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# Factors Impacting Students' Behavioral Intention to Use Digital Learning: A Case Study of a Higher Vocational College in Shandong, China

**Zhao Zhendong***

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## Abstract

**Purpose:** This study investigates the determinants influencing vocational students' intentions to adopt digital learning technologies within China's educational modernization agenda, while developing and validating a practical intervention framework to strengthen engagement in Shandong's vocational education sector. **Research design, data and methodology:** A mixed-methods action research design unfolded in three phases: diagnostic assessment, strategic intervention, and impact evaluation. In the diagnostic phase, survey instruments were validated through expert review and pilot testing. Primary data from 107 vocational students were analyzed with multiple linear regression to identify key predictors of adoption. The intervention phase involved 30 students in a nine-week program combining digital literacy training, interactive teaching activities, and structured support mechanisms. Evaluation employed paired-sample t-tests and follow-up interviews to assess improvements in digital competencies, attitudes, and perceptions. **Results:** Results showed that attitude ($\beta$ =0.274), performance expectancy ($\beta$ =0.247), and digital literacy ($\beta$ =0.236) were the strongest predictors of behavioral intention, explaining 60.1% of the variance. Post-intervention, students demonstrated significant gains in digital literacy, attitude, performance expectancy, and behavioral intention, while infrastructure improvements remained limited. **Conclusions:** By incorporating digital literacy into established acceptance models, this study extends theoretical understanding and provides evidence-based strategies to enhance student competencies and institutional support, offering practical guidance for advancing digital transformation in vocational education.

**Keywords:** Behavioral Intention, Digital Learning, Higher Vocational Education, UTAUT, TAM

**JEL Classification Code:** A20, D83, I23, O30

## 1. Introduction

The rapid development of digital technologies in the 21st century is reshaping human society, influencing fields from social governance to education (Gong & Ribiere, 2021). In education, innovations such as artificial intelligence, big data analytics, and virtual and augmented reality are transforming learning ecosystems (Radianti et al., 2020; Strzelecki, 2024). In China, vocational education has become a central focus of this transformation under the national "Education Modernization 2035" initiative. By 2023, more than 1,400 higher vocational institutions enrolled over 16 million students and offered about 523,000 online courses (Ministry of Education, 2024). Digital learning in this context enhances practical skills and employability by using simulation technologies and online platforms to overcome the resource limits of traditional training (Xu et al., 2024).

Despite these investments, student engagement in digital learning remains low. National data show that although most institutions have developed digital platforms, average usage

1*Zhao Zhendong, Shandong Institute of Commerce & Technology, China. Email: 165698557@qq.com

rates are below 35 percent and course completion rates are only 28.6 percent. At Shandong Institute of Commerce and Technology, challenges include limited alignment between resources and learning needs, difficulties in navigating multiple platforms, and unequal levels of digital literacy (Wang & Chen, 2022). Teachers and students often resist digital methods, quality assurance mechanisms remain weak, and some learners face unequal access due to financial barriers (Hu & Xie, 2019). Employers also show limited recognition of digital learning outcomes, which reduces students' motivation to participate.

These issues point to a clear research gap. Previous studies on technology acceptance have focused largely on higher education, but few have examined vocational colleges in China. Vocational education emphasizes practical skill development and industry relevance, which traditional models often overlook (Hao et al., 2024). Digital literacy is also increasingly critical, yet it has not been fully integrated into models of technology adoption in vocational education.

To address this gap, this study investigates the factors that shape vocational students' behavioral intentions to use digital learning. It integrates the Technology Acceptance Model (Davis, 1989) with the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and introduces digital literacy as an additional construct. Using action research at Shandong Institute of Commerce and Technology, the study identifies key determinants, develops targeted interventions, and evaluates their impact. Theoretically, it extends acceptance models by incorporating digital literacy and applying them in a vocational context. Practically, it provides evidence-based strategies that can guide vocational institutions in improving digital learning adoption and support the Ministry of Education's "Digital Transformation of Vocational Education 2024-2030" initiative.

## 2. Literature Review

### 2.1 Theoretical Background

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are widely used to explain behavioral intention in digital learning. Davis (1989) introduced TAM, showing that perceived usefulness and ease of use shape user attitudes and intentions. Its simplicity and predictive power have been confirmed in many studies, explaining 45-70% of the variance in technology use (Šumak et al., 2011). In vocational education, students often adopt digital tools for their potential to improve employability (Huang et al., 2020).

UTAUT, developed by Venkatesh et al. (2003), integrates elements from eight earlier models. It identifies four key predictors: performance expectancy, effort expectancy, social influence, and facilitating conditions. These factors together account for up to 70% of the variance in adoption. UTAUT has been widely applied in education, including mobile learning (Abu-Al-Aish & Love, 2013) and blended learning (Dakduk et al., 2018).

Integrating TAM and UTAUT gives a fuller picture of digital learning acceptance. TAM emphasizes cognitive evaluation of technology, while UTAUT includes social and contextual factors. Recent extensions improve explanatory power by adding new constructs. For instance, Hoi (2020) introduced attitude, and Nikou and Aavakare (2021) added digital literacy, together explaining about 40% of the variance. Al-Adwan et al. (2023) further showed that combining extensions better captures the complex factors influencing vocational students' adoption of digital learning.

### 2.2 Literature Review of Variables

#### 2.2.1 Behavioral Intention

Behavioral intention has its roots in social psychology. The Theory of Reasoned Action explains that behavior is shaped by intentions, which result from attitudes and social norms (Fishbein & Ajzen, 1975). The Theory of Planned Behavior later added perceived behavioral control as another key factor (Ajzen, 1991).

In technology acceptance studies, Davis (1989) described behavioral intention as a person's willingness to use a technological system. Venkatesh et al. (2003) broadened this definition, describing it as the extent to which a person expects to use information systems in the future. Later work expanded the concept to include usage intention, continuance intention, and recommendation intention (Venkatesh et al., 2012).

Research in educational technology shows that behavioral intention strongly predicts actual system use (Abbad, 2021; Ain et al., 2016). In vocational education, Li et al. (2022) found that students' intentions were driven more by practical value and opportunities for skill development than by ease of use. This suggests that adoption decisions in vocational contexts depend heavily on clear, job-related benefits.

#### 2.2.2 Facilitating Conditions and Behavioral Intention

Facilitating conditions are the external supports that make it easier for individuals to use technology. Early definitions described them as environmental elements that enable behavior (Thompson et al., 1991; Triandis, 1979). Later, researchers highlighted the role of resources such as time, finances, and tools (Taylor & Todd, 1995). Within the Unified Theory of Acceptance and Use of Technology, Venkatesh et al. (2003) defined facilitating conditions as the extent to which people believe that organizational and technical support exists to help them use a system. Recent studies describe them as a mix of infrastructure, instructional support, and resource accessibility in education (Blut et al., 2022; Dwivedi et al., 2019).

In digital learning, facilitating conditions appear in both infrastructure and support services. Stable internet, affordable devices, and effective platforms are essential for access (Patil & Undale, 2023). System quality, reliable information, and technical assistance reduce anxiety and strengthen students' confidence in using digital tools (Ahmed et al., 2024; Alkhwaldi, 2024).

Research consistently shows that facilitating conditions influence behavioral intention. Bayaga and du Plessis (2024) found them to be a strong predictor of students' intention to use learning management systems. Li et al. (2022) also reported that supportive conditions encourage vocational students to adopt blended learning.

These findings suggest that when students have reliable support and resources, they are more willing to use digital learning. Based on this evidence, the study proposes the following hypothesis:

**H1:** Facilitating conditions have a significant impact on students' behavioral intention to use digital learning.

#### 2.2.3 Digital Literacy and Behavioral Intention

Digital literacy is the ability to use and evaluate digital resources effectively (Gilster, 1997). Martin (2006) described it as a mix of technical, cognitive, and critical skills. Ng (2012) expanded this to include technical, cognitive, and socio-emotional dimensions. Later studies added aspects such as digital citizenship, information checking, and responsible content creation (Tomczyk, 2020).

In education, digital literacy is vital for both teachers and students. National standards now emphasize digital competence for educators (Jiang & Yu, 2024; Yeşilyurt & Vezne, 2023). Teachers with stronger digital skills adopt technologies more readily (Antonietti et al., 2022). For students, digital literacy supports self-regulated learning, improves e-learning attitudes, and enhances academic performance and employability (Khan et al., 2022; Muasyaroh & Royanto, 2024; Wang, 2024).

From a theoretical perspective, digital literacy aligns with the effort expectancy construct in UTAUT (Venkatesh et al., 2003) and the perceived ease of use dimension in TAM (Davis, 1989). Both models emphasize that users' technological capability and confidence reduce perceived difficulty and enhance behavioral intention. Digital literacy therefore represents a capability-based extension of these models, capturing how individuals' skills and familiarity with technology influence their willingness to adopt digital learning systems.

Studies also confirm its predictive power. Aesaert et al. (2017) found that digital literacy predicts acceptance of digital tools. Tang and Chaw (2016) reported direct effects on perceived usefulness. Bervell and Umar (2017) showed that students with higher digital literacy expect better performance outcomes, while Phuangthong and Malisuwan (2008) found it explains a large share of usage intention together with acceptance factors.

Overall, digital literacy strengthens students' readiness to adopt digital learning. Thus, the study proposes the following hypothesis:

**H2:** Digital literacy has a significant impact on students' behavioral intention to use digital learning.

#### 2.2.4 Attitude and Behavioral Intention

Attitude reflects how positively or negatively a person evaluates using a system. It was first defined in the Theory of Reasoned Action as feelings toward a behavior (Fishbein & Ajzen, 1975). The Technology Acceptance Model viewed it as the degree of favorable evaluation of system use (Davis et al., 1989). The Theory of Planned Behavior later emphasized its role in shaping intention (Ajzen, 1991).

Research shows that attitude is a strong predictor of behavioral intention. Dwivedi et al. (2019) found it central to technology adoption, while Mailizar et al. (2021) confirmed its importance in education. Studies also show that positive attitudes among teachers and students increase actual use of technology (Bayaga & du Plessis, 2024; Wang et al., 2021).

Positive attitudes not only encourage adoption but also improve learning outcomes. Kumar et al. (2020) found they enhance both acceptance and effectiveness. Alhumaid et al. (2021) showed they sustain engagement in mobile learning. Prior et al. (2016) reported that students with positive attitudes and strong digital literacy build self-efficacy and interact more with peers. Joo et al. (2017) linked positive evaluations of digital textbooks to stronger continuance intentions.

These studies suggest that positive attitudes play a decisive role in digital learning adoption. Based on this, the study proposes the following hypothesis:

**H3:** Attitude has a significant impact on students' behavioral intention to use digital learning.

#### 2.2.5 Performance Expectancy and Behavioral Intention

Performance expectancy is the belief that using technology improves performance (Venkatesh et al., 2003). It extends the idea of perceived usefulness from the Technology Acceptance Model. Later studies linked it to task efficiency, workflow improvement, and comparative advantage (Chen et al., 2020). Its effect is strongest when users see clear benefits for their tasks (Blut et al., 2022; Li et al., 2022).

Research consistently shows performance expectancy as the strongest predictor of behavioral intention. In education, it drives technology adoption in online and mobile learning (Ahmed et al., 2024; Lin et al., 2023). Bayaga and du Plessis (2024) also found it most influential among South African faculty using learning management systems.

In vocational education, performance expectancy is critical. Liu et al. (2018) reported it as the main predictor of mobile learning adoption, explaining over 40 percent of intention variance. Li et al. (2022) confirmed similar patterns that goal commitment strengthens this relationship.

These studies suggest that when students expect digital learning to improve skills and outcomes, they are more likely to adopt it. Therefore, the study proposes the following hypothesis:

**H4:** Performance expectancy has a significant impact on students' behavioral intention to use digital learning.

### 2.2.6 Effort Expectancy and Behavioral Intention

Effort expectancy refers to how easy a system is to use. It originates from the concept of perceived ease of use in the Technology Acceptance Model (Davis, 1989) and draws on complexity from Innovation Diffusion Theory (Rogers, 1995) and cognitive demands from Social Cognitive Theory (Compeau & Higgins, 1995). Venkatesh et al. (2003) defined it as the degree of ease linked to system use, while later studies highlighted factors such as time investment, interface simplicity, cognitive load, and anticipated challenges (Tamilmani et al., 2021).

Research confirms that effort expectancy significantly predicts behavioral intention across technologies (Dwivedi et al., 2019; Scherer et al., 2019). In vocational education, Liu et al. (2018) found it explained nearly 39 percent of variance in behavioral intention, while Wang and Chen (2022) noted that user-friendliness strongly shapes adoption decisions. Other studies show that intuitive system design reduces psychological barriers and increases the likelihood of adoption (Abbad, 2021; Efiloğlu Kurt, 2023; Lin et al., 2023).

These findings suggest that students adopt digital learning more readily when they perceive systems as simple and easy to use. Based on this, the study proposes the following hypothesis:

**H5:** Effort expectancy has a significant impact on students' behavioral intention to use digital learning.

## 3. Research Methods and Materials

### 3.1 Research Framework

This study investigates the key factors that shape vocational college students' behavioral intention to adopt digital learning platforms. The framework is grounded in the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and the Technology Acceptance Model (Davis, 1989). It integrates both internal and external determinants of adoption behavior.

The model examines performance expectancy, effort expectancy, and attitude to capture students' cognitive and affective evaluations of digital learning tools. Digital literacy is included as an essential capability that influences technology use (Nikou & Aavakare, 2021). Facilitating conditions, adapted from Hoi (2020), represent the institutional and technical support available to students.

The framework incorporates five predictor variables: facilitating conditions, digital literacy, attitude, performance expectancy, and effort expectancy. These variables are directly linked to the dependent variable, behavioral intention. To maintain focus on practical insights for vocational education, the model excludes mediating and moderating variables. Instead, it emphasizes direct effects that can guide interventions aimed at improving digital learning adoption.

Supported by established theories and prior empirical studies, this conceptual framework provides a basis for developing strategies to strengthen digital learning in vocational education.

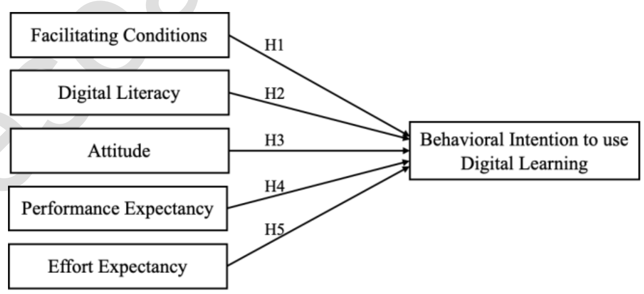


**Figure 1:** Conceptual Framework

### 3.2 Research Methodology

This study adopted a mixed-methods approach to examine vocational college students' behavioral intention to adopt digital learning in Shandong Province, China. A pragmatist stance guided the research, combining quantitative rigor with qualitative insights to capture both general patterns and context-specific factors (Morgan, 2014).

The research was carried out in two sequential phases over six months. The first phase applied a cross-sectional survey design to establish baseline measures of students' behavioral intentions. Questionnaire items were adapted from validated scales, and stratified random sampling ensured representative participation across four colleges. A total of 120 questionnaires were distributed through

Wenjuanxing, a Chinese online survey platform, using WeChat and QQ for delivery. After screening, 107 valid responses were retained for analysis.

The second phase adopted an action research framework to test strategic planning interventions. Multiple linear regression analysis of Phase I data identified key determinants of behavioral intention. Based on these findings, targeted interventions were developed in collaboration with academic leaders. Over a 16-week period, students participated in digital literacy workshops, peer support programs, and monitored learning activities.

Evaluation combined quantitative and qualitative methods. Thirty students completed pre- and post-intervention assessments using the same questionnaire to measure changes in behavioral intention. Paired sample t-tests were conducted in Jamovi software to detect significant differences. In addition, semi-structured interviews with five participants provided qualitative insights into student experiences. All interviews were audio-recorded, transcribed, and thematically analyzed to complement statistical results (Clark, 2019).

Ethical approval was obtained from the institution's research ethics committee. Participation was voluntary, informed consent was secured, and confidentiality was guaranteed. Data were used solely for academic purposes, and the research team maintained non-participatory roles to minimize bias.

This integrated design provided both statistical evidence and contextual insights, enabling a comprehensive understanding of the factors shaping digital learning adoption in vocational education.

## 3.3 Research Population, Sample Size, and Sampling Procedures

### 3.3.1 Research Population

This study was conducted at a leading vocational institution in Shandong Province, China. The institution's name is withheld to protect participant privacy. The total research population included 6,884 full-time students, as recorded in the institution's 2024 student management system. To ensure disciplinary representation and account for different levels of digital literacy, the study used stratified proportional sampling. Students were selected according to the proportion enrolled in each college. This approach ensured balanced participation, including both digitally skilled learners from information technology programs and students from humanities and arts disciplines with varying levels of digital competence. The strategy enhanced the representativeness and explanatory power of the findings.

### 3.3.2 Sample Size

Hair et al. (2014) recommend a minimum of 10 observations per variable in multiple linear regression to ensure stable results. Given that the study included five independent and one dependent variables, the minimum required sample size was 60 respondents. To strengthen reliability and account for potential non-responses or invalid data, the planned survey sample was increased to 120 students. This number exceeded the minimum requirement for testing the conceptual framework.

In addition to the main survey, the study included a strategic planning experimental group of 35 students from comparable colleges during the 2024 academic year, of which 30 students were purposively selected to participate in the intervention. Scholars note that experimental interventions can be conducted with smaller groups when design and controls are carefully managed, provided the size allows for sufficient statistical testing and meaningful interpretation (Creswell & Creswell, 2018). This sampling design met robustness requirements for regression analysis and supported evaluation of the strategic planning intervention.

### 3.3.3 Sampling Procedure

The study used a three-stage sampling process. First, four representative colleges were purposively selected from the institution's 14 secondary colleges, ensuring disciplinary diversity and variation in digital literacy levels. These included the College of Intelligent Finance and Economics Industry, the College of Information Technology, the College of Food Industry, and the College of Culture and Creativity. Second, 120 sophomore students were chosen using stratified random sampling across these colleges to maintain proportional representation. Finally, questionnaires were distributed through an online mini-program platform, applying convenience sampling for efficient delivery.

For the strategic planning phase, purposive sampling identified 30 suitable candidates who could participate in intervention activities. This mixed use of stratified, purposive, and convenience sampling aligns with established recommendations for balancing representativeness and practical feasibility in educational research (Creswell & Creswell, 2018).

## 3.4. Research Instruments

### 3.4.1 Questionnaire Design

The research instrument consisted of three sections designed to assess vocational students' acceptance of digital learning technologies.

Section 1 collected demographic information to contextualize the analysis. Variables included gender, age, and grade level.

Section 2 measured five constructs using validated scales adapted from prior studies. The questionnaire contained 25 items on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The constructs included facilitating conditions (4 items), digital literacy (5 items), attitude (4 items), performance expectancy (4 items), effort expectancy (4 items), and behavioral intention toward digital learning (4 items) (Hoi, 2020; Humida et al., 2022; Ng, 2012; Venkatesh et al., 2003, 2012).

Section 3 applied the Index of Item-Objective Congruence (IOC). Three experts reviewed the questionnaire items to evaluate content validity and ensure accurate measurement.

### 3.4.2 Questionnaire Components

The questionnaire consisted of three parts.

Part 1 included screening questions to confirm respondent eligibility. Examples are: “Do you live in Shanghai, China?”, “Are you over 18 years old?”, and “Do you have more than six months of experience buying tickets to see musicals in theaters?”.

Part 2 contained the measurement items used to assess the five independent variables, which were facilitating conditions, digital literacy, attitude, performance expectancy, and effort expectancy. It also included the dependent variable, behavioral intention.

Part 3 collected demographic information such as gender, age, and income level to describe the characteristics of the research population.

### 3.4.3 IOC Results

Content validity was assessed by a panel of three experts. The panel included two academics with experience in higher education pedagogy and one administrator responsible for digital innovation in higher education. All 25 items were reviewed using the Index of Item-Objective Congruence (IOC). The results showed that each item achieved an IOC score above 0.67, which exceeds the minimum threshold recommended for content validity (Rovinelli & Hambleton, 1977). This finding indicates that all items were consistent with their intended constructs and objectives.

### 3.4.4 Pilot Survey and Pilot Test Results

Reliability reflects the consistency of a research instrument in producing stable results with minimal measurement error (Bannigan & Watson, 2009). To evaluate reliability, a pilot test was conducted with 30 students.

The results, shown in Table 1, indicate strong internal consistency. Cronbach’s alpha coefficients for all constructs exceeded the recommended minimum threshold of 0.70 (Nunnally & Bernstein, 1994), ranging from 0.806 to 0.869. Several values approached the excellent level of 0.90, demonstrating very good reliability across all scales. These findings confirm that the questionnaire has strong psychometric properties and is suitable for formal data collection.

**Table 1:** Pilot Test Result (n=30)

| Variable | No. of Items | Cronbach’s Alpha | Strength of Association |
|---|---|---|---|
| Facilitating Conditions (FC) | 4 | 0.86 | Very Good |
| Digital Literacy (DL) | 5 | 0.869 | Very Good |
| Attitude (AT) | 4 | 0.862 | Very Good |
| Performance Expectancy (PE) | 4 | 0.806 | Very Good |
| Effort Expectancy (EE) | 4 | 0.844 | Very Good |
| Behavioral Intention (BI) | 4 | 0.862 | Very Good |

## 4. Results and Discussion

### 4.1 Results

### 4.1.1 Demographic Information

The demographic profile of this study covers three key variables: gender, age, and grade level. Table 2 presents the frequency and percentage distribution for both the full survey population (n = 107) and the strategic planning (SP) intervention group (n = 30). Although 120 questionnaires were distributed, only 107 valid responses were retained for analysis after screening for completeness and in-scope data.

The sample shows a balanced gender distribution, with a slightly higher proportion of female students. Most participants were between 19 and 21 years old, which reflects the typical age of vocational college students in China. The grade distribution ranged from first-year to third-year students, with freshmen making up the largest group. This spread across academic years ensures that the analysis captures differences in digital learning exposure and adaptation across stages of study.

The demographic composition indicates that the participants represent the diversity of the wider vocational college population, providing a solid basis for examining the factors that influence digital learning adoption.

**Table 2:** Demographic Information

| Demographic and General Data (n=107) | | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 51 | 47.7 |
| | Female | 56 | 52.3 |
| Age | ＜18 | 0 | 0.0 |
| | 18-19 | 41 | 38.3 |
| | 20-21 | 41 | 38.3 |
| | 21-22 | 21 | 19.6 |
| | ＞23 | 4 | 3.8 |
| College | Intelligent Finance and Economics | 34 | 31.8 |
| | Information Technology | 29 | 27.1 |
| | Food Industry | 24 | 22.4 |
| | Culture and Creativity | 20 | 18.7 |

| Demographic and General Data (n=107) | | Frequency | Percentage |
|---|---|---|---|
| Grade | Freshman | 43 | 40.2 |
| | Sophomore | 49 | 45.8 |
| | Junior | 15 | 14.0 |
| **IDI Participants (n=30)** | | **Frequency** | **Percentage** |
| Gender | Male | 18 | 60.0 |
| | Female | 12 | 40.0 |
| Age | ＜18 | 0 | 0.0 |
| | 18-19 | 11 | 36.7 |
| | 20-21 | 11 | 36.7 |
| | 21-22 | 8 | 26.6 |
| | ＞23 | 0 | 0.0 |
| Grade | Freshman | 14 | 46.7 |
| | Sophomore | 10 | 33.3 |
| | Junior | 6 | 20.0 |

**Source:** Constructed by the Author

### 4.1.2 Results of Multiple Linear Regression

Multiple linear regression analysis was conducted using Jamovi version 2.5.8 to examine the factors influencing vocational students' behavioral intention to adopt digital learning. The model showed strong explanatory power, with the five independent variables together accounting for 60.1% of the variance in behavioral intention ($R^2 = .601$, $F(5,101) = 30.4$, $p < .001$).

Attitude was the strongest predictor ($\beta = 0.27$, $p < .001$), indicating that students with positive views toward digital learning were more likely to adopt it. Performance expectancy ($\beta = 0.25$, $p < .001$) and digital literacy ($\beta = 0.24$, $p < .001$) followed closely, showing that both beliefs in improved learning outcomes and strong digital skills play critical roles in adoption. Effort expectancy ($\beta = 0.21$, $p = .009$) also had a significant effect, suggesting that ease of use continues to matter for students' decisions. Facilitating conditions ($\beta = 0.17$, $p = .018$) had the weakest but still significant influence, meaning that access to resources and institutional support remains important, though less decisive than personal attitudes and skills.

Multicollinearity diagnostics confirmed the robustness of the model. Variance Inflation Factor values ranged from 1.20 to 1.63, well below the threshold of 5.0, indicating minimal correlation among predictors.

**Table 3:** Multiple Regression Results of Independent Variables on Students' Behavioral Intention (n=107)

| Variable | Standardized Coefficients Beta Value | t-value | p-value | $R^2$ |
|---|---|---|---|---|
| Facilitating Conditions | 0.168 | 2.41 | 0.018 | 0.601 |
| Digital Literacy | 0.236 | 3.43 | < .001 | |
| Attitude | 0.274 | 3.40 | < .001 | |
| Performance Expectancy | 0.247 | 3.49 | < .001 | |
| Effort Expectancy | 0.209 | 2.67 | 0.009 | |

**Dependent variable:** Behavioral intention
**Note:** p-value <0.05

All five hypotheses were supported. The findings show that adoption of digital learning in vocational education is shaped most strongly by students' attitudes, expectations of performance benefits, and digital literacy, while system usability and institutional support provide additional but smaller contributions.

Drawing from the regression findings, the following hypotheses (H7-H12) were formulated to examine whether significant differences would emerge between the pre- and post-intervention stages of the Strategic Plan:

H7: There is a significant difference in facilitating conditions before and after the implementation of the strategic plan.

H8: There is a significant difference in digital literacy before and after the implementation of the strategic plan.

H9: There is a significant difference in students' attitudes toward digital learning before and after the implementation of the strategic plan.

H10: There is a significant difference in performance expectancy before and after the implementation of the strategic plan.

H11: There is a significant difference in effort expectancy before and after the implementation of the strategic plan.

H12: There is a significant difference in behavioral intention before and after the implementation of the strategic plan.

## 4.2 Strategic Plan Implementation

The strategic intervention followed a structured 16-week framework, summarized in Table 4. Diagnostic findings from preliminary interviews highlighted three major challenges: unstable network performance during peak periods, outdated digital resources, and wide differences in students' digital literacy. High-proficiency students showed strong autonomous learning skills, while low-proficiency students struggled with complex platform functions and evaluating information quality.

**Table 4:** Implementation Timeline and Activities of the Strategic Plan

| No. | Week | Implementation Keywords |
|---|---|---|
| 1 | Week 1 - Week 3 | Pre- strategic plan: Data collection |
| 2 | Week 4 - Week 5 | Diagnosing |
| 3 | Week 6 - Week 11 | Designing and implementing |
| 4 | Week 12 | Evaluating |
| 5 | Week 13 - Week 16 | Post- strategic plan: Data collection and analysis |

**Source:** Constructed by the Author

Baseline assessment revealed moderate scores across constructs. Performance expectancy scored the highest ($M = 3.48$, $SD = 1.21$), reflecting students' optimism about digital learning effectiveness. Effort expectancy scored the lowest ($M = 3.09$, $SD = 0.83$), showing that students perceived digital learning as requiring significant effort. Facilitating conditions (M = 3.17, SD = 1.19) indicated limited infrastructure support. Digital literacy (M = 3.21, SD = 1.06) and attitude (M = 3.34, SD = 1.02) also showed moderate engagement.

The intervention addressed these issues through five components. Infrastructure was strengthened by network upgrades and expanded technical support. Digital literacy was enhanced through training in e-commerce platforms and digital content creation. Attitudes were improved with gamification and peer learning communities. Performance expectancy was increased through VR simulations and AI-powered tutoring that demonstrated clear links between study and career outcomes. Effort expectancy was reduced by introducing progressive skill-building modules and standardized platform interfaces.

Each intervention component was grounded in theory. Infrastructure addressed facilitating conditions (Venkatesh et al., 2003). Digital literacy training targeted capability development (Ng, 2012). Attitude and expectancy interventions supported motivational and cognitive constructs. The program concluded with evaluation in Week 12 and a post-intervention assessment in Weeks 13-16.

### 4.3 Results Comparison between Pre- and Post-SP

Paired-samples t-tests were conducted to evaluate changes in six key variables before and after the 16-week strategic plan. Each construct was measured using validated scales with the same cohort of 30 students. Table 5 presents the results.

**Table 5:** Paired-sample t-test Results (n=30)

| Variable | | Mean | SD | t-value | p-value |
|---|---|---|---|---|---|
| Facilitating Conditions | Pre-SP | 3.17 | 1.186 | -0.929 | 0.360 |
| | Post-SP | 3.37 | 0.848 | | |
| Digital Literacy | Pre-SP | 3.21 | 1.055 | -2.441 | 0.021 |
| | Post-SP | 3.84 | 0.985 | | |
| Attitude | Pre-SP | 3.34 | 1.022 | -2.231 | 0.034 |
| | Post-SP | 3.98 | 0.891 | | |
| Performance Expectancy | Pre-SP | 3.48 | 1.209 | -2.669 | 0.012 |
| | Post-SP | 4.15 | 0.832 | | |
| Effort Expectancy | Pre-SP | 3.09 | 0.829 | -2.343 | 0.026 |
| | Post-SP | 3.63 | 0.997 | | |
| Behavioral Intention | Pre-SP | 3.11 | 1.014 | -2.624 | 0.014 |
| | Post-SP | 3.77 | 0.959 | | |

Five variables showed significant improvement after the intervention. Digital literacy increased by 0.63 points (from 3.21 to 3.84; t = -2.441, p = .021), representing the largest relative gain of almost 20 percent. Performance expectancy showed the largest absolute improvement of 0.67 points (from 3.48 to 4.15; t = -2.669, p = .012), making it the highest post-intervention score. Attitude improved by 0.64 points (from 3.34 to 3.98; t = -2.231, p = .034), suggesting more favorable views of digital learning. Effort expectancy rose by 0.54 points (from 3.09 to 3.63; t = -2.343, p = .026), showing that students found digital platforms easier to use. Behavioral intention increased by 0.66 points (from 3.11 to 3.77; t = -2.624, p = .014), confirming stronger willingness to adopt digital learning.

In contrast, facilitating conditions showed only a modest mean increase of 0.20 points (from 3.17 to 3.37) and was not statistically significant (t = -0.929, p = .360). This indicates that improvements in infrastructure and institutional support were not yet strong enough for students to perceive a meaningful difference.

Post-intervention scores also showed reduced variability, as standard deviations were generally lower. This suggests greater consistency in students' perceptions after the program.

Overall, hypotheses H7 to H12 were supported except for facilitating conditions. The quantitative findings were reinforced by qualitative interviews, where students described shifts from passive technology users to active content creators. Some students also reported applying new digital skills in employment contexts. The convergence of statistical results and personal experiences demonstrates the effectiveness of the strategic plan in enhancing digital learning adoption.

## 5. Conclusions and Recommendation

### 5.1 Discussion of the Results

The analysis confirmed that all five factors significantly influenced vocational students' behavioral intentions toward digital learning. Attitude emerged as the strongest predictor, followed by performance expectancy and digital literacy. This differs from Western studies where usefulness typically dominates (Meet et al., 2022; Tarhini et al., 2017; Venkatesh et al., 2003), suggesting that in this context, positive emotions carry greater weight. Attitude improved by 0.64 points, showing that immersive methods such as simulations and gamification enhanced students' outlook on digital learning.

Performance expectancy also had a strong effect, with the largest mean gain of 0.67 points. Students became more confident in the practical value of digital tools once they experienced them directly. Digital literacy improved by 0.63 points and played a direct role in shaping intention, unlike earlier studies that treated it as secondary (Yeşilyurt & Vezne, 2023). Students moved from passive use to active content creation, with some applying skills in part-time jobs, reflecting social cognitive theory's link between mastery and self-efficacy (Prior et al., 2016).

Effort expectancy showed a weaker effect but still improved by 0.54 points, suggesting that training reduced perceived complexity, although ease of use is now often taken for granted (Chatterjee et al., 2023; Teng et al., 2022). Facilitating conditions had the smallest impact, improving only 0.20 points and showing no significant effect. This indicates that infrastructure alone is insufficient without structured support (Blut et al., 2022).

Behavioral intention itself increased by 0.66 points, supported by interview findings. Students who enjoyed learning developed stronger expectations of outcomes, while those who valued practical benefits grew more positive in their attitudes. This interplay between emotion and cognition highlights a culturally specific adoption pattern. Unlike Western contexts where rational evaluation dominates, Chinese vocational students rely more on emotional engagement, with attitude leading intention.

The study extends technology acceptance models by integrating digital literacy as a direct predictor and by demonstrating how cultural context shapes adoption. It shows that effective digital transformation requires not only infrastructure but also student competencies, positive attitudes, and clear perceptions of value.

### 5.2 Conclusions

This study examined the determinants of digital learning adoption among Chinese vocational college students, filling a gap in technology acceptance research within this context. Using an integrated framework that combined UTAUT with digital literacy, the results showed that adoption depends on both individual capabilities and institutional support.

Attitude, performance expectancy, and digital literacy were the strongest predictors of behavioral intention, explaining 60.1% of the variance ($R^2 = .601$, $F(5,101) = 30.4$, $p < .001$). The nine-week intervention significantly improved digital literacy, attitude, performance expectancy, effort expectancy, and behavioral intention, confirming that adoption can be meaningfully enhanced through targeted strategies.

The study contributes theoretically by extending UTAUT to include digital literacy, demonstrating the value of action research in linking theory with practice, and highlighting a culturally specific pattern in which emotional engagement and rational evaluation jointly drive adoption.

Practically, the results show that digital transformation in vocational education requires more than infrastructure. Despite the presence of digital platforms in 92% of institutions, average student use remains below 35%, confirming that technical solutions alone are insufficient. The study demonstrates that behavioral intention can be shaped through coordinated strategies that foster positive attitudes, strengthen perceived value, reduce effort barriers, and build digital skills. This framework provides vocational institutions with evidence-based strategies to close the gap between technological availability and meaningful student engagement in China's evolving educational system (Zhou & Zhou, 2024).

### 5.3 Recommendations

The findings highlight the importance of digital literacy, attitude, and performance expectancy as primary drivers of digital learning adoption. Based on these results, several recommendations are proposed.

First, educators should go beyond teaching technical skills and focus on fostering students' intrinsic motivation and active engagement with digital tools. Practical interventions such as gamified learning, virtual simulations, and project-based tasks can strengthen both cognitive and emotional drivers, encouraging students to use digital technologies with confidence and curiosity.

Second, vocational institutions should embed digital literacy development into their curriculum design. This can be achieved by offering required courses, creating elective modules, and introducing diagnostic assessments that track progress. Such systematic integration ensures students not only acquire skills but also apply them effectively in practice.

Third, institutions need to build a supportive learning ecosystem that balances technological empowerment with personalized guidance. Providing digital mentors, targeted training programs, and individualized learning support can help students overcome barriers, sustain positive attitudes, and translate digital readiness into meaningful engagement.

Together, these recommendations underscore that effective digital transformation in vocational education requires more than infrastructure. Coordinated strategies that build competencies, enhance perceived value, and strengthen student motivation are essential for ensuring lasting adoption and impact.

### 5.4 Limitation and Further Study

This study has several limitations. First, the cross-sectional survey design limits the ability to capture changes in digital learning experiences over time, which may mask dynamic adoption patterns. Second, the sample was restricted to one vocational institution in Shandong Province, which reduces the generalizability of the findings to other regions of China. Third, the study did not adequately address potential moderating variables such as socioeconomic background, prior technology exposure, and home learning conditions, even though these factors could meaningfully shape behavioral intentions. Finally, the 9-week intervention provided useful short-term evidence but did not allow examination of the long-term sustainability of digital literacy gains.

Future research should address these limitations in several ways. Mixed-methods designs that combine quantitative surveys with qualitative interviews can generate richer insights into digital literacy development and student adoption patterns. Expanding the sample to include vocational institutions from diverse regions and economic contexts would improve external validity. Longitudinal studies could track technology acceptance over extended periods to identify adoption trajectories and sustainability of interventions. Researchers should also examine how emerging technologies such as artificial intelligence, virtual reality, and adaptive learning systems affect student engagement and behavioral intention. In addition, studying contextual factors such as cultural background, disciplinary focus, and institutional support as moderating variables can lead to a more comprehensive theoretical framework for understanding digital transformation in vocational education.

## References


Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies, 26*(6), 7205-7224. https://doi.org/10.1007/s10639-021-10573-5

Abu-Al-Aish, A., & Love, S. (2013). Factors influencing students' acceptance of m-learning: An investigation in higher education. *International Review of Research in Open and Distributed Learning, 14*(5), 82-107. https://doi.org/10.19173/irrodl.v14i5.1631

Aesaert, K., Voogt, J., Kuiper, E., & van Braak, J. (2017). Accuracy and bias of ICT self-efficacy: An empirical study into students' over- and underestimation of their ICT competencies. *Computers in Human Behavior, 75*, 92-102. https://doi.org/10.1016/j.chb.2017.05.010

Ahmed, S. A., Suliman, M. A., Al-Qadri, A. H., & Zhang, W. (2024). Exploring the intention to use mobile learning applications among international students for Chinese language learning during the COVID-19 pandemic. *Journal of Applied Research in Higher Education, 16*(4), 1093-1116. https://doi.org/10.1108/JARHE-08-2022-0268

Ain, N., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development, 32*(5), 1306-1321. https://doi.org/10.1177/0266666916635031

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model to predict university students' intentions to use metaverse-based learning platforms. *Education and Information Technologies, 28*(11), 15381-15413. https://doi.org/10.1007/s10639-023-12055-6

Alhumaid, K., Habes, M., & Salloum, S. A. (2021). Examining the factors influencing mobile learning usage during COVID-19 pandemic: An integrated SEM-ANN method. *IEEE Access, 9*, 102567-102578. https://doi.org/10.1109/ACCESS.2021.3094496

Alkhwaldi, A. F. (2024). Understanding learners' intention toward Metaverse in higher education institutions from a developing country perspective: UTAUT and ISS integrated model. *Kybernetes, 53*(12), 6008-6035. https://doi.org/10.1108/K-01-2023-0066

Antonietti, C., Cattaneo, A., & Amenduni, F. (2022). Can teachers' digital competence influence technology acceptance in vocational education? *Computers in Human Behavior, 132*, 107266. https://doi.org/10.1016/j.chb.2021.107266

Bannigan, K., & Watson, R. (2009). Reliability and validity in a nutshell. *Journal of Clinical Nursing, 18*(23), 3237-3243. https://doi.org/10.1111/j.1365-2702.2009.02939.x

Bayaga, A., & du Plessis, A. (2024). Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries' higher education staff. *Education and Information Technologies, 29*(8), 9689-9714. https://doi.org/10.1007/s10639-023-12194-6

Bervell, B., & Umar, I. N. (2017). Validation of the UTAUT model: Reconsidering nonlinear relationships of exogenous variables in higher education technology acceptance research. *Eurasia Journal of Mathematics, Science and Technology Education, 13*(10), 6471-6490. https://doi.org/10.12973/ejmste/79754

Blut, M., Chong, A. Y. L., Tsiga, Z., & Venkatesh, V. (2022). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean. *AIS Transactions on Human-Computer Interaction, 14*(4), 431-470. https://doi.org/10.17705/1thci.00176

Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2023). The effect of self-efficacy on consumers' adoption of mobile payment services: A meta-analytic structural equation modeling approach. *Information Systems Frontiers, 25*(2), 577-600. https://doi.org/10.1007/s10796-022-10338-w

Chen, C. C., Hsiao, K. L., & Li, W. C. (2020). Exploring the determinants of usage continuance willingness for location-based apps: A case study of bicycle-based exercise apps. *Journal of Retailing and Consumer Services, 55*, 102097. https://doi.org/10.1016/j.jretconser.2020.102097

Clark, V. L. P. (2019). Meaningful integration within mixed-methods studies: Identifying why, what, when, and how. *Contemporary Educational Psychology, 57*, 106-111. https://doi.org/10.1016/j.cedpsych.2019.01.001

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189-211. https://doi.org/10.2307/249688

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Dakduk, S., Santalla-Banderali, Z., & Van Der Woude, D. (2018). Acceptance of blended learning in executive education. *SAGE Open, 8*(3), 2158244018800647. https://doi.org/10.1177/2158244018800647

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 21*(3), 719-734. https://doi.org/10.1007/s10796-017-9774-y

Efiloğlu Kurt, Ö. (2023). Learning with smartphones: The acceptance of m-learning in higher education. *Online Information Review, 47*(5), 862-879. https://doi.org/10.1108/OIR-02-2022-0088

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley. https://people.umass.edu/aizen/f&a1975.html

Gilster, P. (1997). *Digital literacy*. Wiley.

Gong, C., & Ribiere, V. (2021). Developing a unified definition of digital transformation. *Technovation, 102*, 102217. https://doi.org/10.1016/j.technovation.2020.102217

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Pearson Education.

Hao, Y., Zeng, X., Yasin, M. A. I., & Boon Sim, N. (2024). Factors influencing college students' learning intention to online teaching videos during the pandemic in China. *SAGE Open, 14*(3), 21582440241256769. https://doi.org/10.1177/21582440241256769

Hoi, V. N. (2020). Understanding higher education learners' acceptance and use of mobile devices for language learning: A Rasch-based path modeling approach. *Computers & Education, 146*, 103761. https://doi.org/10.1016/j.compedu.2019.103761

Hu, N., & Xie, H. (2019). Analysis of SWOT on the development and internationalization of China's vocational education in the context of "The Belt and Road Initiative" strategy. *Journal of Contemporary Educational Research, 3*(2), 18-23. https://doi.org/10.26689/jcer.v3i2.578

Huang, F., Teo, T., & Zhou, M. (2020). Chinese students' intentions to use the Internet-based technology for learning. *Educational Technology Research and Development, 68*(1), 575-591. https://doi.org/10.1007/s11423-019-09648-9

Humida, T., Al Mamun, M. H., & Keikhosrokiani, P. (2022). Predicting behavioral intention to use e-learning system: A case study in Begum Rokeya University, Rangpur, Bangladesh. *Education and Information Technologies, 27*(2), 2241-2265. https://doi.org/10.1007/s10639-021-10643-y

Jiang, L., & Yu, N. (2024). Developing and validating a teachers' digital competence model and self-assessment instrument for secondary school teachers in China. *Education and Information Technologies, 29*(7), 8817-8842. https://doi.org/10.1007/s10639-024-12529-4

Joo, Y. J., Park, S., & Shin, E. K. (2017). Students' expectation, satisfaction, and continuance intention to use digital textbooks. *Computers in Human Behavior, 69*, 83-90. https://doi.org/10.1016/j.chb.2016.12.025

Khan, N., Sarwar, A., Chen, T. B., & Khan, S. (2022). Connecting digital literacy in higher education to the 21st century workforce. *Knowledge Management & E-Learning, 14*(1), 46-61. https://doi.org/10.34105/j.kmel.2022.14.004

Kumar, J. A., Bervell, B., Annamalai, N., & Osman, S. (2020). Behavioral intention to use mobile learning: Evaluating the role of self-efficacy, subjective norm, and WhatsApp use habit. *IEEE Access, 8*, 208058-208074. https://doi.org/10.1109/ACCESS.2020.3038269

Li, B., Sun, J., & Oubibi, M. (2022). The acceptance behavior of blended learning in secondary vocational school students: Based on the modified UTAUT model. *Sustainability, 14*(23), 15897. https://doi.org/10.3390/su142315897

Lin, E. Y. C., Hsu, H. T., & Chen, K. T. C. (2023). Factors that influence students' acceptance of mobile learning for EFL in higher education. *Eurasia Journal of Mathematics, Science and Technology Education, 19*(6), 2279. https://doi.org/10.29333/ejmste/13200

Liu, X., Zhang, L., & Chen, R. (2018). Factors influencing mobile learning adoption among vocational students. *International Journal of Educational Technology in Higher Education, 15*(1), 1-16. https://doi.org/10.1186/s41239-018-0112-0

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. *Education and Information Technologies, 26*(6), 7057-7077. https://doi.org/10.1007/s10639-021-10557-5

Martin, A. (2006). A European framework for digital literacy. *Nordic Journal of Digital Literacy, 1*(2), 151-162. https://doi.org/10.18261/ISSN1891-943X-2006-02-06

Meet, R. K., Kala, D., & Al-Adwan, A. S. (2022). Exploring factors affecting the adoption of MOOC in Generation Z using extended UTAUT2 model. *Education and Information Technologies, 27*(7), 10261-10283. https://doi.org/10.1007/s10639-022-10956-y

Ministry of Education. (2024). *China education informatization development report (2024)*. Educational Science Press.

Morgan, D. L. (2014). Pragmatism as a paradigm for social research. *Qualitative Inquiry, 20*(8), 1045-1053. https://doi.org/10.1177/1077800413513733

Muasyaroh, H., & Royanto, L. R. M. (2024). Digital literacy, attitudes toward e-learning, and task value roles in college students' distance learning self-regulation. *Psychological Research on Urban Society, 6*(1), 12-24. https://doi.org/10.7454/proust.v6i1.176

Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education, 59*(3), 1065-1078. https://doi.org/10.1016/j.compedu.2012.04.016

Nikou, S., & Aavakare, M. (2021). An assessment of the interplay between literacy and digital technology in higher education. *Education and Information Technologies, 26*(4), 3893-3915. https://doi.org/10.1007/s10639-021-10412-9

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Patil, H., & Undale, S. (2023). Willingness of university students to continue using e-learning platforms after compelled adoption of technology: Test of an extended UTAUT model. *Education and Information Technologies, 28*(11), 14943-14965. https://doi.org/10.1007/s10639-023-11861-4

Phuangthong, D., & Malisuwan, S. (2008). User acceptance of multimedia mobile Internet in Thailand. *The International Journal of the Computer, the Internet and Management, 16*(3), 22-33.

Prior, D. D., Mazanov, J., Meacheam, D., Heaslip, G., & Hanson, J. (2016). Attitude, digital literacy and self-efficacy: Flow-on effects for online learning behavior. *The Internet and Higher Education, 29*, 91-97. https://doi.org/10.1016/j.iheduc.2016.01.002

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education, 147*, 103778. https://doi.org/10.1016/j.compedu.2019.103778

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). Free Press.

Rovinelli, R. J., & Hambleton, R. K. (1977). On the use of content specialists in the assessment of criterion-referenced test item validity. *Tijdschrift voor Onderwijsresearch, 2*(2), 49-60.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' behavioral intention to use technology. *Computers & Education, 128*, 13-35. https://doi.org/10.1016/j.compedu.2018.09.009

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education, 49*(2), 223-245. https://doi.org/10.1007/s10755-023-09748-6

Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in Human Behavior, 27*(6), 2067-2077. https://doi.org/10.1016/j.chb.2011.08.005

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. *Information Systems Frontiers, 23*, 987-1005. https://doi.org/10.1007/s10796-020-10007-2

Tang, C. M., & Chaw, L. Y. (2016). Digital literacy: A prerequisite for effective learning in a blended learning environment? *Electronic Journal of E-Learning, 14*(1), 54-65.

Tarhini, A., Masa'deh, R. E., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modeling approach. *Journal of International Education in Business, 10*(2), 164-182. https://doi.org/10.1108/JIEB-09-2016-0032

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Teng, Z., Cai, Y., Gao, Y., Zhang, X., & Li, X. (2022). Factors affecting learners' adoption of an educational metaverse platform: An empirical study based on an extended UTAUT model. *Mobile Information Systems, 2022*(1), 5479215. https://doi.org/10.1155/2022/5479215

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 125-143. https://doi.org/10.2307/249443

Tomczyk, L. (2020). Skills in the area of digital safety as a key component of digital literacy among teachers. *Education and Information Technologies, 25*(1), 573-585. https://doi.org/10.1007/s10639-019-09980-6

Triandis, H. C. (1979). Values, attitudes, and interpersonal behavior. In H. E. Howe Jr. & M. M. Page (Eds.), *Nebraska Symposium on Motivation* (pp. 195-259). University of Nebraska Press.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Wang, L., & Chen, Y. (2022). Digital learning technologies in vocational education: A mixed-methods exploration of technology acceptance. *Educational Technology Research and Development, 70*(4), 567-590. https://doi.org/10.1007/s11423-022-10091-5

Wang, X., Zhang, R., Wang, Z., & Li, T. (2021). How does digital competence preserve university students' psychological well-being during the pandemic? An investigation from self-determined theory. *Frontiers in Psychology, 12*, 652594. https://doi.org/10.3389/fpsyg.2021.652594

Wang, Y. (2024). Digital transformation of vocational education: Connotation, challenges and pathways. *Region - Educational Research and Reviews, 6*(12), 43. https://doi.org/10.32629/rerr.v6i12.716

Xu, J., Jiang, T., Wei, M., & Qing, Z. (2024). The digital transformation of vocational education: Experience and reflections of Shenzhen Polytechnic University. *Vocation, Technology & Education, 1*(1). https://doi.org/10.62352/vte.20240101

Yeşilyurt, E., & Vezne, R. (2023). Digital literacy, technological literacy, and internet literacy as predictors of attitude toward applying computer-supported education. *Education and Information Technologies, 28*(8), 9885-9911. https://doi.org/10.1007/s10639-023-11832-9

Zhou, H., & Zhou, D. (2024). Transformation of vocational education based on generative artificial intelligence: Impact, opportunity and countermeasures. *Proceedings of the 3rd International Conference on Internet Technology and Educational Informatization (ITEI 2023)*, 1-8. https://doi.org/10.1109/ITEI61209.2023.00045