by Beijing Century Chaoxing Information Technology Development Co., Ltd. Around the mid-2010s, the platform adopts a microservice-based architecture and functions as a comprehensive digital education ecosystem, seamlessly combining teaching, learning, reading, and mobile social interaction within a single interface (Nikou & Maslov, 2021; Yi, 2024). With the support of national policies, LELT has been widely adopted by many universities to effectively support blended teaching and synchronous/asynchronous integrated learning models by dynamically generating teaching resources, providing interactive learning tools, and learning situation analysis functions (Ahmed et al., 2024; Li, 2021).

Although LELT has been rapidly deployed, existing empirical studies have shown that it has not yet achieved optimal utilization. Prior studies indicate that unstable system performance, inadequate detail in teaching materials, and limited interactive functionalities reduce user satisfaction and weaken their intention to persist in using the system (Chen et al., 2020; Nikou & Maslov, 2021). Crucially, as a population crucial to the modernization of China's skilled workforce, the platform adoption rate of vocational college students is significantly lower than that of undergraduates (Li et al., 2024). Previous studies have mostly focused on platform design optimization or learning effectiveness evaluation, but there is still a lack of systematic theoretical construction and in-depth discussion on the behavioral mechanism of continuous use of LELT by vocational students, especially in the context of regional innovation centers such as Wuhu.

Against this backdrop, Anhui Mechanical and Electrical Vocational and Technical College (AMEVTC) represents a particularly relevant research site. As a provincial-level demonstration institution for vocational education and digital transformation, AMEVTC has actively introduced LELT into its curriculum across multiple departments. However, institutional reports and preliminary interviews indicate several persistent challenges: (1) inconsistent student participation rates across departments, with technology-heavy majors showing higher uptake than service-oriented majors; (2) limited integration of LELT performance data into teaching evaluation and scholarship systems, which reduces the incentive for continuous student use; and (3) insufficient digital competencies among a portion of students, which constrains their ability to leverage the full range of LELT functionalities. Addressing these issues is critical for AMEVTC, not only to improve teaching efficiency and learning engagement but also to align with the national policy goal of cultivating high-quality technical and skilled personnel in regional innovation hubs such as Wuhu. This diagnosis highlights why an in-depth examination of the determinants of continuous LELT usage is urgently needed for this institution.

To fill the gaps identified in previous studies, this research integrates three complementary theoretical frameworks. First, the TAM proposed by Davis (1989) advocates that perceived ease of use (PEOU) and perceived usefulness (PU) are the core antecedents of behavioral intention (BI). Second, the UTAUT developed by Venkatesh et al. (2003) builds on TAM by introducing performance expectancy (PE) and effort expectancy (EE), thereby extending the original framework. Third, Bandura (1978)'s Social Cognition Theory (SCT) introduces self-efficacy (SE) and facilitation conditions (FC), which address the primary determinants of technology adoption from both individual and environmental perspectives. By integrating the above theories, this study constructs a simple and comprehensive theoretical model that can cover both cognitive assessment and situational factors on the reception mechanism of LELT.

Empirical studies within Chinese higher education contexts provide additional evidence for the importance of the central constructs of TAM and UTAUT. Duan et al. (2024) showed that integrating hybrid teaching models such as O-AMAS can enhance students' self-directed learning, though their findings were limited to engineering undergraduates. Lin et al. (2020) reported that BYOD-compatible activities improved system flexibility, but the cross-sectional design constrained causal inference. Kuandey et al. (2023) found that computer literacy fosters students' self-efficacy in using learning management systems, highlighting the moderating role of digital competencies. Together, these studies suggest that contextual factors such as academic setting, digital literacy, and access to resources may shape the adoption and sustained use of LELT, thereby guiding the hypotheses of this study.

Drawing on the aforementioned literature, this study proposes a set of hypotheses linking PEOU, PU, PE, SE, EE, and FC to University Students' Perceived Usefulness and behavioral intention to Use LELT. By incorporating SE and FC into the theoretical model, the conceptual framework constructed in this study transcends the theoretical boundaries between traditional TAM and UTAUT, revealing how individual ability beliefs and institutional support jointly influence the formation mechanism of intention to continue use. In addition, this study selects vocational colleges in the national education informatization demonstration zone in Wuhu area as the research object, which further enhances the contextual specificity and policy relevance of the research background.

In summary, this research contributes across three dimensions: theoretical, methodological, and practical. From a theoretical perspective, this research empirically tests the applicability and explanatory power of the extended framework integrating TAM, UTAUT, and SCT in a relatively weak research situation in higher education in China. At the methodological level, a rigorous multi-stage sampling procedure was adopted, and the relationships among variables were examined using structural equation modeling, which strengthened both the robustness and the inferential validity of the findings. At the practical level, the research results can provide a targeted strategic basis for platform developers, institution administrators, and education policymakers to serve the broader digital education equity and advance quality enhancement efforts by promoting greater acceptance and utilization of LELT among vocational college students.

Literature Review

Technology Acceptance Model (TAM)

The TAM proposed by Davis (1989) is one of the most widely applied frameworks for explaining user acceptance of information systems. TAM identifies PEOU and PU as the two central determinants of BI, which in turn predicts actual usage behavior. The model has been extensively validated in educational technology research, particularly in e-learning environments, where students' judgments of ease and utility strongly influence their sustained engagement (Faqih, 2019; Lee, 2006).

Perceived Ease of Use (PEOU)

According to Davis (1989), PEOU refers to the extent to which a person perceives that using a system demands little physical or mental effort. Venkatesh et al. (2003) refined this as users' perception of system operability ease. Lee (2006) contextualized it for e-learning, emphasizing students' assessment of electronic learning systems (ELS) accessibility. Abdelfattah et al. (2022) further described it as users' confidence in overcoming technological difficulties. Collectively, PEOU reflects how users evaluate the simplicity of the system and the degree to which it reduces the effort needed.

H1: PEOU has a significant impact on PU.

H2: PEOU has a significant impact on BI.

Perceived Usefulness (PU)

Davis (1989) described PU as the degree to which users believe that a system enhances the effectiveness of their future tasks. Lee (2006) specified its role in e-learning, where it denotes students' conviction that ELS improves academic performance. Faqih (2019) extended this to educators' and learners' perceived effectiveness in knowledge acquisition. Abdelfattah et al. (2022) emphasized PU as confidence in job performance improvement via technology. PU thus captures the system's value in achieving performance goals.

H3: PU has a significant impact on BI.

Unified Theory of Acceptance and Use of Technology (UTAUT)

Building upon TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) introduced by Venkatesh et al. (2003) integrates eight previous models of technology adoption. UTAUT emphasizes performance expectancy (PE), effort expectancy (EE), social influence, and facilitating conditions (FC) as predictors of behavioral intention and use behavior. This framework has been widely applied in educational technology studies, particularly in contexts where institutional and infrastructural support play a central role.

Performance Expectancy (PE)

Venkatesh et al. (2003) conceptualized PE as the extent to which individuals perceive that using a technology improves their work performance. Wang et al. (2009) applied it to mobile learning, framing it as students' confidence in achieving better learning outcomes. Xu et al. (2022) viewed PE as learners' expectation that online education enhances academic performance. Mittal et al. (2022) confirmed PE as pivotal for understanding technology adoption during crises. PE signifies the anticipated productivity gains from system use.

H4: PE has a significant impact on BI.

Effort Expectancy (EE)

Venkatesh et al. (2003) described EE as the degree to which a system is perceived by users to be user-friendly and easy to navigate. Yadav et al. (2016) viewed it as perceived effortlessness in technology adoption. Tarhini et al. (2017) tied EE to students' inclination toward easy-to-use systems. Xu et al. (2022) defined it as learners' perceived difficulty in navigating online platforms. Sarfraz et al. (2022) highlighted EE as a predictor of usage intention. EE thus measures the anticipated user-friendliness of technology.

H6: EE has a significant impact on BI.

Facilitating Conditions (FC)

Ajzen (1991) conceptualized facilitating conditions (FC) as environmental resources that support the execution of behavior, while Venkatesh et al. (2003) described FC as the availability of technical and infrastructural support. Tarhini et al. (2017) measured FC via students' access to e-learning resources. Xu et al. (2022) emphasized guidance from tools/resources. Kuandey et al. (2023) viewed FC as perceived organizational backing. FC encompasses external enablers for technology adoption.

H7: FC has a significant impact on BI.

Social Cognitive Theory (SCT)

While TAM and UTAUT emphasize technological and organizational determinants, Social Cognitive Theory (SCT) introduced by Bandura (1978) adds a psychological dimension by highlighting the role of self-efficacy (SE) in shaping technology adoption. SCT posits that individuals' confidence in their ability to perform specific tasks directly influences their behavioral choices, especially under challenging circumstances.

Self-Efficacy (SE)

Bandura (1978) introduced SE as confidence in successfully executing tasks. Venkatesh and Davis (2000) contextualized it as self-assessment of technological task proficiency. Pituch and Lee (2006) defined it for e-learning as individuals' belief in achieving goals via ELS. Nikou and Economides (2017) emphasized mobile self-efficacy for task completion. Kuandey et al. (2023) linked it to computer literacy in LMS operation. It reflects users' perceived capability to utilize technology effectively.

H5: SE has a significant impact on BI.

Behavioral Intention (BI)

BI has been described as a planned strategy for actions to be carried out by a person (Fishbein & Ajzen, 1975). Davis (1989) described BI as conscious intent to engage in future behaviors. Turner et al. (2010) equated BI with motivation for technology use. Xu et al. (2022) contextualized it as learners' willingness to sustain online education. Songkram et al. (2023) framed BI as the likelihood of platform adoption. BI signifies the readiness to act based on perceived system value. Across frameworks, BI reflects the readiness to act based on perceived system value and supporting conditions.

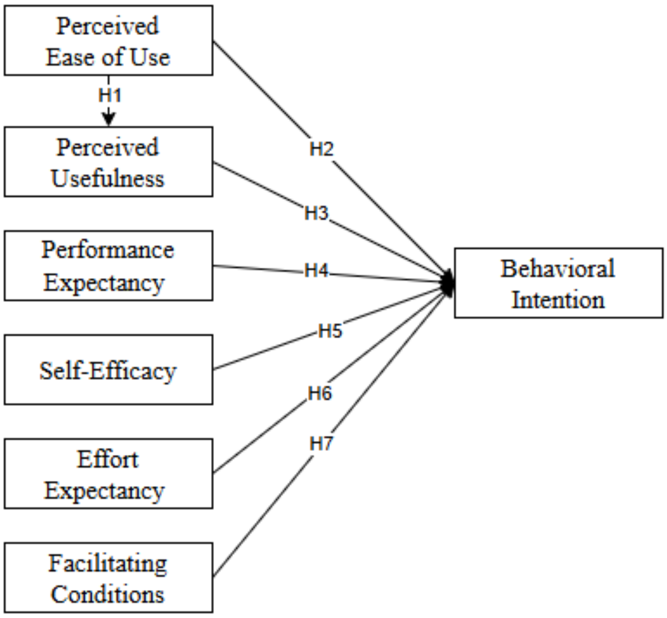
Research Methods and Materials

Research Framework

This study draws on three foundational theories: UTAUT proposed by Venkatesh et al. (2003), TAM developed by Davis (1986), and SCT originally formulated by Bandura (1986) and later extended by Tarhini et al. (2017). Building on these frameworks, a conceptual model for this study has been developed by the researcher and is illustrated in Figure 1.

Figure 1

Conceptual framework



Source: Constructed by the Author

This study aimed to examine the factors influencing university students' adoption of LELT in Wuhu, China. These variables included PU, PEOU, PE, SE, EE, FC, and BI. We analyzed the causal links among these variables to understand the underlying mechanisms through which cognitive perceptions (PEOU, PU, PE, EE), internal drivers (SE), and environmental enablers (FC) collectively shape students' behavioral intention toward e-learning adoption.

Research Methodology

Research Design

Through an online survey platform by Steffens et al. (2014) were distributed questionnaires to the target participants, employing a quantitative method with non-probability sampling. The study targeted students enrolled in eight departments at AMEVTC, located in Wuhu City, Anhui Province. The feedback data collected were analyzed to identify the factors affecting university students' PU and BI toward adopting LELT. The questionnaire was structured into three sections. The first section included screening questions to ensure participants met the eligibility requirements. The second section employed a 5-point Likert scale to assess all study variables and test the seven hypotheses, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). The third section collected demographic details, such as gender, age, academic year, and monthly spending. Before administering the main survey, a pilot study involving 30 participants was conducted, and experts evaluated the questionnaire items using the Item-Objective Consistency Index (IOC) to confirm their validity. Moreover, item selection was guided by established measurement scales adapted from prior TAM, UTAUT, and SCT studies (e.g., Bandura, 1978; Davis, 1989; Venkatesh et al., 2003). Each construct was represented by three to five items to ensure sufficient coverage while avoiding redundancy. Items were slightly reworded to fit the LELT context, thus enhancing face validity.

The questionnaire was evaluated for reliability and and construct validity. Cronbach's Alpha (Hartog & Verburg, 2004) was employed to assess internal consistency reliability, while CFA verified convergent and discriminant validity. These procedures confirmed the appropriateness of the conceptual framework and ensured the robustness of the measurement model. Subsequently, the researcher conducted SEM to examine the causal relationships among the variables.

Research Population and Sample

Non-probability sampling methods, including judgmental and quota sampling, were employed to select eight departments at AMEVTC in Wuhu City, Anhui Province, and the questionnaire was distributed using the online questionnaire platform. Table 1. Showing the specific sampling of this study.

For this research, a survey was designed and distributed to participants in the year 2024, specifically between the months of February and October. The data screening process ensured the appropriateness of the target population. They are students from eight departments of Anhui Vocational College of Mechanical and Electrical Technology in Wuhu City, Anhui Province, China. The deans of the eight departments endorsed the study and encouraged their students to complete the online questionnaire.

The target population consisted of students from eight departments at AMEVTC. A multi-stage non-probability sampling approach was used: judgmental sampling selected the departments, quota sampling determined sample sizes per department, and convenience sampling facilitated data collection. The total sample size was 500 students.

The sample size was determined by considering both SEM sample adequacy guidelines and practical feasibility. With 500 valid responses, the study achieved a sufficient sample-to-parameter ratio, ensuring statistical power and model stability.

Sampling Strategy

To maintain the correctness, validity, and representativeness of the research conclusions, a multi-stage sampling strategy was adopted to cover the widest possible group to reduce bias in overall inferences due to sample specificity, thereby more accurately revealing the intrinsic relationships between variables. Specifically, the judgment sampling method was used to determine the overall target population from 12,334 first- to fourth-year undergraduates in a university in Anhui Province. Subsequently, the stratification is carried out, and the overall group is divided into several subgroups according to key variables such as discipline and grade. Finally, a stratified proportional sampling approach was applied to select 500 sample units, which were allocated to each stratum according to the predetermined ratios. The questionnaire was administered strictly following this sampling framework to ensure that the sample structure accurately represented the target population.

Table 1

Population and Proportional Sample Sizes

Major Name	Population Size	Proportional Sample Size
School of mechanical engineering	1,946	79
School of electrical engineering	2,672	108
School of Internet and Communication	2,071	84
School of Automotive and Rail	1,472	60
School of Art and Design	1,198	49
School of Business and Administration	1,048	42
School of Economics and Trade	1,025	41
School of Aviation and Materials	902	37
Total	12,334	500

Note: Created by the Author

Data Analysis

Before the official data collection, three experts evaluated each item of the questionnaire by the IOC, and 30 respondents were selected for pre-testing. The results indicated that all questionnaire items achieved IOC values above the 0.6 threshold, demonstrating satisfactory content validity. In addition, the reliability analysis of the data before the test showed that Cronbach's α coefficient exceeded 0.9, indicating that the questionnaire had excellent reliability.

Data analysis for this study was conducted using SPSS version 26.0 and AMOS version 28.0. CFA was conducted primarily to evaluate the reliability of the proposed model and to systematically evaluate its structural validity, including model fit indices, reliability, as well as convergent and discriminant validity. Building on this, SEM was applied to comprehensively test the theoretical framework, allowing for an in-depth examination of the plausibility and strength of the hypothesized relationships among the variables. This comprehensive analysis method sets a methodological foundation for drawing effective conclusions from empirical data.

Demographics of Participants

This survey surveyed 500 students from AMEVTC in Wuhu, Anhui Province, across eight colleges and departments. The sample included 260 male students (52%) and 240 female students (48%). By grade level, 133 students were freshmen (26.6%), 119 sophomores (23.8%), 132 juniors (26.4%), and 116 seniors (23.2%). By age, 252 students (50.4%) were aged 19-20, 198 (39.6%) were aged 21-23, and 50 (10.0%) were aged 24-26. In terms of monthly consumption expenditure, 39 people (7.8%) spent less than 1,000 yuan per month, 350 people (70.0%) spent 1,000-2,000 yuan per month, 92 people (18.4%) spent 2,000-3,000 yuan per month, 15 people (3.0%) spent 3,000-4,000 yuan per month, and 4 people (0.8%) spent more than 4,000 yuan per month. Table 2 provides an overview of the participants' demographic information.

Table 2

Demographic Information

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	260	52%
	Female	240	48%
Grade	Freshman	133	26.6%
	Sophomore	119	23.8%
	Junior	132	26.4%
	senior	116	23.2%
Demographic and Behavior Data (N=500)		**Frequency**	**Percentage**
Age	19-20	252	50.4%
	21-23	198	39.6%
	24 -26	50	10.0%
	More than 26 years old	0	0%
Monthly Cost	less than CNY 1,000	39	7.8%
	CNY 1000-2000 yuan	350	70.0%
	CNY 2000-3000 yuan	92	18.4%
	CNY 3000-4000 yuan	15	3.0%
	More than CNY 4000 yuan	4	0.8%

Note: Created by the Author

Results and Discussion

CFA was applied in this study to assess the uniqueness of each construct. Data regarding participants' demographics are displayed in Table 2, all constructs demonstrated Cronbach's α coefficients exceeding 0.7, which corresponds to the reliability standards recommended by Hair et al. (2019), indicating that the scale has a high internal consistency. The factor loadings of all questions range from 0.749 to 0.847, demonstrating a strong measurement relationship. Furthermore, all variables demonstrated composite reliability values exceeding 0.8, and the AVE is above 0.6, which meets the criteria for discriminant validity proposed by Fornell and Larcker (1981).

Table 3

GoF for CFA

Fit Index	Source	Criterion	Practical Values
CMIN/df	(Al-Mamary & Shamsuddin, 2015); (Awang, 2012)	<3.00	1.266
GFI	(Sica & Ghisi, 2007)	≥ 0.85	0.946
AGFI	(Sica & Ghisi, 2007)	≥ 0.80	0.933
NFI	(Wu & Wang, 2006)	≥ 0.80	0.949
CFI	(Bentler, 1990)	≥ 0.80	0.989
TLI	(Hair et al., 2006)	≥ 0.90	0.987
RMSEA	(Pedroso et al., 2016)	<0.08	0.023

Note: Created by the Author

Table 3 provides an explanation of the appropriate indicators of the mean model in this study, which are crucial for assessing how well the theoretical model aligns with the empirical data. The analysis indicated that the CMIN/DF value was 1.266, below the conventional threshold of 3.00, suggesting that the discrepancy between the model and the observed data was minimal and that the model demonstrated good fit.

Additionally, the GFI and AGFI were 0.946 and 0.933, respectively, indicating that the model exhibited strong adaptability in terms of simplicity and fit. The NFI was 0.949, the CFI was 0.989, and the TLI was 0.987, all exceeding the commonly accepted thresholds, demonstrating that the theoretical model provided a superior fit compared to the baseline model. The RMSEA was 0.023, well below the 0.08 cutoff, thus reinforcing the consistency between the model and the observed data. Overall, all key fit indices of the measurement model met standard criteria for confirmatory factor analysis, fully supporting its structural validity.

Table 4

CFA Result, Composite Reliability, and Average Variance Extracted

Variables	Source of Questionnaire (Measurement Indicator)	Items Amount	Cronbach's Alpha	Factors Loading	CR	AVE
PEOU	(Lee, 2006)	4	0.865	0.776 ~0.798	0.865	0.617
PU	(Lee, 2006)	4	0.877	0.788 ~0.810	0.877	0.641
PE	(Alowayr, 2022)	4	0.875	0.749~0.824	0.876	0.639
FC	(Alowayr, 2022)	3	0.848	0.768~0.829	0.848	0.651
SE	(Tarhini et al., 2017)	4	0.885	0.769~0.847	0.885	0.659
EE	(Alowayr, 2022)	4	0.881	0.797~0.827	0.881	0.650
BI	(Alowayr, 2022)	4	0.899	0.817 ~0.847	0.899	0.691

Note: Created by the Author

Table 4 shows that each dimension reported Cronbach's α values greater than 0.8, which reflects strong internal consistency of the scale. The factor loadings of each item was higher than 0.5, the CR was more than 0.8, and the AVE was greater than 0.5, which supported good convergent validity. In Table 5, the diagonal entries represent the square roots of the AVE for each latent variable. These values exceed the correlations between the corresponding latent variables, and all correlation coefficients are below 0.5, indicating satisfactory discriminant validity among the constructs. Overall, all quantitative indicators satisfy psychometric criteria, confirming that the measurement framework possesses robust reliability and validity.

Fornell and Larcker (1981) proposed a commonly used method for evaluating discriminant validity, which involves comparing each construct's AVE with its correlations to other constructs, thereby assessing whether the constructs are empirically distinct. In this study, Table 5 presents the discriminant validity results for the variables, including both the square roots of the AVE and the correlation matrix. Particular attention should be given to the diagonal entries, representing the square root of the AVE for each construct, as they are essential for evaluating whether discriminant validity has been established.

Specifically, the square roots of the AVE values for each latent variable in this study were as follows: PEOU 0.785, PU 0.801, PE 0.799, SE 0.812, EE 0.806, FC 0.807, and BI 0.831. For discriminant validity, each of these values should be greater than the correlation coefficients of the respective construct with all other constructs. Analysis of the correlation matrix shows that the square root of each variable’s AVE is significantly higher than its correlations with other constructs, confirming that the latent variables exhibit strong discriminant validity within the model.

Overall, the results indicate that the square roots of the AVE for all variables are significantly larger than the correlation coefficients between them and other variables. This fully supports the good discriminant validity of the scale and verifies the statistical distinctiveness of each construct in the measurement model.

Table 5

Discriminant Validity

	PEOU	PU	PE	SE	EE	FC	BI
PEOU	0.785						
PU	0.213	0.801					
PE	0.153	0.156	0.799				
SE	0.116	0.136	0.131	0.812			
EE	0.111	0.145	0.158	0.099	0.806		
FC	0.121	0.128	0.097	0.160	0.146	0.807	
BI	0.328	0.337	0.302	0.340	0.303	0.316	0.831

Note: Created by the Author

Structural Equation Modeling (SEM)

The structural model's goodness of fit was evaluated using AMOS software in this research. Table 5 displays the indices for evaluating the model's fit, offering a crucial reference for assessing how well the theoretical framework aligns with the observed data.

The model fitting found that the χ^2/df value was 1.504, which was lower than 3.00, GFI was 0.932, and AGFI was 0.919, all better than the corresponding standards, and NFI, CFI, and TLI were 0.937, 0.978, and 0.976, respectively, and RMSEA was 0.032, all reached acceptable levels, which indicates that the model fit well. The results show that the structural model can effectively characterize the relationship between variables, which further improves the overall accuracy and reliability of the model.

This study employs an integrated framework derived from TAM, UTAUT, and SCT, consisting of seven latent variables:

PEOU - measured by items reflecting whether students find the LELT platform intuitive, simple, and requiring minimal effort.

PU - measured by students' belief that LELT enhances learning effectiveness and academic performance.

PE - captured through items reflecting students' expectation of improved outcomes through LELT usage.

SE - measured by confidence in completing learning tasks using LELT without external assistance.

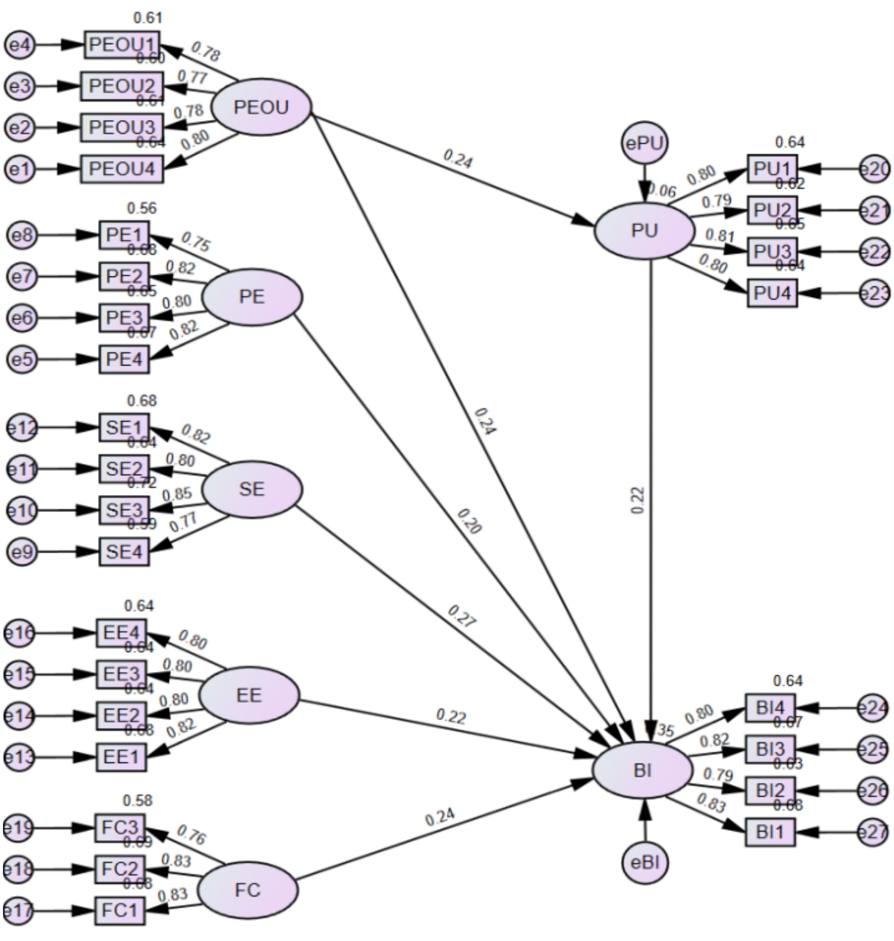
EE - assessed by perceived ease and reduced cognitive effort required to engage with LELT.

FC - measured by availability of institutional resources, technical support, and infrastructure.

BI - measured by students' likelihood of continuing to use LELT in the future.

Figure 2

Structural Model



Source: Constructed by the Author

Table 6

Goodness of Fit for Structural Model

Fit Index	Source	Criterion	Practical Values
CMIN/df	(Al-Mamary & Shamsuddin, 2015); (Awang, 2012)	<3.00	1.504
GFI	(Sica & Ghisi, 2007)	≥ 0.85	0.932
AGFI	(Sica & Ghisi, 2007)	≥ 0.80	0.919

Fit Index	Source	Criterion	Practical Values
NFI	(Wu & Wang, 2006)	≥ 0.80	0.937
CFI	(Bentler, 1990)	≥ 0.80	0.978
TLI	(Hair et al., 2006)	≥ 0.90	0.976
RMSEA	(Pedroso et al., 2016)	<0.08	0.032

Note: Created by the Author

Hypothesis Outcomes

The significance of the study model was evaluated by analyzing the regression weights and R^2 values of each variable. As shown in Table 7, the findings provide support for all the hypotheses put forward in this study. The empirical results demonstrate several significant relationships among the studied constructs. PEOU was found to exert a strong positive influence on both PU ($\beta = 0.243$, $t = 4.715$, $p < 0.001$) and BI ($\beta = 0.236$, $t = 5.055$, $p < 0.001$). Additionally, PU positively influenced BI ($\beta = 0.224$, $t = 4.840$, $p < 0.001$). PE also exhibited a notable positive influence on BI ($\beta = 0.202$, $t = 4.533$, $p < 0.001$). Among all predictors, SE emerged as the strongest determinant of BI ($\beta = 0.271$, $t = 6.070$, $p < 0.001$), followed by EE ($\beta = 0.216$, $t = 4.895$, $p < 0.001$) and FC ($\beta = 0.236$, $t = 5.226$, $p < 0.001$). Overall, these results highlight that both cognitive perceptions (such as PEOU and PU) and contextual or personal factors (including PE, SE, and FC) play critical roles in influencing students' intention to use LELT.

Table 7

Hypothesis Testing Result of the Structural Model

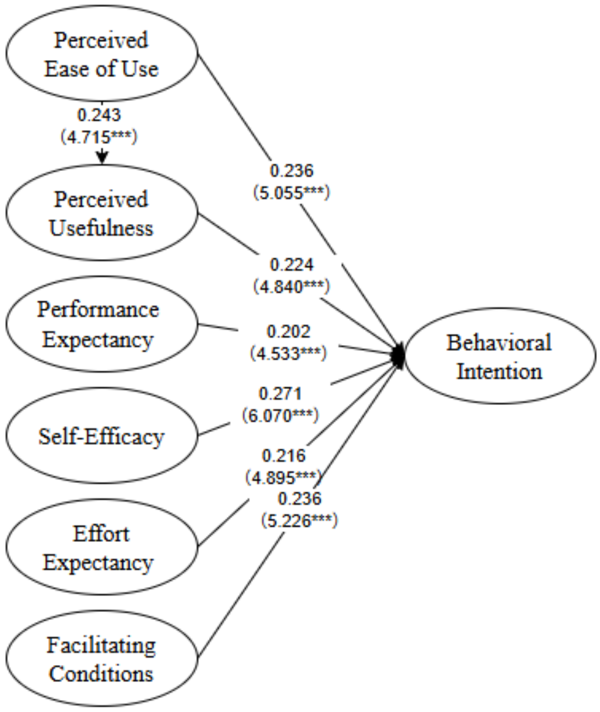
Hypothesis	Paths	Standardized Path Coefficient (β)	t-value	Testing Result
H1	PEOU--->PU	0.243	4.715***	Supported
H2	PEOU--->BI	0.236	5.055***	Supported
H3	PU--->BI	0.224	4.840***	Supported
H4	PE--->BI	0.202	4.533***	Supported
H5	SE--->BI	0.271	6.070***	Supported
H6	EE--->BI	0.216	4.895***	Supported
H7	FC--->BI	0.236	5.226***	Supported

Source: Constructed by the Author

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

Figure 3

Result of the Structural Model



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

Note: Created by the Author

Discussion

The study seeks to identify the primary factors influencing college students' perceptions of usefulness and their behavioral intentions regarding the use of the LELT platform. The results of the hypothesis testing offer an empirical foundation for understanding students' decision-making processes in an online learning context.

The results of the hypothetical H1 test show that PEOU has a significant positive effect on PU ($\beta = 0.243$, $t=4.715$, $p < 0.001$). The study outcomes indicate that PEOU of the Learnmaster E-Learning Technology platform significantly enhances users' positive assessment of its functional utility. This result aligns with Ngafeeson et al. (2024), further confirming that PEOU not only serves as a crucial antecedent of PU but also indirectly fosters the development of BI among college students when using e-learning systems like Learnmaster. Therefore, platform developers should strive to optimize the operation interface and interaction design of the system, and enhance users' PU and BI to use the function value by enhancing user-friendliness.

The results of the hypothetical H2 test show that PEOU has a significant positive effect on BI ($\beta = 0.236$, $t=5.055$, $p < 0.001$). The results show that the improvement of platform ease of use can effectively promote college students' BI to use LELT. This result aligns with conclusions reported by Kosiba et al. (2022) and further reinforces the positive effect of PEOU on users' BI. An e-learning experience that is more user-friendly than traditional learning not only facilitates ease of operation but also fosters more positive and sustained behavioral intentions. Therefore, the development and refinement of e-learning platforms should emphasize enhancing users' PEOU to strengthen their BI and engagement.

The H3 hypothesis test indicates that PU exerts a strong positive influence on BI ($\beta = 0.224$, $t = 4.840$, $p < 0.001$). This suggests that when college students perceive LELT as highly practical, their intention to use the platform correspondingly increases. This result aligns with the conclusions reported by Humida et al. (2022), further confirming that PU serves as a key determinant of users' behavioral intentions in e-learning contexts, and that enhancing PU can effectively stimulate greater willingness to adopt the technology. Therefore, it is recommended that the platform developer highlight the actual functions and application benefits of the system, so as to effectively improve the user's PU, and then enhance their BI to continue to use it.

The H4 hypothesis test results revealed that PE had a substantial positive effect on BI ($\beta = 0.202$, $t=4.533$, $p < 0.001$). This indicates that higher performance expectancy among college students regarding the Learnmaster e-learning technology is associated with stronger behavioral intentions to use the platform. As a key cognitive factor in technology adoption, performance expectations can effectively reduce the cognitive and emotional barriers faced in the process of learning and mastering new systems, and then promote the formation of active use intentions. This result is consistent with Mercado et al. (2023) and further highlights the important influence of performance expectancy on college students' adoption of e-learning technologies.

The results of the H5 hypothesis test showed that SE exerts a strong positive influence on BI ($\beta = 0.271$, $t = 6.070$, $p < 0.001$). This suggests that college students with higher SE regarding the LELT platform demonstrate stronger intentions to use the technology. This result is consistent with Rahman et al. (2023) and further reinforces the strong positive link between SE and BI within e-learning environments. College students with higher SE are more likely to continue using the technology, actively recommend it to others, and show a firmer willingness to adopt it. Therefore, it is recommended to systematically enhance users' self-efficacy by optimizing user experience and designing targeted communication strategies, so as to effectively promote their continued use and active promotion behavior.

The H6 hypothesis test demonstrated that EE exerts a strong positive influence on BI ($\beta = 0.216$, $t = 4.895$, $p < 0.001$). This means that when college students expect to put less effort into using the Learnmaster platform, their intention to adopt the technology increases. This result aligns with Hossain et al. (2024) in digital learning contexts, further confirming that EE acts as an important determinant of BI. The analysis further indicated that students with higher

EE were more inclined to continue using the system independently, but also more willing to recommend it to others. Therefore, it is recommended to systematically raise effort expectations through methods such as interface optimization, task simplification, and guided design, starting from reducing the perceived burden in use, so as to promote more positive and sustained user behavior.

The H7 hypothesis test indicated that FC exerts a strong positive influence on BI ($\beta = 0.236$, $t = 5.226$, $p < 0.001$). Good facilitation conditions help students use the Learnmaster e-learning platform more effectively, thereby enhancing their overall learning experience. According to Hossain et al. (2024), environmental support factors can significantly influence user behavioral intentions. Zhu and Huang (2025) further point out that perfect facilitation conditions can enhance users' intimacy and immersion in the digital learning platform. When college students can obtain sufficient technical and resource support on the platform, it is easier to build trust in the system content and form a positive user experience, thereby enhancing their willingness to continue using the system. Therefore, it is recommended to systematically optimize the promotion conditions of the platform by improving technical support, providing clear operation guidance, and strengthening learning resources, so as to effectively stimulate and maintain users' behavioral intention to use.

Conclusions and Recommendations

Conclusion

This study provides a systematic examination of the primary factors influencing college students' PU and BI of LELT based on the TAM, combined with the UTAUT and SCT, using 500 valid questionnaire data. By incorporating constructs such as self-efficacy and facilitating conditions, the study extends traditional models to capture multi-dimensional influences on students' behavioral intention, offering both theoretical enrichment and practical insights for technology acceptance research.

The findings provide actionable guidance for stakeholders in the online learning ecosystem. For the LELT development team, enhancing system usability through optimized interface design and simplified operation can foster sustained engagement. Instructional designers and trainers can leverage insights on performance expectancy, self-efficacy, effort expectancy, and facilitating conditions to tailor orientation programs, develop targeted training modules, and implement incentive mechanisms aligned with students' psychological and capability needs. Teaching managers at AMEVTC can integrate LELT more strategically into curricula, allocate resources to key adoption processes, and utilize the platform to support visualization of learning outcomes. Moreover, policymakers and educational authorities in Wuhu can draw on these findings to promote equitable access to digital education, guide infrastructure investment, and establish standards for evaluating online learning quality.

In sum, this study highlights the importance of combining individual beliefs, environmental support, and technological attributes to facilitate sustained use of e-learning platforms in vocational education. The proposed framework and practical recommendations offer a foundation for advancing digital education policy, institutional strategy, and future research in similar higher vocational contexts.

Recommendations

Based on the results of this research, the following recommendations are put forward from a policy perspective, technology, and teaching to enhance students' behavioral intention and effective use of the Learnmaster platform in higher vocational colleges in Wuhu.

At the policy level, the significant impact of performance expectancy ($\beta = 0.202$) and facilitating conditions ($\beta = 0.236$) should be given full play, and the effectiveness of platform use should be included in the course evaluation and scholarship evaluation system to enhance students' perceived value. At the same time, it will increase infrastructure investment, improve campus network and terminal performance, promote the seamless connection between the platform and school-level identity authentication and data systems, and lower the threshold for use.

At the technical level, platform providers should prioritize both "ease of use" and "usefulness," while implementing a microservice architecture and real-time learning behavior analytics, and provide explainable AI feedback to enhance the mediation mechanism of perceived usefulness on behavioral intention. Improve the customer service training and technical support system, respond to and solve students' usage problems in a timely manner.

At the teaching level, we should focus on the significant effects of self-efficacy ($\beta = 0.271$) and effort expectancy ($\beta = 0.216$) to develop step-by-step training courses and peer counseling mechanisms to enhance students' confidence. Optimize task design with microlearning strategies, reduce cognitive and operational load, and improve learning experience.

The government, schools and enterprises should jointly build a "government-industry-university-research" collaborative mechanism, incorporate the in-depth application of the platform into the education informatization evaluation system and the construction of the "Double High Plan", and set up special incentives and digital inclusive policies. At the same time, an education data sharing platform will be established, online learning reports will be released regularly, and data-driven model optimization and system iteration will be used to achieve sustainable evolution of the platform and high-quality development of regional digital education.

Limitations and Further Study

The main limitations of this research are as follows. First, although procedural and statistical controls were utilized to control for common method bias (Podsakoff et al., 2003), the cross-sectional design still poses challenges in rigorously establishing causal relationships among variables (Kosiba et al., 2022). Future studies could introduce longitudinal tracking or experimental interventions to collect data at multiple time points to more precisely reveal the dynamic mechanisms between PU and BI (Morgado et al., 2017). Secondly, the sample was only from eight departments of a higher vocational college in Wuhu, and it was mainly mechanical and electrical, business and art majors, and the geographical and discipline representation was limited, so it was necessary to be cautious to extend the conclusion to undergraduate colleges or other regions (Ansong et al., 2017). In future research, the sampling scope should be broadened to encompass universities across various regions and institutional types, and cross-group comparisons ought to be carried out to test the model's stability across different educational contexts (Yan et al., 2021). In addition, although the current model identifies the key mediating role of perceived usefulness, it may still miss potential mediating variables such as perceived pleasure and technical anxiety, as well as moderating variables such as user experience and cultural background, which may help explain the weak direct effect of PEOU. In the future, more psychological and situational variables can be introduced, and mixed research methods can be used to comprehensively explore the multi-level mechanisms affecting students' willingness to continue using from individual, organizational, and even policy levels (e.g., digital governance, copyright system, etc.) (Yousef & Khatiry, 2023).

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