Zibaldone. Estudios Italianos - Vol. X, Issue 2 (2023): 271-285

ISSN: 2255-3576

THE BEHAVIORAL INTENTION OF CHINESE EFL LEARNERS TO USE MOBILE APPS FOR ENGLISH VOCABULARY LEARNING

Sijia Cheng
[a] Faculty of Social Science and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia
Email: 1002163342@ucsiuniversity.edu.my

Sabariah Md Rashid
[a] Faculty of Social Science and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia
Email: sabariah@ucsiuniversity.edu.my

Zhiying Hou
[b] Graduate Business School, UCSI University, Kuala Lumpur, Malaysia
Email: 1001851030@ucsiuniversity.edu.my

Dan Wei
[a] Faculty of Social Science and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia
Email: 1002161820@ucsiuniversity.edu.my

Chenming Lin
[a] Faculty of Social Science and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia
Email: 1002161135@ucsiuniversity.edu.my

Abstract: In contemporary times, the utilization of mobile apps for English vocabulary acquisition is on the rise, gaining popularity among Chinese EFL learners. This research seeks to explore the factors affecting the intention of Chinese EFL learners to utilize mobile apps for English vocabulary learning. To achieve this objective, a conceptual model was formulated through an extensive review of relevant literature. Subsequently, an online survey was conducted to gather data for this study, which was then analyzed using PLS-SEM methodology. The study's results reveal that the intention to use mobile apps for English vocabulary learning is positively influenced by factors such as performance expectancy, learning attitudes, and user satisfaction. This research not only contributes to the existing body of knowledge on technology-enhanced language learning but also provides valuable insights for app developers and designers. It suggests that the

Recibido: 27 October 2023 / aceptado: 23 November 2023 / publicado: 08 December 2023

development of engaging and user-friendly mobile applications can foster positive attitudes and overall satisfaction among learners, consequently boosting their intentions to persist in using such apps for vocabulary acquisition.

Keywords: behavioral intention; social influence; effort expectancy; performance expectancy; learning attitudes; satisfaction

1. Introduction

In the contemporary landscape of language education, technological advancements have revolutionized traditional learning methodologies, particularly in the domain of vocabulary acquisition. Chinese students have been employing mobile applications to assist in learning English vocabulary. Chinese EFL learners encounter persistent challenges in grasping and retaining English vocabulary due to linguistic differences and varying language structures. To address these challenges, the integration of mobile applications tailored for English vocabulary acquisition has gained substantial traction within educational spheres. Some vocabulary-learning apps, such as Baicizhan, Youdao, and Hujiang Happy Dictionary, have gained popularity in China. These apps are used for vocabulary learning and have been evaluated for their effectiveness (Yang, 2022). The importance of vocabulary in language learning and the persistent challenges it presents to Chinese students and teachers have been acknowledged. Mobile apps offer a solution to these challenges by providing a platform for vocabulary practice (Ying, 2022). Mobile applications have been developed and tested for their effectiveness in vocabulary teaching, with some specifically created for Chinese learners of English (Basal et al., 2016).

This research aims to analyze the behavioral intention of Chinese EFL (English as a Foreign Language) learners to use mobile applications to study English vocabulary. Understanding the factors, such as social influence, that predict and influence EFL learners' usage of Mobile English Learning Resources is vital to enhancing the design and implementation of these resources (Shen et al., 2023). It's essential to grasp how students utilize various mobile learning applications to facilitate their English vocabulary study. This insight can further inform the development and refinement of such educational tools (Li, 2021). On the other hand, by understanding the behavioral intention of Chinese EFL learners to use mobile applications to study English vocabulary, educators and platform developers can enhance learning experiences and outcomes (S. Yu & Lee, 2014).

2. Theoretical Background

2.1 The Unified Theory of Acceptance and Use of Technology (UTAUT) Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a comprehensive theoretical framework designed to elucidate and forecast the adoption and utilization of technology among end users (Ahn et al., 2016). UTAUT amalgamates a spectrum of established theories and models pertaining to technology adoption, including the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Theory of Reasoned Action (TRA) (Ghobakhloo et al., 2012). This integrated model takes into account various factors that play a pivotal role in shaping technology acceptance, encompassing performance expectancy, effort expectancy, and social influence (Holden & Karsh, 2010; Im et al., 2008).

UTAUT has gained widespread recognition and has been extensively employed in diverse contexts to gain insights into technology acceptance and adoption. The present study endeavors to scrutinize the influence of performance expectancy, effort expectancy, and social influence on individuals' behavioral intentions to employ mobile learning applications for English vocabulary acquisition.

3. Hypotheses Development

Social influence, as defined by Tan et al. (2014), encompasses the sway that external factors hold over an individual's thoughts, emotions, and actions. This influence plays a significant role in shaping behavioral intentions within the realm of mobile payment systems, as demonstrated by Gupta and Arora (2020). Tan et al. (2014) delved into the factors impacting the use of English e-learning websites and discovered that social influence had a constructive effect on behavioral intention. This leads us to posit the following hypothesis:

H1: Social influence has a positive impact on behavioral intention.

Park et al. (2012) scrutinized the technology acceptance model and unearthed that social influence profoundly enhances behavioral intent to employ mobile learning among university students. This suggests that when students perceive social support for mobile learning, they are more inclined to develop a favorable attitude and intent to engage in this mode of learning. Hashim et al. (2015) explored adult learners' willingness to embrace mobile learning and determined that attitude positively influenced their intent. This implies that when learners harbor a positive disposition toward mobile learning, they are more likely to be swayed by social factors and intent on adopting it. This leads us to posit the following hypothesis:

H2: Social influence positively affects learning attitudes.

In a study on the impact of perceived value on purchase intent within the realm of social commerce, Gan and Wang (2017) discovered that utilitarian, hedonic, and social values significantly and positively influence satisfaction. This leads to posit the following hypothesis:

H3: Social influence positively affects satisfaction.

Effort expectancy refers to the perceived simplicity and ease associated with using a specific technology, as outlined by Venkatesh et al. (2003). It is a pivotal determinant in user acceptance and adoption of technology, as highlighted by Holden and Karsh (2010). Effort expectancy has been found to wield a considerable influence on intent to adopt new educational technologies (Rutto et al., 2022). This brings to the following hypothesis:

H4: Effort expectancy positively influences learning attitudes.

Liu et al. (2022) conducted a study on the adoption of mobile health services using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The study revealed that effort expectancy exerts a substantial positive influence on users' behavioral intention. Consequently, this brings to the following hypothesis:

H5: Effort expectancy positively affects behavioral intention.

Alwahaishi and Snásel (2013) introduced a UTAUT and flow-based theoretical model to comprehend consumer acceptance and usage of information and communications technology. Their research suggests that effort expectancy plays a role in user satisfaction due to its ease of use. This leads to posit the following hypothesis:

H6: Effort expectancy positively affects satisfaction.

Performance expectancy stands as a critical factor in determining individual acceptance and usage of technology across various domains, as noted by Wigfield and Eccles (2000). It pertains to the degree to which individuals believe that a system enhances their performance, as defined by Chao (2019). In the context of learning English as a foreign language, Zhao and Shang (2022) conducted a study on integrated teaching and discovered that factors such as the teacher's personality, professional knowledge, enthusiasm, commitment, and classroom management skills directly and significantly influence learners' motivation to learn. This implies that positive performance expectations, combined with effective teaching practices, can foster positive attitudes toward learning. Therefore, the following hypothesis is posited:

H7: Performance expectancy positively influences learning attitudes.

Venkatesh et al. (2003) proposed a unified view of user acceptance of information technology and found that performance expectancy positively influenced satisfaction. They argued that when individuals perceive that a technology will enhance their performance, they are more likely to be satisfied with its use. Gefen et al. (2003) examined the relationship between trust, performance expectancy, and satisfaction in the context of online shopping. Their findings suggest that performance expectancy positively influences satisfaction. Hence, the following hypothesis is posited:

H8: Performance expectancy positively affects satisfaction.

Slade et al. (2015) investigated the factors influencing consumers' adoption intentions of remote mobile payments, extending the UTAUT model to include innovativeness, risk, and trust. Their study revealed that performance expectancy, along with effort expectancy and social influence, significantly impacts behavioral intent, which, in turn, influences usage behavior. This leads to the following hypothesis:

H9: Performance expectancy positively influences behavioral intention.

Banahene et al. (2018) explored the impact of Higher Education Performance on students' satisfaction and academic performance in Ghanaian universities. Their study indicates that attitude towards learning has a positive and statistically significant relationship with students' satisfaction, implying that positive attitudes towards learning contribute to higher satisfaction levels. This brings to the following hypothesis:

H10: Learning attitudes positively affect satisfaction.

Mercier et al. (2023) concentrated on middle school students' attitudes toward physical activity and physical education, highlighting the influence of attitudes on behavioral intent and subsequent behavior. Therefore, the following hypothesis is brought:

H11: Learning attitudes positively affect behavioral intention.

Rita et al. (2019) examined the impact of e-service quality and customer satisfaction on customer behavior in online shopping. Their findings suggest that customer satisfaction positively influences customer behavior, indicating that satisfied customers are more likely to engage in positive behaviors. This leads to the following hypothesis:

H12: Satisfaction positively affects behavioral intention.

Based on the proposed hypotheses, the following conceptual framework has been proposed in **Figure 1**.

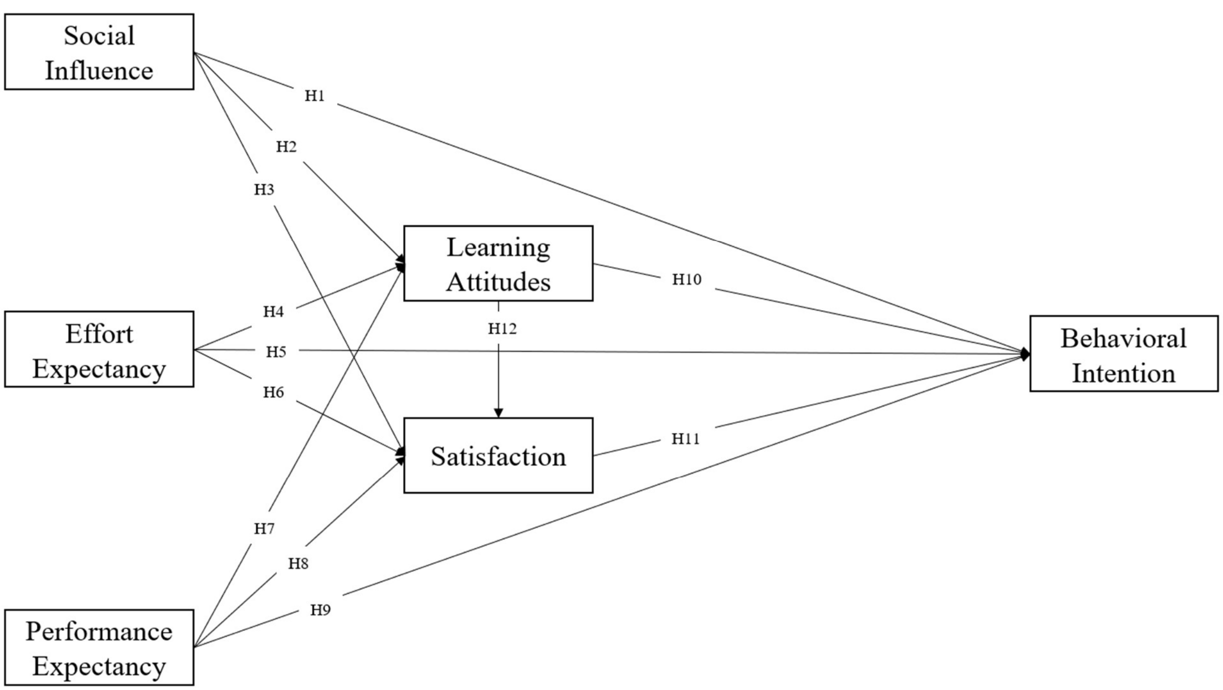

Figure 1 Conceptual Framework

3. Research Methodology

3.1 Data Collection

The target population of this research is Chinese university students. The sample was collected through the online platform. The minimum sample size is 92 which was calculated by G power with the F test being selected for the Linear Multiple Regression statistical test (Effect size, $f^2 = 0.15$, Probability of error, $\alpha = 0.05$, Power level $(1 - \beta) = 0.8$ and the number of predictors = 5). This research collected 353 qualified respondents, which exceeds the minimum sample size. The questionnaire was distributed through online platforms on Chinese social media: WeChat, Xiaohongshu, Douban, Sina microblog and etc..

3.2 Measurement Development

The self-administered questionnaire was designed, and the measurement items of this research were adapted and adopted from previous literature. The sources of each measurement item are shown in **Table 1**.

Table 1. Number and Sources of Measurement Items

Constructs	Number of Measurement Items	Sources
Social Influence	3	(Tan et al., 2014)
Effort Expectancy	5	(Chao, 2019)
Performance Expectancy	4	(Chao, 2019)
Learning Attitudes	7	(Hwang & Chang, 2011)
Satisfaction	5	(Chao, 2019)
Behavior Intention	3	(Tan et al., 2014)

3.3 Profile of Respondents

The 353 respondents were made of 257 female respondents and 96 male respondents. Online learning studies show that female learners often prove to be more perseverant and engaged than their male counterparts (Yu, 2021). There are 275 diploma students, 43 bachelor's degree students, 26 postgraduate students and 9 without college degree in respondents.

4. Data Analysis

4.1 Statistical Analysis

The Partial Least Squares Structural Equation Modelling (PLS-SEM) is particularly suitable when the analysis is concerned with testing a theoretical framework from a prediction perspective (Hair et al., 2019). Thus, this research conducted PLS-SEM as the data analysis method and conducted by the Smartpls software version 4.0.

4.2 Assessing the Outer Measurement Model

During the assessment of the outer measurement model, it is imperative to validate both reliability and validity (Hair et al., 2021). Internal consistency refers to the degree to which items within a measurement instrument are related to each other and measure various aspects of the same characteristic or construct (Revicki, 2014). For adequate convergence or internal consistency, composite reliability should be 0.7 or above (Hair et al., 2019). As shown in **Table 2**, all values of composite reliability are higher than 0.7, thus, the construct reliability was acceptable. Construct reliability refers to the consistency with which a set of measurement item produces similar results under consistent conditions (Krabbe, 2017). Factor loading and Average Variance Extracted (AVE) higher 0.5 that reflect the convergent validity was acceptable. According to **Table 2**, all constructs meet the convergent validity requirement. On the other hands, to ensure the discriminant validity, the Hetero-trait-mono-trait (HTMT) was tested, according to **Table 3**, the discriminant validity is not an issue in this study (Hair et al., 2019; Tan & Ooi, 2018).

Table 2: Convergent Validity and Construct Reliability

Constructs	Items	Loading	Composite Reliability (rho-c)	Average Variance Extracted (AVE)
Behavioral Intention	BI1	0.894	0.906	0.764
	BI2	0.909		
	BI3	0.817		
Effort Expectancy	EE1	0.795	0.919	0.695
	EE2	0.843		
	EE3	0.871		
	EE4	0.865		
	EE5	0.792		
Learning Attitudes	LA1	0.783	0.935	0.643

	LA2	0.818		
	LA3	0.699		
	LA4	0.842		
	LA5	0.834		
	LA6	0.865		
	LA7	0.826		
	LA8	0.732		
Performance Expectancy	PE1	0.837	0.925	0.754
	PE2	0.861		
	PE3	0.885		
	PE4	0.891		
Satisfaction	SA1	0.89	0.968	0.857
	SA2	0.916		
	SA3	0.953		
	SA4	0.931		
	SA5	0.938		
Social Influence	S1	0.884	0.755	0.518
	S2	0.715		
	S3	0.511		

Table 3: Hetero-Trait-Mono-Trait ($HTMT_{.85}$)

Constructs	Behavioral Intention	Effort Expectancy	Learning Attitudes	Performance Expectancy	Satisfaction
Effort Expectancy	0.736				

Learning Attitudes	0.892	0.812			
Performance Expectancy	0.859	0.809	0.877		
Satisfaction	0.841	0.757	0.863	0.803	
Social Influence	0.487	0.506	0.526	0.480	0.461

4.3 Inspecting the Inner Structural Model

The result of hypotheses testing is shown in **Table 4**. The P value lower than 0.05 reflects the regression model is significant (Hair et al., 2021; Ng et al., 2022). The T statistics higher than 1.96 reflected the hypothesis testing was supported (Hair et al., 2019; Tan & Ooi, 2018). Thus, H2, H4, H6, H7, H8, H9, H10, H11 and H12 are supported, and H1, H3 and H5 are unsupported.

Table 4: Hypothesis Testing

Hypotheses	Paths	Path Coefficients	T Statistics	P Values	Remarks
H1	**S→BI**	0.023	0.626	0.266	**Unsupported**
H2	**S→LA**	0.128	3.284	0.001	**Supported**
H3	**S→SA**	0.023	0.557	0.289	**Unsupported**
H4	**EE→LA**	0.302	6.796	0.000	**Supported**
H5	**EE→BI**	-0.012	0.229	0.409	**Unsupported**
H6	**EE→SA**	0.156	2.918	0.002	**Supported**
H7	**PE→LA**	0.526	10.954	0.000	**Supported**
H8	**PE→SA**	0.198	2.266	0.012	**Supported**
H9	**PE→BI**	0.262	3.047	0.001	**Supported**
H10	**LA→BI**	0.354	4.507	0.000	**Supported**
H11	**SA→BI**	0.272	3.456	0.000	**Supported**
H12	**LA→SA**	0.532	6.412	0.000	**Supported**

4.4 Predictive Relevance and Effect Size

Table 5 shows the effect size (f^2), if the value below 0.02, the independent variable has no effect (Hair et al., 2019). Thus, effort expectancy doesn't influence customer's behavioral intention, also, social influence doesn't have effect on satisfaction and behavioral intention. On the contrary, the other relationships make sense in this study. R-square value higher than 0.26 reflect endogenous latent variable are assessed (Cohen, 1988). According to **Table 6**, all R-square are high 0.26, thus, all endogenous latent variables are assessed in this study. **Table 7** shows the Q-square, the r-square are equal and higher than zero reflect the model exhibits predictive relevance (Hair et al., 2019). Thus, the path in this research exhibits acceptable predictive relevance.

Table 5: Effect size (f^2)

Constructs	Behavioral Intention	Learning Attitudes	Satisfaction
Effort Expectancy	0.000	0.142	0.033
Learning Attitudes	0.091		0.279
Performance Expectancy	0.067	0.430	0.042
Satisfaction	0.070		
Social Influence	0.001	0.044	0.001

Table 6: R-square

Constructs	R-square	R-square adjusted
Behavioral Intention	0.683	0.678
Learning Attitudes	0.704	0.701
Satisfaction	0.699	0.696

Table 7: Q-square

Constructs	Q-square
Behavioral Intention	0.510
Effort Expectancy	0.000
Learning Attitudes	0.447
Performance Expectancy	0.000
Satisfaction	0.593
Social Influence	0.000

5. Discussion

As shown from the result of data analysis, H1, H3 and H5 were unsupported, which indicated that social influence doesn't have a positive impact on behavioral intention and satisfaction of using mobile apps to learn English vocabulary. Effort expectancy also doesn't have a positive impact on behavioral intention to use mobile apps to learn English vocabulary in this study. On the contrary, H2, H4, and H7 were supported, indicating that learning attitudes of EFL learners were influenced positively by social influence, effort expectancy and performance expectancy. H6, H8 and H12 were supported, indicating that satisfaction was influenced positively by effort expectancy, performance expectancy and learning attitudes of EFL learners. H9, H10 and H11 were supported, indicating that behavioral intention was positively influenced by performance expectancy, learning attitudes and satisfaction.

6. Research Implications

6.1 Theoretical Implications

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a framework to understand the acceptance and use of technology among users (Slade et al., 2015). This research applies UTAUT model in mobile learning area to investigate Chinese EFL (English as A Foreign Language) learners' behavioral intention to use mobile applications to study English vocabulary. This research uses learning attitude to reflect people's emotional factors, which will provide reference for future research.

6.2 Practical Implications

This research finds that Chinese people's behavioral intention in use mobile applications to study English vocabulary was positively influenced by performance expectancy, learning attitudes and satisfaction. Thus, this research has some practical implications in mobile application development for Chines EFL (English as A Foreign Language) learners to study English vocabulary. Firstly, the mobile applications for English vocabulary study should improve the motivational elements to foster positive learning attitudes, for example, offering personalized learning paths and adapting to individual's learning pace and style to enhance satisfaction. On the other hand, the manager could periodically gather feedback on user experience and satisfaction through surveys or in-app feedback mechanisms to measuring the customer satisfaction and regularly update content and features based on user feedback to maintain and enhance satisfaction levels. Finally, the mobile application designer should ensure apps deliver clear, tangible benefits to enhance performance expectancy.

7. Limitations and recommendations for future research

One of this research limitation is the structural composition of respondents in this study, diploma student is accounted of 77.9%. Due to the questionnaire being distributed through online platform, it is possible to generate sample bias. According to survey, 98% of college-aged students are on social media (Columnist, 2023), which could explain why the main respondents in this research was diploma students. Future research is suggested to try different methods to collect data to avoid sample bias.

References

Ahn, M., Kang, J., & Hustvedt, G. (2016). A model of sustainable household technology acceptance. *International Journal of Consumer Studies*, *40*(1), 83–91. https://doi.org/10.1111/ijcs.12217

Alwahaishi, S., & Snásel, V. (2013). Acceptance and Use of Information and Communications Technology: A UTAUT and Flow Based Theoretical Model. *Journal of Technology Management & Innovation*, *8*(2), 61–73. https://doi.org/10.4067/S0718-27242013000200005

Banahene, S., Kraa, J. J., & Kasu, P. A. (2018). Impact of HEdPERF on Students'Satisfaction and Academic Performance in Ghanaian Universities; Mediating Role of Attitude towards Learning. *Open Journal of Social Sciences*, *6*(5), Article 5. https://doi.org/10.4236/jss.2018.65009

Basal, A., Yilmaz, S., Tanriverdi, A., & Sari, L. (2016). Effectiveness of Mobile Applications in Vocabulary Teaching. *Contemporary Educational Technology*, *7*(1). https://doi.org/10.30935/cedtech/6162

Chao, C.-M. (2019). Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. *Frontiers in Psychology*, *10*.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed). L. Erlbaum Associates.

columnist, E. Z. | contributing. (2023, February 9). *Opinion | Social media has turned college students into mass consumers.* The Breeze. https://www.breezejmu.org/opinion/opinion-social-media-has-turned-college-students-into-mass-consumers/article_65ac8052-a7d9-11ed-9930-272f82cad2b1.html

Gan, C., & Wang, W. (2017). The influence of perceived value on purchase intention in social commerce context. *Internet Research*, *27*(4), 772–785. https://doi.org/10.1108/IntR-06-2016-0164

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Ghobakhloo, M., Hong, T. S., Sabouri, M. S., & Zulkifli, N. (2012). Strategies for Successful Information Technology Adoption in Small and Medium-sized Enterprises. *Information*, *3*(1), Article 1. https://doi.org/10.3390/info3010036

Gupta, K., & Arora, N. (2020). Investigating consumer intention to accept mobile payment systems through unified theory of acceptance model: An Indian perspective. *South Asian Journal of Business Studies*, *9*(1), 88–114. https://doi.org/10.1108/SAJBS-03-2019-0037

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hashim, K. F., Tan, F. B., & Rashid, A. (2015). Adult learners'intention to adopt mobile learning: A motivational perspective. *British Journal of Educational Technology*, *46*(2), 381–390. https://doi.org/10.1111/bjet.12148

Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

Hwang, G.-J., & Chang, H.-F. (2011). *A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students*.

Im, I., Kim, Y., & Han, H.-J. (2008). The effects of perceived risk and technology type on users'acceptance of technologies. *Information & Management*, *45*(1), 1–9. https://doi.org/10.1016/j.im.2007.03.005

Krabbe, P. F. M. (2017). Chapter 7—Validity. In P. F. M. Krabbe (Ed.), *The Measurement of Health and Health Status* (pp. 113–134). Academic Press. https://doi.org/10.1016/B978-0-12-801504-9.00007-6

Li, R. (2021). Modeling the Continuance Intention to Use Automated Writing Evaluation Among Chinese EFL Learners. *SAGE Open*, *11*(4), 21582440211060782. https://doi.org/10.1177/21582440211060782

Liu, Y., Lu, X., Zhao, G., Li, C., & Shi, J. (2022). Adoption of mobile health services using the unified theory of acceptance and use of technology model: Self-efficacy and privacy concerns. *Frontiers in Psychology*, *13*. https://www.frontiersin.org/articles/10.3389/fpsyg.2022.944976

Mercier, K., Simonton, K., Centeio, E., Barcelona, J., & Garn, A. (2023). Middle school students'attitudes toward physical activity and physical education, intentions, and physical activity behavior. *European Physical Education Review*, *29*(1), 40–54. https://doi.org/10.1177/1356336X221106051

Ng, F. Z.-X., Yap, H.-Y., Tan, G. W.-H., Lo, P.-S., & Ooi, K.-B. (2022). Fashion shopping on the go: A Dual-stage predictive-analytics SEM-ANN analysis on usage behaviour, experience response and cross-category usage. *Journal of Retailing and Consumer Services*, *65*, 102851. https://doi.org/10.1016/j.jretconser.2021.102851

Park, S. Y., Nam, M.-W., & Cha, S.-B. (2012). University students'behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British Journal of Educational Technology*, *43*(4), 592–605. https://doi.org/10.1111/j.1467-8535.2011.01229.x

Revicki, D. (2014). Internal Consistency Reliability. In A. C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (pp. 3305–3306). Springer Netherlands. https://doi.org/10.1007/978-94-007-0753-5_1494

Rita, P., Oliveira, T., & Farisa, A. (2019). The impact of e-service quality and customer satisfaction on customer behavior in online shopping. *Heliyon*, *5*(10), Article 10. https://doi.org/10.1016/j.heliyon.2019.e02690

Rutto, L. K., Njeje, D., & Yano, R. (2022). Selected Factors and Adoption of Electronic Performance in Public Secondary School Teachers in Bomet Central Sub-County. *Journal of Information and Technology*, *6*(1), Article 1. https://doi.org/10.53819/81018102t4074

Shen, F., Liang, L., & Feng, Y. (2023). A study on factors influencing Chinese undergraduate EFL learners'self-directed use of mobile English learning resources. *Frontiers in Psychology*, *14*. https://www.frontiersin.org/articles/10.3389/fpsyg.2023.1189055

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling Consumers'Adoption Intentions of Remote Mobile Payments in the United Kingdom: Extending UTAUT with Innovativeness, Risk, and Trust. *Psychology & Marketing*, *32*(8), 860–873. https://doi.org/10.1002/mar.20823

Tan, G. W.-H., & Ooi, K.-B. (2018). Gender and age: Do they really moderate mobile tourism shopping behavior? *Telematics and Informatics*, *35*(6), Article 6. https://doi.org/10.1016/j.tele.2018.04.009

Tan, G. W.-H., Ooi, K.-B., Leong, L.-Y., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. *Computers in Human Behavior*, *36*, 198–213. https://doi.org/10.1016/j.chb.2014.03.052

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

Wigfield, A., & Eccles, J. S. (2000). Expectancy–Value Theory of Achievement Motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Yang, Y. (2022). An Evaluation of Popular Vocabulary Learning Mobile Applications in China and Their Implications for Language Learning? *World Journal of Educational Research*, *9*, p47. https://doi.org/10.22158/wjer.v9n1p47

Ying, S. (2022). Learn About Vocabulary Learning in Mobile Apps through Web Surveys. *2022 Second International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE)*, 1–5. https://doi.org/10.1109/ICATIECE56365.2022.10047347

Yu, S., & Lee, I. (2014). An analysis of Chinese EFL students'use of first and second language in peer feedback of L2 writing. *System*, *47*, 28–38. https://doi.org/10.1016/j.system.2014.08.007

Yu, Z. (2021). The effects of gender, educational level, and personality on online learning outcomes during the COVID-19 pandemic. *International Journal of Educational Technology in Higher Education*, *18*(1), 14. https://doi.org/10.1186/s41239-021-00252-3

Zhao, Q., & Shang, H. (2022). Study on the integrated teaching of English education, mental health and students'wellbeing. *Frontiers in Psychiatry*, *13*. https://www.frontiersin.org/articles/10.3389/fpsyt.2022.953325