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# Understanding the Impact of Self-efficacy, Personal Innovativeness and Content Quality on Mobile Learning Usage in Higher Vocational Colleges

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**Abstract:** The advent of internet technology has led to a surge in interest in mobile learning, particularly among students in higher vocational colleges. Despite this growing interest, there are still some challenges such as low usage rate and unsatisfactory effect of mobile learning among students in higher vocational colleges in China. The objective of the research is to determine how students' intention to use mobile learning could be enhanced in Chinese higher vocational colleges. The extended UTAUT model was employed to investigate the factors influencing the intention and use behavior of mobile learning among Chinese vocational college students. Three variables of self-efficacy, personal innovativeness, and content quality were incorporated. A total of 636 higher vocational college students in seven regions of China were selected, and there was little difference in the prior knowledge level of all students. This study demonstrates that self-efficacy, personal innovativeness, and content quality have a positive and significant influennce on the use of mobile learning based on the UTAUT model. Additionally, self-efficacy has a significant impact on the four constructs of UTAUT model. The findings suggest that higher vocational colleges and mobile learning developers should implement effective strategies for mobile learning.

**Keywords:** mobile learning; utaut; self-efficacy; personal innovativeness; content quality.

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## 1. Introduction

With the rapid improvement of information technology, learning expectations have evolved significantly. Traditional learning methods no longer suffice, and mobile learning has emerged to meet these changing needs. Mobile learning has transitioned the educational environment from traditional classrooms to media supported by information and communications technology (Meet, Kala, & Al-Adwan, 2022). This shift is especially prevalent in higher education, where daily use of mobile devices, for example smartphones, for learning and teaching is increasing. In contrast to traditional teaching, which is often perceived as a challenging and uninteresting experience for students, usage of mobile devices for knowledge acquisition is widely accepted. As institutions of learning adapt to this trans-formative shift, they are concurrently contemplating strategies to enhance academic outcomes through mobile learning, thereby enabling students to derive greater benefit from this innovation.

Mobile learning means the acquisition of knowledge with personal mobile devices connected to internet (Almaiah & Alismaiel, 2019). Mobile phones are pervasive in contemporary society, with applications in diverse fields, including health and education. Nevertheless, numerous higher vocational colleges in China have reverted to traditional classrooms following the adoption of M-learning, as the study outcomes have not met expectations. Consequently, a few researches have suggested that implementation of M-learning continues to encounter significant obstacles, including the necessity for substantial infrastructure investment and a relatively low level of acceptance (Li, Islam, & Spector, 2022). Moreover, the current developers of mobile learning have not yet fully comprehended students' attitudes towards mobile learning, which entails further analysis.

This paper introduces three new variables: self-efficacy, personal innovativeness, and content quality. Building upon other past researches that have used the UTAUT model and its extended version, this paper incorporates personal and quality factors to obtain a more nuanced comprehension of perceptions of M-learning. This advances theories in this specific field. As previously stated by Kim, Lee and Rha (2017), it is crucial to ascertain the effect of individual variables in M-learning. Furthermore, Li et al. (2022) declared the importance of investigating the quality of online resources as a significant factor. This study focuses on researching and solving the following three problems:

Question 1: How do self-efficacy, personal innovativeness, and content quality affect the intention and use behavior of mobile learning?
Question 2: What are the primary factors affecting behavioral intention and actual use of M-learning among higher vocational students in China?
Question 3: How can the extended UTAUT model be validated?

This study updates the UTAUT model theoretically and clarifies the impacts of self-efficacy, personal innovativeness, and content quality on the use of mobile learning. Meanwhile, it provides insights for higher vocational colleges, developers and designers of mobile learning, helping them to promote and implement mobile learning more effectively.

## 2. Literature Review

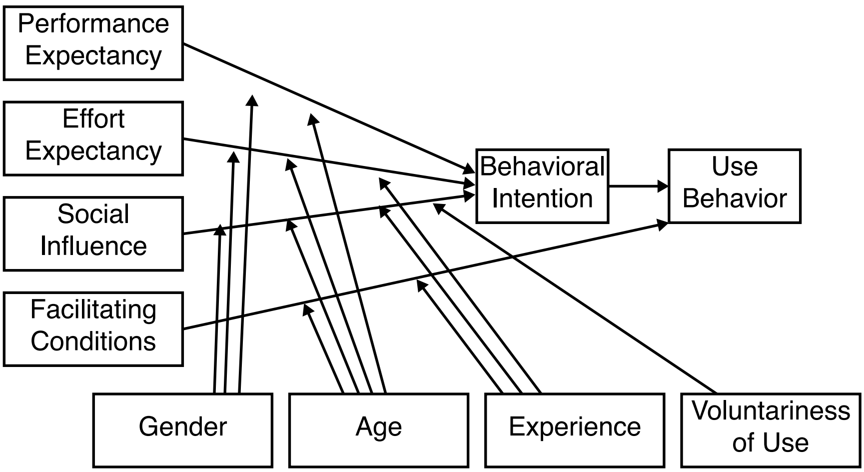
### *2.1. Mobile learning in higher vocational colleges*

In contrast to academic higher education, higher vocational colleges in China offer a shorter period of study that focuses on developing practical job skills to prepare students for the workforce (Li et al., 2022). As a result, students from higher vocational colleges exhibit different learning habits, motivations. They often lack self-control and struggle to study efficiently and intensively in the classroom for extended periods. Many students feel fatigued by traditional, book-based instruction. Being naturally lively and interested in new experiences, they prefer modern learning resources that are visual, audio-visual, and aligned with current trends. The advent of M-learning can satisfy the personalized learning needs of higher vocational students, through which students can have flexible access to learning resources catering to their own needs. They can also choose from diverse resources, including class recordings and high-quality open courses, to supplement the knowledge that cannot be covered in traditional classes.

### *2.2. The UTAUT Model*

New technology adoption has been a topic of much interest in academics and many of such models have been preferred. Venkatesh et al. (2003) has developed UTAUT on the bases of the comparison and combination of eight models which include the comparison and selection of the variables of the eight models. The eight separate models significantly under perform in terms their research compared to the UTAUT model which reached an R square of 69%. This means that UTAUT model is more effective as a predictor of technology intention. Fig. 1 shows the relationships of four constructs to Technology Intention and use behavior using the UTATU model. Most importantly, the model is shown to be valid in M-learning (Alowayr, 2022). Using UTAUT, Al-Adwan, Al-Adwan and Berger (2018) explored the factors associated with the adoption of M learning. It was found that intention was influenced by PE and EE, and social influence was significant. Nevertheless, subsequent studies confirm the effect of FC to intention (Lutfi et al., 2022; Venkatesh, Thong, & Xu, 2012). Therefore, this study bases upon UTAUT model and investigates the effect of four above mentioned variables on the intention of M-learning.

**Figure 1: UTAUT Model.**




Although the UTAUT is widely used, some people still cast doubt on its predictability towards individual technology adoption, which indicates that the UTAUT needs to be extended (Chao, 2019). Several researchers; Alowayr (2022), Maillet, Mathieu, & Sicotte, (2015) have suggested that including additional external variables could enhance the model's predictive capacity for technology adoption. Additionally, it was observed that a crucial element absent is the individual who engages in the behavior, which may influence their behavior. Previous research indicates that self-efficacy and personal innovativeness are highly effective in M-learning (Kumar et al., 2020; Sidik & Syafar, 2020). Moreover, mobile learning encompasses more than merely accessing information through smartphones. This technology should consider pedagogical aspects such as the learning process and learning content (Chavoshi & Hamidi, 2019). Almaiah and Al Mulhem (2019) revealed that content quality affects intention to use mobile learning. Therefore, this research would integrate these three new factors from individual and pedagogical perspectives to investigate the factors influencing mobile learning usage in China.

### *2.3. UTUAT Model Constructs*

PE and EE represent two of primary factors influencing technology adoption. The performance expectancy (PE), reflects the belief that technology enhances job performance, and effort expectancy (EE), relates to the perceived ease of use. Social influence (SI) highlights the impact of peer and societal expectations on adoption decisions (Venkatesh et al., 2003). Consequently, following hypotheses were put forth:

H1: PE have a positive influence behavioral intention.
H2: EE have a positive influence behavioral intention.

The effect of SI on intention has been established in educational field (Alshehri, Rutter, & Smith, 2019; Lwoga & Komba, 2015) such as Web based learning. Regarding mobile learning, when we use the technology, people are more likely to persuade their friends and schoolmates to use it (Chavoshi & Hamidi, 2019). Subjective norms were used as a proxy for social influence in some studies (Yeap, Ramayah, & Soto-Acosta, 2016). Research work has confirmed that SI plays a crucial role in many studies; such as peer students and instructors (Alshehri et al., 2019; Tarhini et al., 2017; Yeap et al., 2016).

The UTAUT, although showing that FC significantly affect actual usage only, has other studies that found also that FC influence BI (Ab Jalil, Rajakumar, & Zaremohzzabieh, 2022; Li et al., 2022), arguing that the more the students believe the organizational and technical support is to be good, the more likelihood they have to use new technologies (Lwoga & Komba, 2015). The finding that FC had an impact on intention is demonstrated by Meet et al. (2022). Consequently, this study proposes following hypotheses:

H3: SI has a positive effect on behavioral intention. H4: FC has a positive effect on behavioral intention.

### *2.4. Individual factors*

The characteristics of individuals vary depending on their education level, gender, age, and interests (Hamidi & Chavoshi, 2018). The characteristics of students in universities and colleges are markedly disparate. In comparison to university students, higher vocational college students exhibit a lack of consciousness, a deficiency in motivation to learn, a diminished capacity for learning, and a reduced confidence in the operation of new technologies. These personal characteristics exert a direct or indirect effect on behavioral intention (Hamidi & Chavoshi, 2018). Based on previous research, the following personal factors, which are introduced in this paper, have been demonstrated to be highly effective (Kim et al., 2017; Kumar et al., 2020).

*2.4.1. Self-Efficacy*

It is referred to as an individual's judgment of what they can do with a task (Bandura & Schunk, 1981). There are higher self efficacy meaning that people know more about their skills are more informed are more likely to be successful in tasks that they do. Moreover, Compeau and Higgins (1995) delineated the three dimensions of self-efficacy: strength, magnitutde, and geeralization. Self-efficacy magnitude represents completing challenging tasks independently without support and help if needed. Thus, this situation is, people who have more strength of pc self-efficacy are averse to being furious at obstacles. The term used for self efficacy generalization would be using new system interfaces without delay. SE has been identified as a determinant of intention and technology utilization in a wide range of education studies (Almaiah, Alamri, & Al-Rahmi, 2019; Kumar et al., 2020; Tarhini et al., 2017). In M-learning, Kumar et al. (2020) identified self-efficacy as having the most influential determinant on the behavioral intention out of five determinants. Consequently, following hypotheses are put forth:

H5: Self-efficacy has a positive influence behavioral intention to use mobile learning;
H6: Self-efficacy have a positive influence use behavior of mobile learning;

According to Compeau and Higgins (1995), individuals who have a higher level of self-efficacy are less likely to be defeated by obstacles. Those that demonstrated high levels of self-efficacy are able to complete computer tasks and are competent in the use of different systems. This implies that an individual with high self-efficacy regards the system as straightforward and beneficial. Similarly, Hill, Smith and Mann (1987) reported that an individual's expectation of the outcomes was influenced by self-efficacy. A considerable number of studies have incorporated SE into the TAM model, demonstrating that SE can predict PEOU and PU (Althunibat, 2015). It is well established that the constructs of PE and EE are derived from the constructs of PU and PEOU, respectively. These constructs exhibit a high degree of similarity. Additionally, studies have incorporated self-efficacy, demonstrating that SE has a positive effect on both PE and EE (Altalhi, 2021; Li et al., 2022; Shaya, Madani, & Mohebi, 2023). Hypothesis 7 and 8 were therefore develoepd:

H7: SE has a positive effect on performance expectancy. H8: SE has a positive effect on effort expectancy.

Few researches have explored the influence of self-efficacy on facilitating conditions and social influence. Li et al. (2022) integrated self-efficacy into the UTAUT model and confirmed its significant impact on both FC and SI. Similarly, Yeap et al., (2016) demonstrated self-efficacy had substantial influence on perceived behavioral control, a construct akin to facilitating conditions. Kumar et al. (2020) demonstrated that SE is a predictor of subjective norms, which is a construct analogous to social influence. Consequently, following hypotheses are proposed:

H9: Self-efficacy will positively influence social influence.
H10: Self-efficacy will positively influence facilitating conditions.

### 2.4.2. Personal Innovativeness

In this study, personal innovativeness represents the degree to which an individual adopts mobile learning faster and more easily than other individuals. Those who have a higher level of innovativeness are more comfortable with new experiences, more willing to take risks, and more interested in trying new technology (Milošević et al., 2015). Lee and Rha (2016) have suggested that PI is a important determinant, especially in the education field (Farooq et al., 2017; Pinho, Franco, & Mendes, 2021). To be more specific in mobile learning, PI is an important predictor of both intention and use behavior (Alturki & Aldraiweesh, 2022; Kim et al., 2017; Lisana, 2023). Accordingly, hypothesis 11 and 12 are stated:

H11: PI has a positive effect on behavioral intention. H12: PI has a positive effect on behavior.

### 2.5. Content Quality

Information quality is pivotal according to Delone and McLean (2003) Information System Success Model. The core of mobile learning is not restricted to providing information, instead, it must accurately follow pedagogical and theoretical approaches to assist learners in achieving better benefits with the platform. The most commonly used measurement of information quality in the field of education is content quality (Lee, Yoon, & Lee, 2009), all learning content, digital resources created for use on mobile platforms. Content quality is described as timeliness, accuracy, completeness, consistency, and relevancy of these resources with the content (Elmunsyah et al., 2023). Since its content aligns with the curriculum but doesn't contain personalized, valuable material for students (Hamidi & Chavoshi, 2018). Low quality material (Lutfi et al., 2022) requires high quality content to achieve learning objectives. Mobile learning offers students more advantages than other traditional forms of instruction, especially a wealth of educational content as well as engaging teaching methodologies. It is a positive learning experience for the students because of this perception of usefulness. Numerous studies (Almaiah & Al Mulhem, 2019; Almaiah & Alismaiel, 2019; Lutfi et al., 2022) have showed that content quality contributes positively to the intention of mobile learning use. This means students are comfortable with mobile learning when the content meets the students' needs. Other scholars also revealed that the effect of content quality on actual use in online learning (Elmunsyah et al., 2023) and mobile learning (Almaiah et al., 2019) can also be realized. Thus, the following hypotheses are put forth:

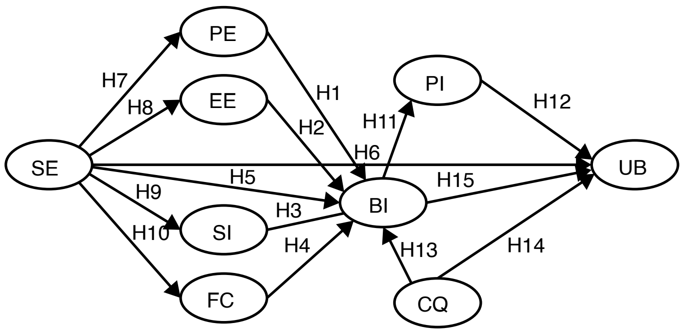
H13: Content quality will positively influence behavioral intention. H14: Content quality will positively influence use behavior.

### 2.6. Behavioral intention (BI) and use behavior (UB)

A large number of studies employ behavioral intention as the only dependent variable, and in this paper, use behavior is also incorporated into the model as the dependent variable. The term "use behavior" refers to the action of using or implementing mobile learning (Yeap et al., 2016). BI can be defined as the readiness a student to utilize mobile learning. Many researchers discovered a correlation between behavioral intention and the use of mobile learning (Almaiah et al., 2019; Almaiah & Alismaiel, 2019; Farooq et al., 2017; Tarhini et al., 2017). Accordingly, the following hypothesis is put forth:

H15: Behavioral intention will positively influence use behavior of mobile learning. Fig. 2 has shown the proposed relationship.

**Figure 2: The Proposed Research Model.**

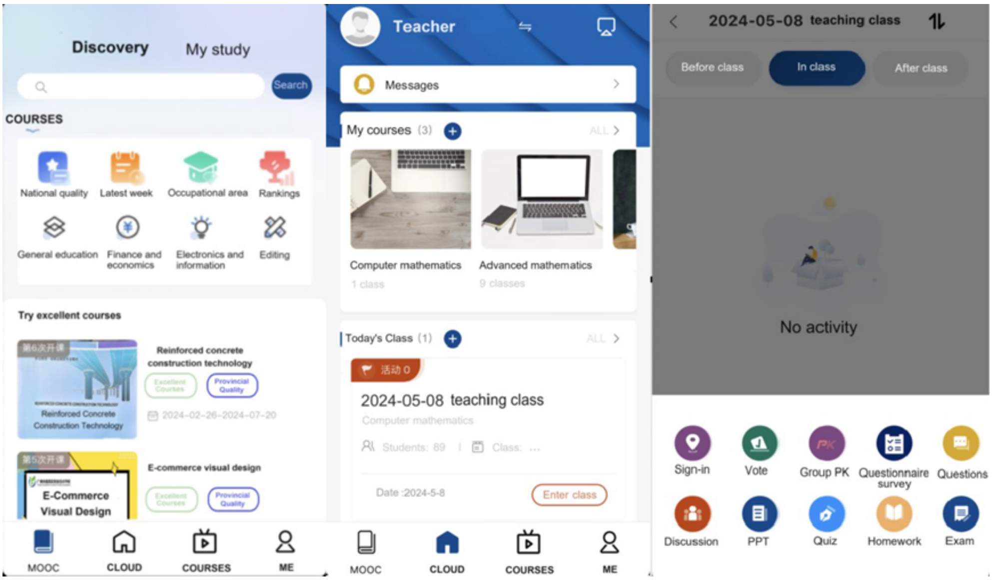



## 3. Methodology

### *3.1. Respondents and Contexts*

The target population consisted of higher vocational college students from seven regions in China, with consideration given to the varying economic conditions and technological levels of the different regions. This approach allows for a more accurate development of recommendations fpr the research objective. The students had completed at least one mobile learning course. Consequently, the participants were able to assist in the identification of the primary factors influencing the utilization of mobile learning from their individual perspectives.

**Figure 3: Interface of ICVE.**



Higher vocational colleges have acknowledged the advantages of mobile learning, including portability and personalization (Gumbheer, Khedo, & Bungaleea, 2022), and have actively promoted the development of mobile learning. The platforms of M-learning utilized by higher vocational colleges offer comparable functional modules, teaching objectives, and interactive experiences. The mobile learning platforms in question are the Intelligent Center of Vocational Education (ICVE), Cloud Class, and Treenity. To illustrate, consider ICVE. Fig. 3 depicts the homepage, the learning course page and class activities, including PowerPoint presentations, discussions, quizzes, homework assignments of ICVE.

### *3.2. Data Collection*

Nine latent variables in this research model included 21 observed variables and 57 questions. Each question was evaluated on a five-point Likert scale. Each question was derived from previous literature and deemed suitable for this research, thus ensuring the reliability and validity. Questionnaire also included 6 questions about the demographic's characteristics. Two scholars proficient in Chinese and English translated the questionnaires into Chinese. These scholars, with extensive experience, ensured that the Chinese version accurately reflects the original questionnaires, addressing cultural differences effectively. Additionally, since students may have varying perceptions of mobile learning, a definition of mobile learning was included at the very beginning.

Among the nine latent variables identified in this study, this research chooses 7 independent variables, which, therefore, include PE, EE, SI, FC, SE, PI and CQ. Moreover, there are two dependent variables which are BI and UB added. In achieving its objectives, PE makes use of three observed variables to measure the expected push and performance of ML. Variable EE has two factors, namely perceived ease of use and ease of use which were advanced by Alyoussef (2021). SI is an abstract variable which has two observed variables. Incorporated under the social influence construct are subjective norm, selected from Venkatesh et al. (2003), and social factors selected from Altalhi (2021). Perceived behavioural control and facilitating conditions are two dimensions of FC borrowed from Venkatesh et al. (2003). SE has two dimensions. These are confidence and capability, respectively, and are from Venkatesh et al. (2003), Chavoshi and Hamidi (2019) and Alowayr (2022). Specifically, PI has two observed variables, behaviours, and states, behaviours and states derived from Agarwal and Prasad (1998) and Lisana (2023). CQ has two perspectives- informativeness and accessibility, which are applied to illustrate the aspects of mobile learning content quality out of Almaiah et al. (2019) and Elmunsyah et al. (2023). The first dependent variable BI in this study uses 3 observed variables used by the majority of prior researches. The three items represent the students' future behavioural intention with regards to the use of mobile learning. There are relatively fewer studies on the second dependent variable, UB. However, we have also identified suitable items for this study, which are measured from the three dimensions of preference, frequent use, and recommendation. The items were selected from Alyoussef (2021) and Almaiah and Alismaiel (2019).

Prior to the formal data collection, the study carried out a pilot survey with a sample size of 30 students. Reliability testing was performed, and the Cronbach Alphas were greater than 0.7, indicating the consistency of the items. Since the development of



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mobile learning in higher vocational colleges varies across regions, we selected one college from each region using stratified random sampling. The proportion of each region was calculated by dividing the figure of participants in each region by the total participants. This figure was then multiplied by the sample size to obtain the sample of each region. A total sample of 636 students was selected (Table 1).

**Table 1: Sample Characteristics (N=636).**

| Measure | Item | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 352 | 55.35% |
| | Female | 284 | 44.65% |
| Age | 18 – 19 | 109 | 17.14% |
| | 20 – 21 | 186 | 29.25% |
| | 22 – 23 | 304 | 47.80% |
| | Over 24 | 37 | 5.82% |
| Grade | Freshman year | 124 | 19.50% |
| | Sophomore year | 307 | 48.27% |
| | Junior year | 205 | 32.23% |
| Region of this research | Northeast | 43 | 6.76% |
| | North | 67 | 10.53% |
| | Northwest | 43 | 6.76% |
| | Central | 112 | 17.61% |
| | East | 179 | 28.14% |
| | Southwest | 98 | 15.41% |
| | South | 94 | 14.78% |
| Use mobile phone for internet per day | Less than 1 hour | 23 | 3.62% |
| | 1-2 hours | 207 | 32.55% |
| | More than 2 hours | 406 | 63.84% |
| Mobile learning experience | 0-1year | 134 | 21.07% |
| | 1-2 years | 140 | 22.01% |
| | 2 years and more | 362 | 56.92% |

### *3.3. Data Analysis*

This study used SPSS 27.0 to implement the descriptive analysis and reliability test. Amos 23 was used to carry out the confirmatory factor analysis and structural equation modelling. This study use Cronbach's Alpha to evaluate the reliability and CFA to show how well the measurement fit the proposed model.

## 4. **Results of the Research**

### *4.1. Model Evaluation*

Two tests of the measuring model were examined: validity and reliability. Table 2 presents the pertinent reliability and validity indicators, such as AVE, Cronbach's alpha, CR, and factor loading. CFA was used to evaluate validity, including goodness of fit, convergence validity and discriminant validity. The evaluation of consistency between empirical data and conceptual framework is reflected by goodness of fit. The goodness-of-fit indexes are $c^2$/df = 1.279, CFI=0.979, GFI=0.907, TLI=0.978, RMSEA = 0.021, SRMR=0.036. All the indicators satisfied the criteria. Convergence validity requires that there is a strong correlation under the same latent variable. The measurement criteria are (1) factor loading is significant and greater than 0.6 (Hulland, 1999), (2) CR > 0.7, (3) AVE > 0.5. The factor loading of PE_PU4, EE_EU3, FC_FC4 and CQ_A5 are 0.495, 0.524, 0.469 and 0.545, so the four items were removed. Then we recalculated all indexes according to the revised model and obtained Table 2. The factor load, CR and AVE in the revised model all reached the convergence validity standard.

**Table 2: Evaluation of the Model.**

| | Mean | Std. Dev. | Factors | Cronbach's Alpha | CR | AVE |
|---|---|---|---|---|---|---|
| | | | **Performance Expectancy** | | | |
| PE_PU1 | 3.66 | 1.22 | 0.765 | 0.917 | 0.921 | 0.565 |
| PE_PU2 | 3.64 | 1.25 | 0.759 | | | |
| PE_PU3 | 3.63 | 1.20 | 0.697 | | | |
| PE_RA1 | 3.65 | 1.21 | 0.756 | | | |
| PE_RA2 | 3.76 | 1.18 | 0.757 | | | |
| PE_RA3 | 3.71 | 1.17 | 0.748 | | | |
| PE_OE1 | 3.71 | 1.17 | 0.749 | | | |
| PE_OE2 | 3.67 | 1.21 | 0.772 | | | |
| PE_OE3 | 3.71 | 1.22 | 0.762 | | | |
| | | | **Effort Expectancy** | | | |
| EE_PEU1 | 3.60 | 1.17 | 0.831 | 0.877 | 0.916 | 0.646 |
| EE_PEU2 | 3.60 | 1.28 | 0.788 | | | |
| EE_PEU3 | 3.65 | 1.23 | 0.773 | | | |
| EE_EU1 | 3.53 | 1.26 | 0.878 | | | |
| EE_EU2 | 3.62 | 1.24 | 0.778 | | | |
| EE_EU4 | 3.63 | 1.28 | 0.767 | | | |
| | | | **Social Influence** | | | |
| SI_SN1 | 3.77 | 1.15 | 0.76 | 0.882 | 0.882 | 0.555 |
| SI_SN2 | 3.77 | 1.16 | 0.743 | | | |
| SI_SN3 | 3.75 | 1.13 | 0.734 | | | |
| SI_SF1 | 3.82 | 1.17 | 0.751 | | | |
| SI_SF2 | 3.75 | 1.20 | 0.777 | | | |
| SI_SF3 | 3.73 | 1.17 | 0.702 | | | |
| | | | **Facilitating Conditions** | | | |
| FC_PBC1 | 3.80 | 1.14 | 0.78 | 0.875 | 0.886 | 0.565 |
| FC_PBC2 | 3.73 | 1.15 | 0.759 | | | |
| FC_PBC3 | 3.71 | 1.27 | 0.799 | | | |
| FC_FC1 | 3.73 | 1.22 | 0.756 | | | |
| FC_FC2 | 3.71 | 1.19 | 0.684 | | | |
| FC_FC3 | 3.74 | 1.15 | 0.728 | | | |
| | | | **Self-efficacy** | | | |
| SE_CE1 | 3.59 | 1.28 | 0.898 | 0.912 | 0.913 | 0.639 |
| SE_CE2 | 3.72 | 1.23 | 0.781 | | | |
| SE_CE3 | 3.64 | 1.20 | 0.697 | | | |
| SE_CY1 | 3.72 | 1.24 | 0.8 | | | |
| SE_CY2 | 3.67 | 1.11 | 0.837 | | | |
| SE_CY3 | 3.71 | 1.20 | 0.767 | | | |
| | | | **Personal Innovativeness** | | | |
| PI_B1 | 3.56 | 1.28 | 0.701 | 0.806 | 0.807 | 0.512 |
| PI_B2 | 3.61 | 1.25 | 0.725 | | | |
| PI_S1 | 3.56 | 1.34 | 0.694 | | | |
| PI_S2 | 3.56 | 1.28 | 0.74 | | | |
| | | | **Content Quality** | | | |
| CQ_I1 | 3.84 | 1.06 | 0.832 | 0.906 | 0.912 | 0.596 |
| CQ_I2 | 3.83 | 1.18 | 0.761 | | | |
| CQ_I3 | 3.81 | 1.16 | 0.757 | | | |
| CQ_A1 | 3.79 | 1.20 | 0.791 | | | |
| CQ_A2 | 3.83 | 1.17 | 0.758 | | | |
| CQ_A3 | 3.82 | 1.16 | 0.737 | | | |
| CQ_A4 | 3.78 | 1.18 | 0.763 | | | |
| | | | **Behavioral Intention** | | | |
| BI1 | 3.74 | 1.26 | 0.808 | 0.845 | 0.829 | 0.617 |
| BI2 | 3.76 | 1.23 | 0.772 | | | |
| BI3 | 3.71 | 1.22 | 0.776 | | | |
| | | | **Use Behavior** | | | |
| UB_P1 | 3.62 | 1.25 | 0.762 | 0.894 | 0.891 | 0.577 |
| UB_P2 | 3.62 | 1.23 | 0.767 | | | |
| UB_FU1 | 3.59 | 1.27 | 0.778 | | | |
| UB_FU2 | 3.61 | 1.22 | 0.747 | | | |
| UB_FU3 | 3.61 | 1.25 | 0.765 | | | |
| UB_R1 | 3.58 | 1.24 | 0.738 | | | |

The necessary condition to meet discriminant validity is that there shall be difference between latent variables. This confirms that the reliability as well as validity aspects requirements were satisfied. Table 3 clearly shows that all latent variables are in the requirement standard.

**Table 3: Validity Evaluation.**

| | AVE | UB | BI | CQ | PI | FC | SE | SI | EE | PE |
|---|---|---|---|---|---|---|---|---|---|---|
| UB | 0.577 | **0.760** | | | | | | | | |
| BI | 0.617 | 0.539 | **0.785** | | | | | | | |
| CQ | 0.596 | 0.288 | 0.519 | **0.772** | | | | | | |
| PI | 0.512 | 0.344 | 0.450 | 0.223 | **0.716** | | | | | |
| FC | 0.565 | 0.309 | 0.395 | 0.228 | 0.198 | **0.752** | | | | |
| SE | 0.639 | 0.402 | 0.651 | 0.170 | 0.240 | 0.303 | **0.799** | | | |
| SI | 0.555 | 0.360 | 0.646 | 0.203 | 0.288 | 0.317 | 0.466 | **0.745** | | |
| EE | 0.646 | 0.378 | 0.669 | 0.288 | 0.249 | 0.347 | 0.481 | 0.379 | **0.804** | |
| PE | 0.565 | 0.172 | 0.385 | 0.232 | 0.243 | 0.051 | 0.209 | 0.194 | 0.227 | **0.752** |

*4.2. Hypothesis Analysis*

After the adjustment and improvement of reliability and validity, the model is improved and fully satisfied with the testing standards. Thus, structural equation model analysis can be implemented. The goodness-of-fit indexes are $c^2$/df = 1.345, CFI=0.977, GFI=0.907, TLI=0.975, RMSEA = 0.024, SRMR=0.066 indicating that hypothesized model had satisfactory goodness of fit.

**Table 4: SEM Results.**

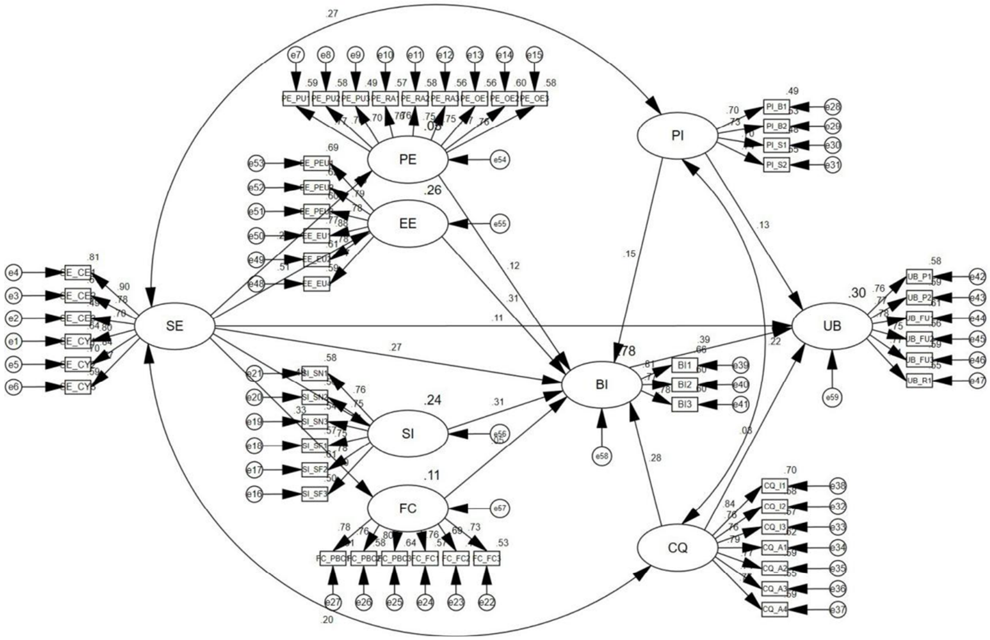
| Paths | Estimates | Standard Error | p-value | Supported? |
|---|---|---|---|---|
| H1: PE → BI | 0.125 | 0.032 | *** | Yes |
| H2: EE → BI | 0.31 | 0.036 | *** | Yes |
| H3: SI → BI | 0.31 | 0.045 | *** | Yes |
| H4: FC → BI | 0.052 | 0.037 | 0.101 | No |
| H5: SE → BI | 0.268 | 0.033 | *** | Yes |
| H6: SE → UB | 0.106 | 0.049 | 0.075 | No |
| H7: SE → PE | 0.224 | 0.035 | *** | Yes |
| H8: SE → EE | 0.5 | 0.035 | *** | Yes |
| H9: SE → SI | 0.484 | 0.032 | *** | Yes |
| H10: SE → FC | 0.325 | 0.032 | *** | Yes |
| H11: PI → BI | 0.151 | 0.035 | *** | Yes |
| H12: PI → UB | 0.129 | 0.048 | 0.007 | Yes |
| H13: CQ → BI | 0.286 | 0.036 | *** | Yes |
| H14: CQ → UB | 0.029 | 0.052 | 0.549 | No |
| H15: BI → UB | 0.387 | 0.071 | *** | Yes |

Table 4 and Figure 6 shows the standardized path coefficients. Among the predictors of mobile learning behavioral intention, 6 out of 7 could predict behavior intention. In other words, H1, H2, H3, H5, H11, and H13 are consistent with the hypotheses. PE (β = 0.125), effort expectancy (β = 0.31), social influence (β = 0.31), SE (β = 0.268), PI (β = 0.151), CQ (β = 0. 286) all significantly affected the behavior intention of mobile learning. The positive correlation indicated that a one-unit increase in EE or SI caused a 0.31-unit increase in behavior intention. Specifically, the three additional factors, SE, PI, and CQ, were all found to have effects on mobile learning behavior intention. Nevertheless, the results ($p$ = 0.101) indicated that FC had no significant impact. Therefore, H4 was not supported. Among the predictors of mobile learning usage behavior, only BI and PI exhibited significant effects, with β=0.397 and β=0.129, respectively. These findings supported H12 and H15. Among the three additional variables, only PI had a significant effect on usage behavior. The results indicated that SE and CQ had no significant effect on actual use. Consequently, H6 and H14 were not supported.

### *4.3. Mediation Effect*

Based on previous results, it can be reasonably assumed that SE has a direct effect on BI. The indirect impact of SE on BI through PE, EE, social influence, and FC are evaluated in this sub-section. It was found that SE exerted a significant effect on PE, effort expectancy, SI, and FC, with path coefficients of 0.224, 0.5, 0.484, and 0.325, respectively. Consequently, hypotheses H7, H8, H9, and H10 were validated. Given that FC exerts no significant influence on BI, three of the four mediation effects are significant. However, the SE → FC → BI pathway is rejected. In other words, SE exerted a significant indirect influence on the intention, which was mediated by PE, EE, and SI. The indirect effects are 0.028, 0.155 and 0.150 respectively. Adding to the direct effects, the total effects are 0.296, 0.423 and 0.418 respectively.

**Figure 4: Structural Model Results.**




## 5. Discussion

The objectives of this study was considered and used to develop the study objectives. The study adopted three additional variables to the UTAUT framework—self-efficacy, personal innovativeness, and content quality are incorporated to explore the factors affecting mobile learning usage from both personal and quality perspectives.



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### *5.1. Self-efficacy, Personal Innovativeness, and Content Quality*

#### *5.1.1. Effect of Self-efficacy*

SE was referenced in the study proposed UTAUT model, yet was not selected as a predictor in this paper (Venkatesh et al., 2003). The present study sought to ascertain the impact of self-efficacy on both BI and UB of mobile learning. The results indicated that SE only influenced BI, which was in line with researches conducted by Kumar et al. (2020), Han and Shin (2016), Mohammadi (2015), and Almaiah et al. (2019) regarding mobile learning. Additionally, the results supported the conclusions of Tarhini et al., (2017), and Yeap et al., (2016), in information technology (IT). The findings indicate that when students possess adequate computer skills, they would like to use technology. Consequently, it can be inferred that colleges should consistently cultivate students' abilities by conducting training courses on the effective utilization of M-learning systems.

This paper also found that self-efficacy predicted PE and EE, which is similar to previous research conducted by Li et al. (2022) and Shaya et al. (2023). This finding also aligns with Islam (2016), and Althunibat (2015) where researchers used terms such as PEOU and PU. One explanation for this phenomenon can be found in Bandura & Schunk, (1981) work, which posits that self-efficacy is an important factor in individuals' acceptance, implementation, and adherence to specific behaviors. When an individual possesses a robust sense of self-efficacy regarding mobile learning, it may be easier for him to think of this technology as useful and straightforward to utilize (Chao, 2019). Chao (2019) discovered that students who have high self-efficacy tend to find enjoyment from using mobile learning. In addition, this study found that SE influences on SI and FC, which corresponds with the conclusions of Li et al. (2022), Yeap et al., (2016), and Kumar et al. (2020). These findings suggest that students with a strong sense of self-efficacy are eager to adopt suggestions from important people and are better at discovering mobile learning resources. Consequently, we demonstrated that self-efficacy exerts an indirect influence on behavioral intention via PE, EE, and SI. Consequently, higher vocational colleges should prioritize the factors that enhance students' self-efficacy.

#### *5.1.2. Effect of Personal Innovativeness*

As for the second personal factor, our result showed that PI had an important effect on intention, which corresponds to previous work by Lisana (2023) and Kim et al. (2017). Personal innovativeness was also shown to be an important predictor of actual use of mobile learning, as was found by Farooq et al. (2017), Pinho et al. (2021) and Larsen and Sorebo (2005) in the context of information systems adoption. The results of this study therefore provide support for the importance of PI in UB in the context of mobile learning. This facilitates mobile learning developers' designing innovative functions with the intention of appealing new students who have higher innovativeness.

#### *5.1.3. Effect of Content Quality*

The content quality was discovered to influence the intention to use mobile learning. This implies that providing students with accurate, relevant, timely, and engaging content is crucial. Previous researches have also examined the impact of CQ on intention (Almaiah & Alismaiel, 2019; Lutfi et al., 2022; Mohammadi, 2015). Some of these studies use the term as "information quality". Additionally, the results suggest that designers of mobile learning application content should consider students' needs. Beyond basic information requirements, such as accuracy and timeliness, designers should focus on content formats like graphics, charts, videos, and animations to make learning more vivid and attractive through mobile learning applications. The provision of supplementary learning content to cater to the diverse needs of learners, ensuring that they derive enjoyment from the learning process. Conversely, if the available learning resources are inadequate and the practicality is poor, the experience will be perceived as meaningless by the learners, leading to a lack of acceptance or even rejection of mobile learning. Consequently, colleges and mobile learning developers should integrate existing learning resources and create targeted content based on students' preferences and characteristics. This approach is essential for the sustainable development of mobile learning.

### *5.2. The Extended UTAUT Model*

#### *5.2.1. Factors Influencing BI*

It was observed that PE, effort expectancy, SI, SE, PI and CQ are factors affecting BI, among which EE and SI are the most significant predictors (β=0.31) , which is in line with the conclusions of Al-Adwan et al. (2018) and Sidik and Syafar (2020). This suggested that the more students think of mobile learning as an easy tool to learn, the more they would engage in mobile learning (Al-Adwan et al., 2018). Also, students' intention was affected by the classmates, teachers and college supports. This indicates that the aspect of social environment is an important consideration in the process of decision making.

The factors affecting BI followed are CQ (β=0.286) and SE (β=0.268), which are two additional variables. This suggests that colleges should improve the students' self-confidence for mobile learning and focus on the content of learning resources of mobile learning platforms. For the UTAUT model, many researchers have identified four constructs that significantly impact mobile learning behavioral intention (Al-Adwan et al., 2018; Sidik & Syafar, 2020; Venkatesh et al., 2012). However, in this study, facilitating conditions did not significantly affect mobile learning BI, consistent with Alowayr (2022). This indicates that students are not concerned with the infrastructure and technical support of mobile learning technology.

#### *5.2.2. Factors Influencing UB*

The study posited that SE, PI, CQ, and BI exert a direct influence on UB. As anticipated, BI had an effect on UB, similar to numerous researches (Almaiah et al., 2019; Farooq et al., 2017; Lutfi et al., 2022). Among the three additional variables, only PI was verified as the predictor of actual use. The present results provide guidance for higher vocational colleges and decision-makers in China regarding the mobile learning implementation.

### *5.3. Model Verification Effect*

This research also finds out that all the posited influence relationships of UTAUT framework are also valid. In other words, the constructs of PE, EE and SI have a positive influence on BI and BI influences the use behavior. When developing the UTAUT framework, the authors did not postulate the influence of FC on behavioral intention. Based on the research, the following parameters influence the behavior intention of m-learning: the more so the EE and SI, the CQ and SE and at a lesser extent the PI and PE. This research proved the applicability of the research conceptual framework known as the UTAUT. However, the comparative analysis using UTAUT framework has been used by many researchers, but the outcomes may differ with the educational and cultural settings.

This study found that PE was the least important among several factors (β=0.125), while in UTAUT or its extended models, some other studies showed that PE was the most significant (Almaiah et al., 2019; Alowayr, 2022). The results of this study diverge from other previous studies, and one potential explanation is that the subject of this study is students in higher vocational colleges, whereas previous studies have focused on university students. Higher vocational college students exhibit a weaker motivation to learn and a more pessimistic outlook regarding the potential impact of their educational experiences.

## 6. Conclusion

This study used an UTAUT framework to investigate the factors influencing behavioral intention (BI) and use behavior (UB) of mobile learning in Chinese higher vocational colleges. In addition to the original UTAUT variables, self-efficacy (SE), personal innovativeness (PI), and content quality (CQ) were incorporated, all of which significantly predict mobile learning adoption. SE impacts BI directly and indirectly through PE, EE), SI, and FC. PI is a key determinant of both BI and UB, while CQ significantly influences BI. Among the predictors of BI, EE and SI are the most influential, followed by CQ and SE, with BI and PI being the strongest determinants of UB. These findings validate the extended UTAUT framework applicability in explaining mobile learning adoption and highlight the combined effects of PE, EE, and SI in shaping BI within Chinese higher vocational colleges. Nevertheless, FC is not statistically significant.

The findings of this study benefit both students and educational institutions. When selecting mobile learning programs and platforms, colleges and teachers should prioritize the predictors identified in this study. They should choose platforms that offer the greatest ease of use, highest content quality, and desired performance. Encouraging mobile learning among students is highly recommended. When students feel confident and satisfied with the mobile learning platforms, they will utilize them more frequently and achieve superior learning outcomes.

The findings of this study indicate the necessity for numerous recommendations. Primarily, educators should provide students with a plethora of diverse resources and personalized guidance through mobile learning platforms, allowing students to pursue individualized learning based on their specific needs. Additionally, educators should leverage the capabilities of big data to oversee students' learning behaviors and promptly adjust teaching strategies through system feedback. Secondly, higher vocational education institutions should proactively develop talent training models that align with the specific job requirements and work environments of students across different majors. They should also continuously integrate and leverage mobile learning platforms to provide students with a diverse range of teaching resources. Third, teachers should be encouraged to share their experiences with mobile learning and participate in teaching observation, exchange, and other activities. This will facilitate the creation of a repository of knowledge that can inform the practices of other teachers in higher vocational colleges. By doing so, the potential of mobile learning can be more effectively harnessed with its effectiveness enhanced in these institutions. This research has some limitations. First, it focuses only on seven Chinese higher vocational colleges. Different results may be obtained by selecting other colleges in China or other countries. Future studies could also examine K-12 schools or universities. Second, this research did not include any control constructs. Future study can explore more about the model by incorporating control variables.

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