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Factors influencing Chinese university EFL Students' Adoption of Mobile Technology-Integrated Vocabulary Learning Towards SCL: An Empirical Research

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Abstract: The purpose of this study is to investigate the factors influencing Chinese university EFL students' adoption of mobile technology-integrated vocabulary learning towards student-centered learning (SCL). The theoretical framework extends the Unified Theory of Acceptance and Use of Technology (UTAUT2) model to include the additional constructs of privacy, trust, personal innovativeness, and information quality to examine their impact on behavioral intentions ues behavior. This study uses a questionnaire survey method to conduct quantitative research. The sample was 300 EFL students from two universities in Fujian Province, China. Data were analyzed using SPSS (22.0) and AMOS (24.0) software. Structural equation modeling and regression path analysis were used to verify relationships between variables and test hypotheses. The results show that performance expectancy, effort expectancy, social influence, convenience conditions, hedonic motivation, habits, personal innovativeness and information quality have significant positive effects on EFL students' behavioral intention to adopt mobile technology-integrated vocabulary learning towards student-centered learning. Price value and privacy concerns have had significant negative impacts. Hedonic motivation, price value, privacy concerns, and information quality have become important predictors of behavioral intentions among Chinese university EFL students. This study enriches research on the acceptance and use of mobile learning technologies, providing valuable insights and effective suggestions for EFL teachers, vocabulary course designers and mobile technology developers.

Keywords: EFL students, mobile technology, vocabulary learning, SCL.

1. Introduction

For most college students in China, English as a foreign language (EFL) learning occupies almost their entire college career. Learning EFL well has become the urgent desire of college students. The basis for EFL learning is to master the vocabulary. It is one of the most important factors in the development of the four language abilities (listening, oral expression, reading and written expression skills). In EFL learning content, the importance of vocabulary learning has been widely acknowledged and well documented (Ardasheva et al., 2019). Therefore, studying vocabulary is seen as an essential skill for EFL students since having a restricted vocabulary prevents effective communication (Alqahtani, 2015). However, there are some problems in EFL education in China at the present stage. The exam-oriented teaching mode hinders students' interest in learning. In traditional teacher-centered teaching mode, vocabulary acquisition can be rote and lacks emphasis on practical, communicative language skills. Under this teaching mode, students cannot maintain their enthusiasm and motivation to learn EFL vocabulary.

The integration of mobile technology in educational settings has transformed the dynamics of teaching and learning. Using mobile technologies to learn EFL vocabulary offers numerous advantages related to student-centeredness. Learners can access vocabulary materials anytime, anywhere, providing flexibility in their learning schedule. Students can make use of fragmented time in mobile learning to carry out vocabulary acquisition. Many mobile apps use adaptive learning algorithms to tailor content to individual learner needs, learners can progress at their own pace and receive targeted practice based on their performance. Mobile technology empowers learners to take control of their learning journey, fostering a sense of autonomy and self-directed learning. Mobile devices support the integration of multimedia elements, such as audio and video, which can enhance vocabulary learning by providing real-life context and pronunciation examples. Visual aids, like images and videos, can help reinforce the meaning of words and promote a deeper understanding. Mobile apps often incorporate interactive and engaging activities, such as quizzes, games, and multimedia content, making the learning process more enjoyable.

Integrating mobile technology into vocabulary learning has emerged as a potential solution to enhance engagement, motivation, and overall learning outcomes. However, the key to the success of mobile learning lies in whether users accept mobile learning. The factors influencing learner' adoption of mobile technology-integrated vocabulary learning in the context of student-centered learning remain a subject of interest. Therefore, This study aims to explore the factors that influence Chinese university EFL students' behavioral intention to adopt mobile technology for vocabulary learning towards student-centered learning.

2. Literature Review

2.1. The Background of Student-Centeredness

The 1970s saw the rise of communicative language teaching, which advocated changing English language instruction away from a teacher-fronted model and toward a learner-centered one (An and Mindrila, 2020). This coincided with the rise of student-centered learning. The use of CLT resulted in the establishment of diversified courses that represented the various communication requirements of students. This needs-based approach also served to bolster another educational movement that was gaining traction at the same time, which was known as learner-centered education (Oyelana et al., 2022).

2.2. Effectiveness of Technology- Integrated Vocabulary Learning

Both teaching and acquiring vocabulary in a second language may provide significant challenges for instructors of English as a foreign language and their students. Teachers may have difficulty creating and sustaining student motivation to acquire L2 vocabulary because students may feel irritated with the large quantities of L2 words that need to be learnt and recalled to allow their successful understanding and communication in a new language. Therefore, the acquisition of new vocabulary and the long-term retention of that vocabulary should always be considered significant objectives for language learners and the educators who work with them. In addition, the researcher demonstrates the benefits of learning L2 vocabulary using a variety of technologies and suggests that the use of technology may improve learners' ability to remember newly learned terms over the long term. Because mobile devices and mobile learning were shown to have more noticeable benefits, this finding suggests that L2 vocabulary acquisition may be at its most effective when students are allowed to utilize mobile phones and are not constrained by classroom settings. The findings also highlight many critical aspects as modifiers of the efficiency of mobile technology-integrated vocabulary acquisition. These variables include the kind of device used, the game condition, the environment, the test format, and the stated dependability. As a result, it is recommended that these factors be considered throughout the process of lesson preparation for mobile technology-integrated second language vocabulary acquisition.

2.3. Theoretical Framework

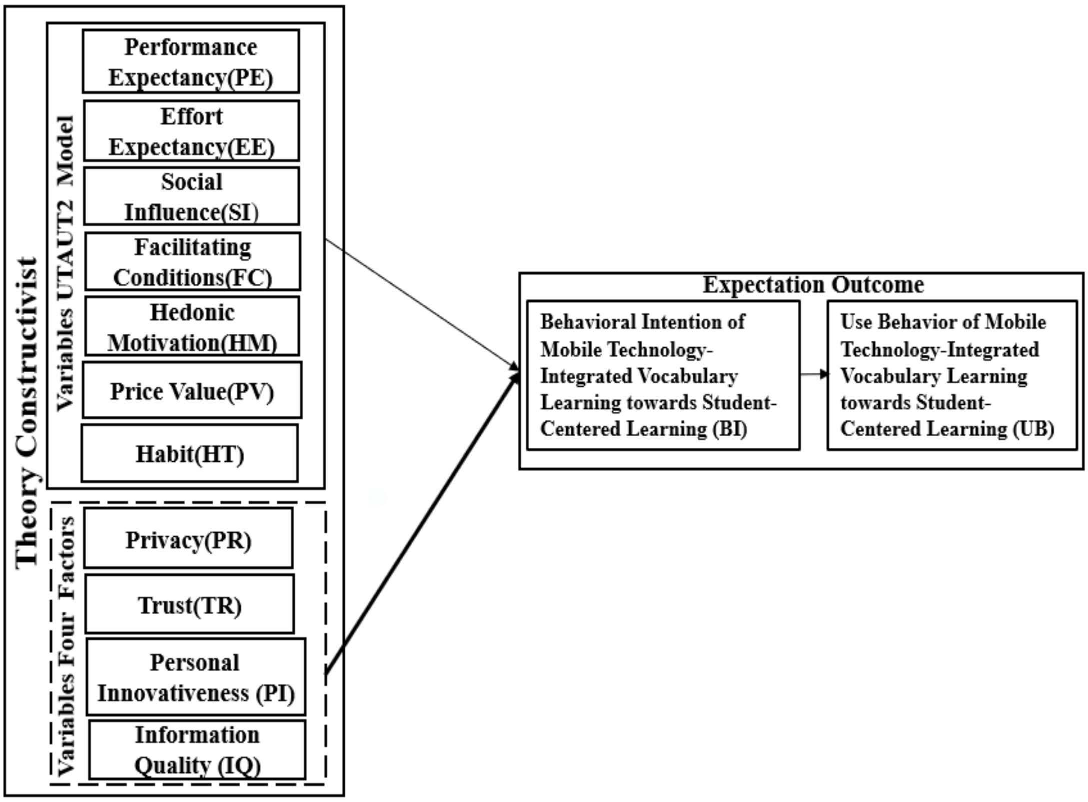

Figure 1. Theoretical Framework

3. Research Hypotheses

In order to investigate how exogenous and endogenous variables interact in the conceptual model, the researcher proposed twelve hypotheses that assisted her to address the research objectives.

H1 There is a positive relationship between performance expectancy and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H2 There is a positive relationship between effort expectancy and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H3 There is a positive relationship between social influence and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H4 There is a positive relationship between facilitating conditions and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H5 There is a positive relationship between hedonic motivation and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H6 There is a positive relationship between habit and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H7 There is a negative relationship between price value and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H8 There is a negative relationship between privacy and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H9 There is a positive relationship between trust and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H10 There is a positive relationship between personal innovativeness and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H11 There is a positive relationship between information quality and behavioral intention for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

H12 There is a positive relationship between behavior intention and use behavior for EFL university learners to adopt the mobile technology-integrated vocabulary learning towards student-centered learning.

4. Method

In this study, the researcher employed quantitative research methods to explore the factors influence EFL university students' adoption of mobile-integrated vocabulary learning toward student-centered learning. Questionnaire survey method was used in the study.

4.1. Sample and Sampling Method

The target population for this study is Chinese EFL university learners adopting mobile technology-integrated vocabulary learning by using student-centered learning framework. The sample is selected from a population of 2642 EFL students from the 2 Chinese universities by random sampling method. According to ROSCOE'S SIMPLE RULES OF THUMB (Roscoe, 1975), it is advised to employ a sample that is 10% the size of the parent population between these bounds (30 to 500). Therefore, 300 samples were selected. The sample framework included EFL mobile technology-integrated vocabulary learners in two universities of Fujian province.

4.2. Instrument Development

A questionnaire on Mobile Technology-Integrated Vocabulary Learning towards Student-Centered Learning was designed with reference to UTAUT2 questionnaire (Venkatesh et al., 2012). Dimensions on privacy, trust, personal innovation, and information quality were added to the questionnaire to examine their effects along with original UTAUT2 determinants, which was evaluated by two Chinese experts in the field of pedagogy. The survey consisted of two components. The first section covers demographic data on participants' age, gender, educational background, prior learning experiences, and the usage of mobile technologies. The second part was meant to elicit participant input on their experiences using mobile technologies to learn English at Chinese universities, with the goal of identifying the factors influencing their intention to adopt mobile technology-integrated vocabulary learning. The samples give their opinion on a five-point Likert scale.

4.3. Statistical Analysis

Structural Equation Modelling (SEM)and regression path analysis were used through AMOS (version 24) to examine the complex relationship among variables and test the hypotheses.

Before proceeding with the data analysis, data screening and cleaning of the raw data were performed to guarantee the reliability and correctness of the outcomes. The data was then analyzed using the Statistical Package for the Social Sciences (SPSS). The demographic profile and user characteristics of the respondents highlight key information about the sample size and distribution across different variables. Descriptive analysis helps researchers identify patterns, trends, and variations within the data. The assessment of normality confirmed that the dataset reasonably approximated a normal distribution, supporting the assumption for subsequent statistical analyses. Three types of validity, construct validity, convergent validity and discriminant validity analysis were conducted to ensure the accuracy and appropriateness of the measurement scales. The significance and level of correlation among the variables were examined using the Pearson correlation coefficient.

The SEM analysis was the core of this study, addressing the 12 formulated hypotheses. It allowed for the examination of multiple relationships simultaneously and gave a comprehensive understanding of the elements influencing behavioral intention to use mobile devices for EFL learning. Regression path analysis allows researchers to validate the relationships between constructs and test the research hypotheses using the data collected. This analysis helps in determining whether the proposed research hypotheses are supported or not based on the observed data.

5. Findings

5.1. Demographic Profile of Respondents

The demographic data and user characteristics of the respondents are shown in table 1. which highlights the key information about the sample size and distribution across different variables.

Table 1. Demographic profile of respondents

		Frequency	Percent
gender	male	134	46.9
	female	152	53.1
age	18-20 years old	107	37.4
	21-22 years old	115	40.2
	23 years and over	64	22.4
Education background	freshman	95	33.2
	sophomore	73	25.5
	Junior	76	26.6
	Senior	42	14.7
Past mobile technology learning experiences	Learning from online resources	87	30.4
	MOOC study	74	25.9
	Blended learning of different technologies	125	43.7
Use Baici to cut client time	1-3 months	86	30.1
	4-6 months	122	42.7
	7 months and above	78	27.3
The average weekly time of using Baicizhan APP	1-3 hours	71	24.8
	4-6 hours	123	43
	7 hours and above	92	32.2
The first time to use the Baicizhan APP	4-6 months ago	208	72.7
	7 months ago and above	78	27.3
Frequency of using Baicizhan APP in the past 6 months	1-4 times	85	29.7
	5-8 times	138	48.3
	9 times and above	63	22

5.2. Reliability Analysis

The reliability of each scale in the questionnaire was evaluated using Cronbach's coefficient, as is shown on table 2. The scales of PE, EE, SI, FC, TR, PI, IQ, and UB exhibited high internal reliability, as their Cronbach's coefficients are larger than 0.9. Besides, the scales HM, HT, PV, PR, and BI demonstrated high reliability, falling within the range of 0.8 to 0.9. All of the dimension's coefficients are above the 0.7 level cutoff value, which demonstrating satisfactory consistency in measuring their constructs (Oliveira & Roth, 2012).

Table 2. The Cronbach’s coefficients of variables

scale	Cronbach's Alpha	N of Items
PE	0.934	4
EE	0.940	4
Si	0.924	4
FC	0.954	6
H M	0.886	3
HT	0.893	3
PV	0.891	3
PR	0.895	3
TR	0.952	5
P.I.	0.932	4
IQ	0.910	3
BI	0.894	4
UB	0.961	6

5.3. Validity Analysis

The KMO value is reported as 0.918, exceeds 0.9, which indicates a high sampling adequacy (Field et al, 2013). With a test statistic of 14298.078 and a p-value of 0.0000.05, the Bartlett's test of sphericity shows that the null hypothesis that there are no intercorrelations among the variables may be rejected. The total variance analysis revealed that 13 main factors could be extracted from the scale. The eigenvalues associated with these factors are greater than 1, suggesting that each factor explains a substantial amount of variance in the data (Kaiser, 1958). Furthermore, the cumulative variance contribution rate is reported as 83.720%, which suggests that the factor analysis results are reliable and give a thorough understanding of the scale's underlying structure. The rotation component matrix reveals the loadings of each item on the extracted factors. Every item's loading on its respective factor is more than 0.5, indicating a strong association between the items and their underlying factors (Comrey et al,1992). Additionally, there is no significant cross-loading of items, meaning that each item primarily contributes to its corresponding factor and is not strongly associated with other factors.

A confirmatory factor analysis (CFA) was used to evaluate how well the measurement scale fit the model. The analysis of the model fitness indicators in table shows that the suggested measurement model matches the obtained data well.

The results of the convergent validity analysis of the scale are presented in table 3. The measurement scale demonstrates satisfactory convergent validity. The standardized factor loadings exceed 0.7, providing evidence for convergent validity (Barclay et al, 1995). The CR values are above 0.6, indicating good internal consistency and reliability of the factors (Hair et al., 2009). Moreover, the AVE values are greater than 0.5, demonstrating that each component accounts for a substantial portion of the variance in the observed variables. (Shrestha, 2021).

Table 3. Results of the convergent validity analysis of the scale

dimension	item	Normalized factor loadings	CR	AVE
PE	PE1	0.848	0.935	0.782
	PE2	0.912		
	PE3	0.890		
	PE4	0.885		
EE	EE1	0.861	0.941	0.799
	EE2	0.897		
	EE3	0.872		
	EE4	0.943		
Si	SI1	0.846	0.926	0.757
	SI2	0.828		
	SI3	0.873		
	SI4	0.930		
FC	FC1	0.826	0.955	0.779
	FC2	0.847		
	FC3	0.889		
	FC4	0.922		
	FC5	0.908		
	FC6	0.899		
H M	HM1	0.876	0.890	0.730
	HM2	0.850		
	HM3	0.836		
HT	HT1	0.893	0.895	0.741
	HT2	0.805		
	HT3	0.881		
PV	PV1	0.860	0.893	0.735
	PV2	0.783		
	PV3	0.924		
PR	PR1	0.882	0.895	0.741
	PR2	0.811		
	PR3	0.887		
TR	TR1	0.868	0.952	0.800
	TR2	0.878		
	TR3	0.885		
	TR4	0.914		
	TR5	0.925		
PI.	PI1	0.780	0.935	0.782
	PI2	0.897		
	PI3	0.909		
	PI4	0.943		
IQ	IQ1	0.838	0.913	0.777
	IQ2	0.894		
	IQ3	0.911		
BI	BI1	0.790	0.898	0.687
	BI2	0.838		
	BI3	0.815		
	BI4	0.870		
UB	UB1	0.857	0.961	0.804
	UB2	0.881		
	UB3	0.891		
	UB4	0.925		
	UB5	0.919		
	UB6	0.904		

The findings of the scale's discriminant validity analysis are shown in table 4. Fornell and Larcker (1981) claimed that strong discriminant validity was demonstrated by the square root of AVE on the appropriate diagonal being bigger than the correlation coefficients between the latent variables. It suggests that the variables in this study are distinct and can be accurately measured by the scale.

Table 4. Results of the discriminant validity analysis of the scale

	PE	EE	Si	FC	H M	HT	PV	PR	TR	P.I.	IQ	BI	UB
PE	0.884												
EE	0.350	0.894											
Si	0.362	0.391	0.870										
FC	0.341	0.407	0.338	0.883									
H M	0.412	0.421	0.391	0.302	0.854								
HT	0.361	0.343	0.378	0.332	0.424	0.861							
PV	-0.184	-0.303	-0.187	-0.232	-0.117	-0.107	0.857						
PR	-0.022	-0.118	-0.127	-0.088	-0.129	-0.128	0.361	0.861					
TR	0.424	0.473	0.436	0.378	0.479	0.438	-0.134	-0.081	0.894				
P.I.	0.326	0.308	0.327	0.282	0.357	0.439	-0.149	-0.130	0.302	0.884			
IQ	0.363	0.469	0.412	0.354	0.428	0.450	-0.173	-0.119	0.388	0.494	0.881		
BI	0.495	0.560	0.520	0.480	0.556	0.538	-0.381	-0.320	0.512	0.536	0.610	0.829	
UB	0.322	0.270	0.368	0.256	0.337	0.405	-0.058	-0.069	0.368	0.492	0.511	0.509	0.897

5.4. Correlation Analysis

Correlation analysis of research variables show that the variables PE, EE, SI, FC, HM, HT, TR, PI, IQ, and BI are all significantly positively correlated, with correlation coefficients of 0.458, 0.531, 0.493, 0.457, 0.503, 0.509, 0.487, 0.510, and 0.563, respectively. This indicates a positive relationship between these variables. On the other hand, the variables PV, PR, and BI are significantly negatively correlated, with correlation coefficients of -0.325 and -0.273, respectively. Furthermore, the variables BI and UB are significantly positively correlated, with a correlation coefficient of 0.479. Besides, all the correlation coefficients among the variables are less than 0.7, indicating that there is no multicollinearity among the variables in this study (Dormann et al., 2013).

5.5. Structural Equation Modeling

Structured equation modeling (SEM) is a to data analysis method that can be used to evaluate premised hypotheses about the causal connections between measurable or latent variables (Ralph O. Mueller et al., 2018). In this study, the researcher employed the structural equation model constructed using AMOS 24.0 software, which is shown in figure 2. The model includes thirteen constructs. PE, EE, SI, FC, HM, HT, PV, PR, TR, PI, IQ are exogenous variables, whereas BI and UB are endogenous variables. The author aims to explore how the exogenous variables impact the endogenous variables and understand the overall mechanism governing behavioral intention (BI) and use behavior (UB).

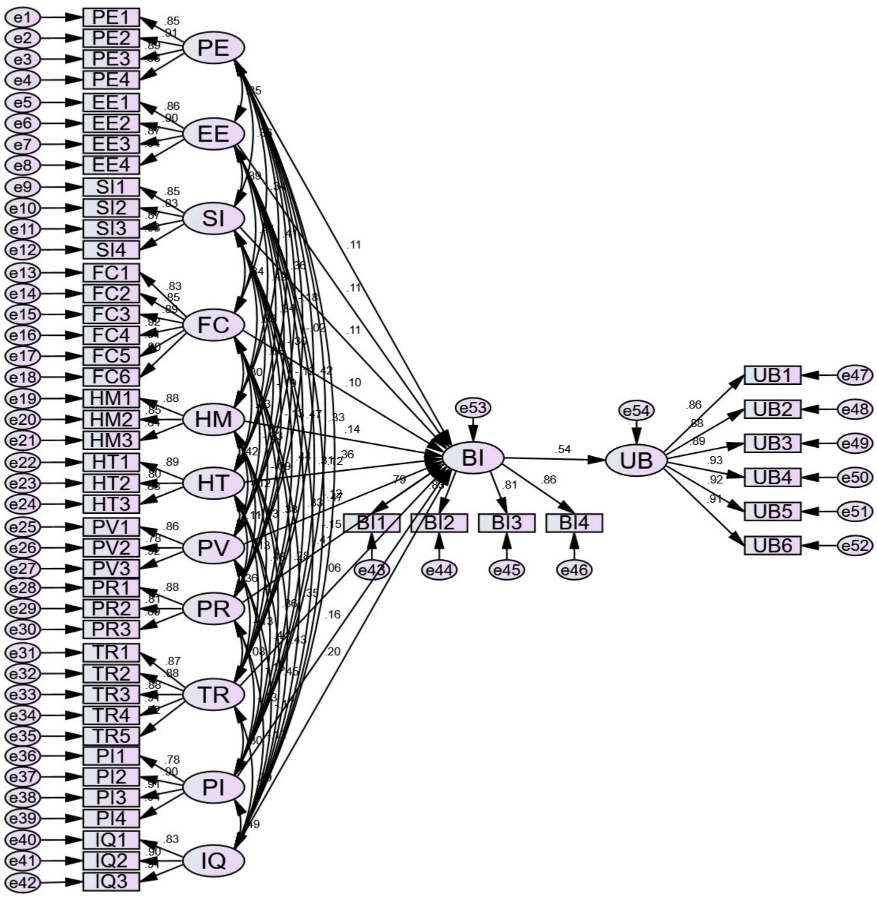

Figure 2. Structural Equation Modeling

Table 5. Fit Index results for the model

index	absolute fit index		Value-Added Fit Metrics			parsimony fit index	
Specific classification	X 2 / df	RMSEA	IFI	TLI	CFI	PGFI	PNFI
Judgment criteria	<5	<0.08	>0.9	>0.9	>0.9	>0.5	>0.5
Fitting effect	1.577	0.045	0.951	0.945	0.950	0.701	0.797

Table 5 provides a detailed explanation of the model fitness. The absolute fitting indices, RMSEA value of 0.045, as shown in table 5, is less than the threshold of 0.08, which suggests that the model and the data fit each other more closely. (Sokolov., 2019). The X^2/df ratio, another measure of absolute fit, is reported as 1.577, less than 5, suggesting that the model and the data fit each other well (Joreskog and Sorbom,1993). The value-added fitting indicators, including the incremental fit index (IFI), Tucker-Lewis index (TLI), and comparative fit index (CFI), are reported as 0.951, 0.945, and 0.950, all exceed the threshold of 0.9, indicating a good fit and suggesting that the proposed model provides a better fit compared to the null model (Garson, 2006). The parsimony goodness-of-fit index (PGFI) and parsimony normed fit index (PNFI), respectively are stated as being 0.701 and 0.797 for parsimonious fitting indices, both exceed the threshold of 0.5, indicating a good fit and suggesting that the model achieves an appropriate balance between model complexity and fit (Mulaik,1998). The fit indices' findings demonstrate the proposed model fits the observed data well.

5.6. Regression Path Analysis

Table 6. Regression weights for each path analysis

suppose	path			B	SE	CR	P	beta	Whether established
H1	BI	<---	PE	0.093	0.041	2.271	0.023	0.111	set up
H2	BI	<---	EE	0.105	0.049	2.146	0.032	0.113	set up
H3	BI	<---	Si	0.098	0.044	2.222	0.026	0.109	set up
H4	BI	<---	FC	0.094	0.044	2.142	0.032	0.100	set up
H5	BI	<---	H M	0.115	0.045	2.574	0.010	0.138	set up
H6	BI	<---	HT	0.095	0.042	2.255	0.024	0.119	set up
H7	BI	<---	PV	-0.108	0.041	-2.641	0.008	-0.125	set up
H8	BI	<---	PR	-0.118	0.037	-3.226	0.001	-0.146	set up
H9	BI	<---	TR	0.055	0.046	1.206	0.228	0.063	invalid
H10	BI	<---	P.I.	0.160	0.049	3.287	0.001	0.164	set up
H11	BI	<---	IQ	0.174	0.049	3.528	***	0.196	set up
H12	UB	<---	BI	0.583	0.068	8.578	***	0.536	set up

In this study, an extended analysis is conducted to examine the regression weights and their significance. Table 6 presents the regression weights for each path analysis proposed in the research hypothesis. A significant coefficient suggests that the predictor and outcome variables are related, while the magnitude of the coefficient reflects the strength of the relationship. The coefficient's sign (+ or -) indicates whether the relationship is positive or negative. By examining the significance of these weights, researchers can determine whether the relationships observed are statistically meaningful.

Hypothesis H1-H6, H10-H11 suggests a positive connection between Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Personal Innovativeness (PI), Information Quality (IQ) with Behavioral Intention (BI). The regression weights corresponding to these paths in table 6 show significant positive coefficients, indicating that all these predictor variables have a significant impact on behavioral intention. Hypothesis H7, H8 suggests a negative relationship between Price Value (PV), Privacy (PR) with Behavioral Intention (BI). The regression weights corresponding to these paths in table 6 show significant negative coefficients, indicating that these two predictor variables have a significant impact on behavioral intention. Besides, hypothesis H12 suggests a positive relationship between Behavioral Intention (BI) and Use Behavior (UB). The regression weight for this path in table 6 also shows a significant positive coefficient, confirming that behavioral intention strongly influences the use behavior of the participants.

On the other hand, hypothesis H9 suggests trust (TR) and behavioral intention (BI) do not significantly relate to one another. So, hypothesis 9 is not established. The regression weight corresponding to this path in table 6 shows a positive coefficient but lack of significance, suggesting that trust does not have a substantial impact on behavioral intention of the participants.

6. Conclusion

This study proposed an extended UTAUT2 model incorporating additional constructs of privacy, trust, personal innovativeness and information quality to investigate the factors influencing Chinese EFL students' adoption of mobile technology-integrated vocabulary learning towards student-centered learning. The conceptual model hypothesized relationships between the exogenous variables of performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, price value, privacy concerns, trust, personal innovativeness and information quality with the endogenous variables of behavioral intention and use behavior. The researcher tested and examined the relationships between variables and validated the hypotheses using structural equation modeling (SEM) and regression path analysis with AMOS (version 24).

The analysis supports the proposed hypotheses, highlighting the significance of performance expectations, effort expectations, facilitating conditions, social influence, hedonic motivation, habit, price value, personal innovativeness, information quality and privacy concerns in shaping EFL students' behavioral intentions. Among these factors, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, habit, personal innovativeness and information quality as key drivers, while privacy and price value emerged as notable barriers. The study also shows that behavioral intentions did influence real use behavior. However, the behavior intentions of EFL students did not demonstrate a meaningful connection to trust. While further confirmatory research is needed, the current investigation successfully adapted a powerful technology adoption framework to understand the factors influencing EFL students' adoption of mobile technology-integrated vocabulary learning towards student-centered learning.

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