pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 – 868x © 2021 AU-GSB e-Journal.
https://assumptionjournal.au.edu/index.php/AU-GSB

Understanding What Drives Gen Y Users in Chengdu, China to Study English via Mobile Apps

Zhenzhen Wang*

Received: June 5, 2024. Revised: July 31, 2024. Accepted: February 22, 2025.

Abstract

Purpose: The study aims to examine how Gen Y users in Chengdu, China, are influenced in their intentions regarding English learning behavior by utilizing popular English word learning applications in China. The conceptual framework contains system quality, information quality, service quality, perceived usefulness, attitude, technology characteristics, task-technology fit, and behavior intention. **Research design, data, and methodology:** The research employs quantitative and nonprobability sampling techniques, including quota and convenience sampling. Data from 473 Chengdu residents using China's top three English word-learning applications were collected via a network self-administered questionnaire. Confirmatory factor analysis and structural equation modeling were used as statistical tools to analyze data accuracy and the impact of key variables. **Results** Findings indicate that behavioral intention strongly influences the attitude toward using mobile applications for English word learning. System quality, information quality, service quality, attitude, technology characteristics, task characteristics, and personal perception significantly affect the behavioral intention to use these applications. However, technology characteristics has no significant impact on task-technology fit. **Conclusions:** The alignment of learning content and technology is crucial in the diverse landscape of English learning apps, and determines users' experiences and satisfaction.

Keywords: System Quality, Information Quality, Service Quality, Technical Characteristics, Task Characteristics

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With many years of reform of internet-based teaching, several learning platforms have been introduced in English teaching. At the same time, auxiliary teaching applications are carried out in and outside class, especially in vocabulary learning (Mukul & Büyüközkan, 2023). More and more students study by themselves before class. In traditional learning, students are inclined to memorize vocabulary purely instead of figuring out how to use it in a context. As a result, they can simply memorize the spelling and explanation of vocabulary in a dictionary, which makes the memory hard to last. Therefore, to solve such problems, more and more English vocabulary learning Applications have been developed (Fengyu, 2023). In 2019, Baicizhan became one of the first batch of educational applications officially approved by the Ministry of Education of China, aiming for students from junior high school, senior high school, CET4/ CET6, postgraduate entrance examination English, TOFEL/IELTS, professional English Band 4 and 8, SAT/ GRE/ GMAT. The content's comprehensiveness solves the problems, including the fuzzy classification for vocabulary and grades. In addition, the scope and pertinence of the vocabulary are clearer for all kinds of examinations. In addition to the wideness of the range of vocabulary, contextual learning is also used in vocabulary learning, which provides a better way to help memorize (Feng & Jia, 2024). Apart from providing context, it summarizes the vocabulary formation methods so learners can learn more about vocabulary formation through roots and affixes. Moreover, on the technical level, with the

1*Zhenzhen Wang, School of Foreign Languages & Culture and Tourism, Chengdu Textile College, China. Email: 327241649@qq.com

increasing popularization of 5G network service, the advantages of these Applications such as interestingness, convenience, and low consumption in time and money, allowing users to repeat new words in a personalized way, which makes such vocabulary learning Applications more widely used (Wang & Li, 2019).

Meanwhile, the pandemic covid-19 in 2020 has further accelerated the pace of Internet-based teaching, allowing more traditional learning materials to be represented by the Internet. Even though offline traditional education can be restored, the hybrid learning mode has become the mainstream way of education and teaching, especially in adult education, such as English. The wide use of smartphones provides more stable users for these Applications, and this kind of personalized vocabulary learning application is user-oriented, which makes learners feel comfortable in the process of using, thus enhancing their intention to use. In terms of teaching methods, it is more in line with the modern teaching mode that centers learners, helping learners obtain greater satisfaction and improve learning efficiency.

The purpose of this study is to investigate the positive behavior intention of adult English learners in the use of English vocabulary applications, which method is designed based on the Internet, solving the problems in systematic course learning, breaking the limitations of space, practice, and learning resources.

2. Literature Review

2.1 System Quality

Ease of use is an important indicator for measuring mobile system quality (Abbas, 2016; Bagchi & Peeter, 2010; Lin & Hsieh, 2011). Petter and McLean (2009) define system quality as the degree to which users can understand, learn, connect, and enjoy a specific system. ISO 2000 defines system quality as a product's effectiveness, satisfaction, and efficiency in achieving goals in a specific use environment.

Brodie et al. (2009) points out that the association of learning software brands is linked to learners' perceptions and evaluations of the software system's quality. Cronin et al. (2000) Emphasize that understanding system quality is crucial for service effectiveness, customer satisfaction, and loyalty, especially in learning environments. Thus, this study proposes a hypothesis:

H1: System quality has a significant impact on perceived usefulness.

2.2 Information Quality

DeLone and McLean (2003) defined system information quality as accuracy, comprehensiveness, and reliability, which are key for effective information systems. Cheng (2012) noted that a system's diversity and effectiveness in course content positively influence user perceptions of its accuracy and effectiveness. Scholars have also clearly pointed out the significant impact of information quality on user satisfaction (Jung et al., 2015) and actual use (Correa et al., 2017). Information quality is associated with the timeliness and accuracy of information and the comprehensibility of knowledge coverage in mobile learning software. Thus, this study proposes a hypothesis:

H2: Information quality has a significant impact on perceived usefulness.

2.3 Service Quality

Understanding service quality in the context of e-learning systems is crucial. It typically refers to a system that arises from the disparity between the anticipated and actual perceptions of the service provided by the product. This encompasses tangible service, service reliability, feedback response, and service empathy (Cheng, 2012). In short, service quality means the gap between the expected and the final experience of the e-learning system (Roca et al., 2006).

Grace and O'Cass (2005) observed that various service attributes, including core services, staff interaction, page design, and overall brand perception, shape learners' experiences with different mobile software brands. This experience plays a crucial role in forming the service brand image, as Padgett and Allen (1997) described. Such an image significantly influences user behavior and intentions, a concept also supported by Johnson et al. (2009) and Fishbein (1967). Thus, this study proposes a hypothesis:

H3: Service quality has a significant impact on perceived usefulness.

2.4 Perceived Usefulness

Perceived usefulness is also referred to as performance expectation. Research by Venkatesh (2000) suggests that performance expectation is a primary predictor of the intention to use a system. Ju et al. (2007) further explained that perceived usefulness impacts users' experiences and attitudes, affecting their intention to use the products. Bhattacherjee (2001) suggests that users' initial perceptions or sensations about a product can influence their acceptance even before using it. Similarly, Saeed et al. (2003) demonstrated that service quality significantly impacts perceived usefulness. Thus, this study proposes a

hypothesis:
H4: Perceived usefulness has a significant impact on attitude.

2.5 Technology Characteristics

In e-learning, Alavi and Leidner (2001) they were noted that technical characteristics significantly influence user learning motivation and cognitive awareness. Goodhue and Thompson (1995) highlighted the concept of task-technology fit, indicating that aligning technical characteristics with task requirements enhances performance. However, the impact of system quality on student attitudes toward application software learning may be moderated by the interplay of individual and technological characteristics. Recent studies, including those by Wang et al. (2016) and Yu & Yu (2010), have shown that students increasingly utilize mobile software platforms to boost learning efficiency. Thus, this study proposes a hypothesis:
H5: Technology characteristics has a significant impact on task-technology fit.

2.6 Task Characteristics

Goodhue and Thompson (1995) define "task feature" as the process where individuals transform input into output, fulfilling personal information needs. Research by Carlos and Tiago (2016) indicates that task characteristics influence the degree of fit between users and systems. This relationship is further supported by studies from Khan et al. (2017) and Lu and Yang (2014), showing a positive correlation between task characteristics and system fit. Martin (2002) developed an instrument to measure how well an organization's information systems meet the information needs of its managers based on a managerial decision-making task model. Thus, this study proposes a hypothesis:
H6: Task characteristics has a significant impact on task-technology fit.

2.7 Task-Technology Fit

Lin and Wang (2012) define TTF as the congruence between system capabilities and task execution, focusing on user satisfaction. Echoing this, Lu and Yang (2014) consider TTF to be indicative of technology's role in facilitating task completion and fulfilling user needs. D'Ambra et al. (2013) emphasize TTF's criticality in leveraging organizational technology effectively. Yen et al. (2010) describe TTF as a crucial measure for reflecting user preferences and predicting technology adoption. Gu and Wang (2009) observe that TTF effectively captures the interplay between personal qualities and performance, aiding in the study of variables connecting actual TTF use to anticipated performance. Thus, this study proposes a hypothesis:
H7: Task-technology fit has a significant impact on behavior intention.

2.8 Attitude

The attitude of behavior refers to the extent to which the person feels favorable or disadvantageous toward action (Ajzen, 1991). Davis (1989) believed that attitude referred to a person's positive or negative behavioral feelings toward a goal. Davis (1993) also pointed out whether potential users use the system depends on their overall attitude. Karahanna and Straub (1999) pointed out that users express their attitude toward using technology through perceived usefulness and ease of use. Noh and Lee (2016) found that the user's attitude towards mobile banking applications has an important impact on their intention to use them. At the same time, similar results have been found in the online retail and mobile game industries (O'Cass & French, 2003). So, it also shows the relationship between attitude and system use. Thus, this study proposes a hypothesis:
H8: Attitude has a significant impact on behavior intention.

2.9 Behavior Intention

Behavioral intent was also determined by the attitude toward individual behavior and the normative pressure of personal experience (Ajzen, 1991; Venkatesh et al., 2012). Behavioral intention comprises internal and external motives (Davis et al., 1992). Behavioral intention refers to individuals' willingness to adopt or use a certain technology, such as a mobile library (Davis, 1989).

Hsu et al. (2014) noted that subjective norms directly or indirectly impact user attitudes and intentions in information system usage. Research by Hsiao et al. (2015) emphasize the role of internal factors like self-efficacy and user recognition in shaping individual behavioral motives and intentions. Cheng (2012) highlights that external variables influence users' behavioral intentions toward new technologies via perceived in the technology acceptance model.

3. Research Methods and Materials

3.1 Research Framework

The study presents a conceptual framework comprising five research models that explore the relationship between the research and conceptual frameworks. Based on an

established theoretical model, this research framework aids in developing conceptual and previous research frameworks. As depicted in Figure 1, previous empirical research serves as the basis for this study, which focuses on examining user perceptions of usefulness and attitude concerning system quality, information quality, and service quality. The conceptual framework introduces five variables for investigation, enabling the study of behavioral intent, usability, and attitude. Hu and Zhang (2016) earlier research framework, influenced by The DeLone and McLean Model and the Technology Acceptance Model, serves as the foundation for this study, considering the impacts of system, information, and service quality on perceived usefulness and attitudes.

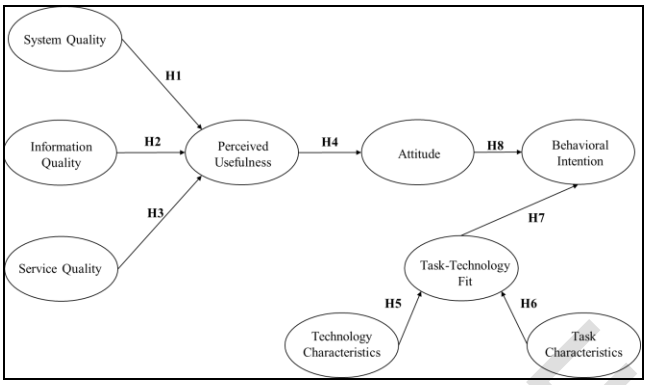

Figure 1: Conceptual Framework

H1: System quality has a significant impact on perceived usefulness.
H2: Information quality has a significant impact on perceived usefulness.
H3: Service quality has a significant impact on perceived usefulness.
H4: Perceived usefulness has a significant impact on attitude.
H5: Technology characteristics has a significant impact on task-technology fit.
H6: Task characteristics has a significant impact on task-technology fit.
H7: Task-technology fit has a significant impact on behavior intention.
H8: Attitude has a significant impact on behavior intention.

3.2 Research Methodology

Polonsky and Waller (2015) defined quantitative research methods as data analysis techniques for many respondents, and the information can represent the population. Surveys are one of the main quantitative research methods. This study carried out quantitative research, and data were collected using the survey technique.

The survey technique was used to collect raw data. The characteristics of statistical analysis are carried out through statistical analysis (Stangor & Walinga, 2014). It is descriptive that the treatment he takes is more formal and severe. Roni et al. (2020) indicated that if researchers want to collect measurement data for research, quantitative research is one of the appropriate choices. However, in the questionnaire, the same question is used to select researchers and use questions. In quantitative research, standardized questionnaires used by researchers can manage variables in better-structured environments (Rutberg & Bouikidis, 2018).

In this research, quantitative methodologies were employed, including the project-objective consistency (IOC) test and Cronbach's Alpha test. A panel of three experts evaluated the Index of Item-Objective Congruence (IOC) to ensure that each item accurately measured its intended construct, thereby enhancing the assessment's validity. A pilot test conducted with 50 participants yielded a Cronbach's Alpha score exceeding 0.7, indicating reliable measurement of the specified construct and reinforcing the overall reliability of the test results, in accordance with Nunnally and Bernstein's (1994) guidelines. After data collection, confirmatory factor analysis and structural equation modeling were used as statistical tools to analyze data accuracy and the impact of key variables.

3.3 Population and Sample Size

The study targets faculty members in Chengdu, China, who have experience with mobile applications. The age group is between 21 to 40 (Generation Y, born in 1981 to 2000) and Researchers employ non-probabilistic sampling methods. The sample size aims to 500 participants.

3.4 Sampling Technique

Babbie (1990) noted that positive or decision sampling is a general non-probabilistic sampling method. Researchers can take samples according to their research purpose and understanding of the subject. Intentional or deterministic sampling allows researchers to select sample units according to individual judgments to achieve or verify research objectives. Kervin (1992) showed that a sample selected by an intentional or discriminatory sampling method allows the researchers to control the sample more strongly. That is, the researcher can select units according to the purpose.

The study targets faculty members in Chengdu, China, who have experience with mobile applications. The age group is between 21 to 40 (Generation Y, born in 1981 to 2000) and Researchers employ non-probabilistic sampling methods. Specifically, the study utilizes quota and

convenience sampling techniques to select participants. Data were collected from 500 faculty members who use China's top three English word-learning applications through a network self-administered questionnaire. To ensure data accuracy and examine the impact of key variables, the study employs confirmatory factor analysis and structural equation modeling as statistical tools. After the data screening, 473 sample was valid.

Table 1: Sample Units and Sample Size

Number of faculty members	Population Size	Proportional Sample Size
Southwest Jiaotong	2448	178
Xihua University	2267	165
Chengdu Textile College	2148	156
Total	**6863**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 shows male respondents (43.6%) and female respondents (56.4%). According to the 7th Chengdu Population Census (2020), the population of young males aged 20-24 in Chengdu is 812825, and the population of females is 805745. Therefore, the respondents of this study can reflect the characteristics of the local population of Chengdu. Regarding age distribution, most respondents are 21-30 years old, accounting for 94.5%, while respondents between 31-40 years old or above account for 5.5%.

Table 2: Demographic Profile

Demographic and General Data (N=473)		Frequency	Percentage
Gender	Male	206	43.6%
	Female	267	56.4%
Age	21-30 years old	447	94.5%
	31-40 years old	26	5.5%

4.2 Confirmatory Factor Analysis (CFA)

CFA is a statistical tool widely used in various quantitative analyses for its flexibility, accuracy, and strength. This method is usually used when a researcher adopts a questionnaire to conduct research and establish a framework. Moore (2012) pointed out that CFA is a structural equation modeling that can successfully measure the relationship between scale equations and potential variables. Stangor and Walinga (2014) believed that CFA supported the SEM in explaining whether the data gathered by the researchers fulfilled the assumption. It often describes the correlation between measurement items and potential variables.

The researchers found that the factor loadings for each measurement item were greater than 0.5, indicating a good relationship between the measurement items and the structure. In addition, all t-values were above 1.98, with a significance level 0.001. Meanwhile, the CR values of each construct are greater than 0.7. The AVE values are also greater than 0.5. In addition, each CR value is also greater than the AVE value. Therefore, the results indicate high convergence effectiveness.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
System Quality (SSQ)	DeLone and McLean (1992)	3	0.879	0.770-0.840	0.850	0.650
Information Quality (IQ)	Ahn et al. (2007)	4	0.911	0.790-0.980	0.940	0.830
Service Quality (SQ)	Lin et al. (2011)	4	0.927	0.840-1.000	0.980	0.910
Perceived Usefulness (PU)	Venkatesh (2000)	4	0.941	0.920-0.960	0.970	0.880
Technical Characteristics (TC)	Goodhue and Thompson (1995)	3	0.949	0.910-0.950	0.950	0.870
Task Characteristics (TAC)	Peter and Olson (2010)	2	0.874	0.850-0.870	0.850	0.740
Task-Technology Fit (TTF)	D'Ambra and Wilson (2004)	3	0.910	0.700-0.810	0.810	0.590
Attitude (AT)	Davis (1989)	4	0.909	0.950-0.980	0.980	0.940
Behavioral Intention (BI)	Ajzen (1991)	3	0.925	0.870-0.900	0.910	0.780

The confirmatory factor analysis employed GFI, AGFI, NFI, CFI, TLI, and RMSEA as model fit indicators. The values for convergent validity and discriminant validity exceed the acceptable threshold for this study, as demonstrated in Table 4. Adequate assurance is provided for both convergent validity and discriminant validity.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3 (Hair et al., 2010)	1.636
GFI	>0.90 (Bagozzi & Yi, 1988)	0.928
AGFI	>0.85 (Sica & Ghisi, 2007)	0.909
NFI	> 0.95 (Arbuckle, 1995)	0.968
CFI	>0.95 (Hu & Bentler, 1999)	0.987
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.037
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index and RMSEA = root mean square error of approximation

Solimun and Fernandes (2017) believed that discriminant validity means no redundant scale scale to the measurement model. Stangor and Walinga (2014) pointed out that the measured value measures the degree of no relation to other measurement variables. Brown (2015) showed no significant correlation between items in different structures. Fornell and Larcker (1981) determined that the validity of potential variables differed from that of others.

Table 5: Discriminant Validity

	SSQ	IQ	SQ	PU	TC	TAC	TTF	AT	BI
SSQ	**0.650**								
IQ	0.310	**0.830**							
SQ	0.310	0.310	**0.910**						
PU	0.350	0.340	0.350	**0.880**					
TC	0.250	0.200	0.090	0.310	**0.870**				
TAC	0.380	0.240	0.320	0.710	0.230	**0.740**			
TTF	0.100	0.130	0.250	0.070	-0.200	0.110	**0.590**		
AT	0.390	0.270	0.250	0.200	0.150	0.170	0.100	**0.940**	
BI	0.530	0.370	0.420	0.600	0.330	0.610	0.360	0.400	**0.780**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

Whether the proposed model was compatible with the data by examining the model fit was the purpose of the SEM to be implemented (Hox & Bechger, 1999). Hair et al. (2013) described that a structural model was the same as a measurement model, showing the relationship between constructs. Likewise, the structural model

The structural model, as Ramlall (2016) explains, is instrumental in revealing the causal connection between the endogenous variables (those influenced by other variables in the model) and the exogenous variables (those that influence other variables but are not influenced by them).

The researcher applied six fit indices to check the model fit for structural models as x2/for CMIN/df, GFI, AGFI, CFI, TLI, and RMSEA which will be summary in a table below.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	<3 (Hair et al., 2010)	2.030
GFI	>0.90 (Bagozzi & Yi, 1988)	0.910
AGFI	>0.85 (Sica & Ghisi, 2007)	0.890
NFI	> 0.95 (Arbuckle, 1995)	0.980
CFI	>0.95 (Hu & Bentler, 1999)	0.980
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.050
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The research model in this article primarily assesses the significance of relationships among its variables by standardizing regression weights and variances. A significance level of $p<0.05$ is considered significant. As indicated in the results presented in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SSQ→PU	0.25	4.93***	Supported
H2: IQ→PU	0.329	5.476*	Supported
H3: SQ→PU	0.22	4.72***	Supported
H4: PU→AT	0.20	4.30***	Supported
H5: TC→TTF	0.107	2.229	Not Supported
H6: TAC→TTF	0.19	4.07***	Supported
H7: TTF→BI	-0.32	-6.45***	Supported
H8: AT→BI	0.18	3.61***	Supported
H9: TTF→AT	4.25	3.74***	Supported

Note: *** p<0.001, * p<0.05
Source: Created by the author

H1: The standardized path coefficient between System Quality and Perceived Usefulness (0.25, t-value = 4.93***) suggests a significant positive relationship, supporting H1.

H2: The standardized path coefficient between Information Quality and Perceived Usefulness (0.22, t-value =4.72***) suggests a significant positive relationship, supporting H2.

H3: Similarly, the standardized path coefficient between Service Quality and Perceived Usefulness (0.20, t-value =4.30***) suggests a significant positive relationship, supporting H3.

H4: The significant relationship between Perceived Usefulness and Attitude (0.19, t-value =4.07***) supports H4.

H5: The significant relationship between Technology Characteristics and Task-Technology fit (-0.32, t-value = -6.45***) supports H5.

H6: Task Characteristics also significantly relate to Task-Technology fit (standardized path coefficient: 0.18, t-value = 3.61***), supporting H6.

H7: Task-Technology fit significantly influences Behavior Intention (standardized path coefficient: 4.25, t-value = 3.74***), supporting H7.

H8: Attitude significantly predicts Behavior Intention (standardized path coefficient: 0.22, t-value = 6.78***),

supporting H8.

H9: Lastly, Task-Technology fit significantly affects Attitude (standardized path coefficient: 0.11, t-value = 2.19*), supporting H9.

5. Conclusion and Recommendation

5.1 Conclusion

Building upon the findings of these studies, this research not only considers the impact of system quality, information quality, and service quality on perceived usefulness but also discusses the influence of technological characteristics and content characteristics fit on attitude. These influences ultimately have significant implications for users' attitudes and behavioral intentions.

Based on the analysis of adult English learners in Chengdu, China, focusing on gen Y users, researchers have concluded that among the five independent variables related to English learning software and three mediating variables, all of the independent variables significantly impact student satisfaction. Specifically, System Quality influences the mediating variables more than the other two. The three mediating variables positively and significantly impact both satisfaction and intention. Perceived usefulness, task-technology fit, and attitude all positively influence behavioral intention. Therefore, to enhance users' intention to choose English learning apps, software developers must focus on improving system quality, content, and technological compatibility.

5.2 Recommendation

Based on the results of the analysis, all the dimensions influence how adult learners choose English learning apps. Therefore, this study can provide the following recommendations to users:

Firstly, software system quality is crucial. The system quality of an app determines its stability and smoothness of usage, which are essential experiences during usage. Although the correlation between content and service quality was insignificant in this study, these factors also manifest through the system's overall quality. Hence, enhancing the overall system quality is essential.

The second recommendation is the alignment of content and technology. The alignment of learning content and technology is crucial in the diverse landscape of English learning apps. It determines users' experiences and satisfaction. An important design consideration is whether the content can be well presented through technology and help English learners while meeting personalized needs.

The final recommendation is to prioritize maintaining user satisfaction based on perceived usefulness and technological alignment of content. Continuously updating content and service feedback is beneficial for achieving this goal.

5.3 Limitation and Further Study

This study has several limitations. Firstly, the use of nonprobability sampling techniques, including quota and convenience sampling, may limit the generalizability of the findings, as the sample may not fully represent the broader population of Gen Y in Chengdu, China. Secondly, the data collection method, relying on self-administered questionnaires, could introduce response biases, such as social desirability or inaccurate self-reporting. Additionally, the focus on users of only the top three English word-learning applications in China may overlook insights from users of other potentially significant applications. Furthermore, while the study employs confirmatory factor analysis and structural equation modeling to analyze data, the cross-sectional nature of the research design does not allow for the assessment of changes over time or causal relationships. Lastly, the study's conceptual framework did not find technology characteristics to significantly impact task-technology fit, suggesting that additional variables or alternative models may be necessary to fully capture the dynamics of behavioral intention in this context.

References

Abbas, T. (2016). Social factors affecting students' acceptance of e-learning environments in developing and developed countries a structural equation modeling approach. *Journal of Hospitality and Tourism Technology, 7*(2), 200-212. https://doi.org/10.1108/jhtt-11-2015-0042

Ahn, T., Ryn, S., & Han, I. (2007). The impact of web quality and playfulness on user acceptance of online retailing. *Information & Management, 44*(3), 263-275. https://doi.org/10.1016/j.im.2006.12.008

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

Alavi, M., & Leidner, D. E. (2001). Technology mediated learning: a call for greater depth and breadth of research. *Information Systems Research, 12*(1), 1-10. https://doi.org/10.1287/isre.12.1.1.9720

Arbuckle, J. L. (1995). *AMOS for Windows Analysis of Moment Structures. Version 3.5.* Small Waters Corp.

Babbie, E. R. (1990). Survey research methods. Massachusetts: Cengage Learning Press. Bandura, A. (1982). Self-efficacy mechanism in human agency, *American Psychologist, 37*(2),122-47.

Bagchi, D., & Peeter, J. K. (2010). An assessment of customers' e-service quality perception. *International Journal of Information Management, 30*(6), 481-492. https://doi.org/10.1016/j.ijinfomgt.2010.03.005

Bagozzi, R., & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Sciences, 16*, 74-94. http://dx.doi.org/10.1007/BF02723327

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation confirmation mode. *MIS Quarterly, 25*(3), 351-370. https://doi.org/10.2307/3250921

Brodie, R. J., Whittome, J. R., & Brush, G. J. (2009). Investigating the service brand: a customer value perspective. *Journal of Business Research, 62*(3), 345-355.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). The Guilford Press.

Carlos, T., & Tiago, O. (2016). Performance impact of mobile banking: using the task-technology fit (TTF) approach. *International Journal of Bank Marketing, 34*(4), 434-457.

Cheng, Y. M. (2012). The effects of information systems quality on nurses' acceptance of the electronic learning system. *Journal of Nursing Research, 20*(1), 19-30. https://doi.org/10.1097/jnr.0b013e31824777aa

Correa, A. S., de Almeida, V. L., & Lope, B. M. V. (2017). The Influence of Non-Steroidal Anti-Inflammatory Drugs and Paracetamol Used for Pain Control of Orthodontic Tooth Movement: A Systematic Review. *Anais da Academia Brasileira de Ciências, 89*, 2851-2863. https://doi.org/10.1590/0001-3765201720160865

Cronin, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of Retailing, 76*(2), 193-218. https://doi.org/10.1016/s0022-4359(00)00028-2

D'Ambra, J., & Wilson, C. S. (2004). Explaining perceived performance of the World Wide Web: Uncertainty and the task-technology fit model. *Internet Research, 14*(4), 294-310. https://doi.org/10.1108/10662240410555315

D'Ambra, J., Wilson, C. S., & Akter, S. (2013). Application of the task-technology fit model to structure and evaluate the adoption of E-books by academics. *Journal of the American Society for Information Science and Technology, 64*(1), 48-64.

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

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal Man-Machine Studies, 38*(3), 475-487. https://doi.org/10.1006/imms.1993.1022

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

DeLone, W., & McLean, E. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems, 19*(4), 9-30.

DeLone, W. H., & McLean, E. R. (1992). Information system success: the quest for the dependent variable. *Information System Research, 3*(1), 60-95. https://doi.org/10.1287/isre.3.1.60

Feng, Z., & Jia, X. (2024). Education in China: An Introduction. In L. Niancai, F. Zhuolin & W. Qi (Eds.), *Education in China and the World* (pp. 1-45). Springer. https://doi.org/10.1007/978-981-99-5861-0_1

Fengyu, Z. (2023). The Impact of Vocabulary Learning Methods on Students' Vocabulary Application Skills. *English Language Teaching and Linguistics Studies, 5*(4), 206. https://doi.org/10.22158/eltls.v5n4p206

Fishbein, M. (1967). A behavior theory approach to the relations between beliefs about an object and the attitude toward the object. In M. Fishbein (Ed.), *Readings in attitude theory and measurement* (pp. 389-400). John Wiley & Sons.

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research, 18*, 382-388. http://dx.doi.org/10.2307/3150980

Goodhue, D., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*, 213-236. http://dx.doi.org/10.2307/249689

Grace, D., & O'Cass, A. (2005). Service Branding: Consumer Verdicts on Service Brands. *Journal of Retailing and Consumer Services, 12*, 125-139. https://doi.org/10.1016/j.jretconser.2004.05.002

Gu, L., & Wang, J. (2009). A study of exploring the 'big five' and task technology fit in web-based decision support systems. *Issues in Information Systems, 10*(2), 210-217.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning, 46*, 1-12. https://doi.org/10.1016/j.lrp.2013.01.001

Hox, J., & Bechger, T. (1999). An Introduction to Structural Equation Modeling. *Family Science Review, 11*(4), 1-10.

Hsiao, C., Chang, L. J., & Tang, K. (2015). Exploring the Influential Factors in Continuance Usage of Mobile Social Apps: Satisfaction, Habit, and Customer Value Perspectives. *Telematics and Informatics, 33*, 342-355. https://doi.org/10.1016/j.tele.2015.08.014

Hsu, C., Yu, C., & Wu, C. (2014). Exploring the continuance intention of social networking websites: empirical research. *Information Systems and e-Business Management, 12*(2), 139-163.

Hu, J., & Zhang, Y. (2016). Chinese students' behavior intention to use mobile library apps and effects of education level and discipline. *Library Hi Tech, 34*(4), 639-656. https://doi.org/10.1108/lht-06-2016-006

Hu, L. T., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. *Structural Equation Modeling, 6*, 1-55. http://dx.doi.org/10.1080/10705519909540118

Johnson, R. D., Gueutal, H., & Falbe, C. M. (2009). Technology, trainees, metacognitive activity, and E-learning effectiveness. *Journal of Managerial Psychology, 24*(6), 545-566. https://doi.org/10.1108/02683940910974125

Ju, X. T., Kou, C. L., & Christie, P. (2007). Changes in the Soil Environment from Excessive Application of Fertilizers and Manures to Two Contrasting Intensive Cropping Systems on the North China Plain. *Environmental Pollution, 145,* 497-506.

Jung, T., Chung, N., & Leue, M. C. (2015). The determinants of recommendations to use augmented reality technologies: the case of a Korean theme park. *Tourism Management, 49*(1), 75-86. https://doi.org/10.1016/j.tourman.2015.02.013

Karahanna, E., & Straub, D. W. (1999). The psychological origins of perceived usefulness and ease-of-use. *Information and Management, 35*(4), 237-250. https://doi.org/10.1016/s0378-7206(98)00096-2

Kervin, J. E. (1992). *Methods for Business Research* (1st ed.). Harper Collins Publishers.

Khan, I. U., Hameed, Z., Yu, Y., Islam, T., Sheikh, Z., & Khan, S. U. (2017). Predicting the acceptance of MOOCs in a developing country: application of task-technology fit model, social motivation, and self-determination theory. *Telematics and Informatics, 35*(4), 964-978.

Lin, F. Y., Fofanah, S. S., & Liang, D. (2011). Assessing citizen adoption of e-government initiatives in Gambia: a validation of the technology acceptance model in information systems success. *Government Information Quarterly, 28*(2), 271-279. https://doi.org/10.1016/j.giq.2010.09.004

Lin, J. S. C., & Hsieh, P. L. (2011). Assessing the self-service technology encounters: development and validation of SSTQUAL scale. *Journal of Retailing, 87(*2), 194-206. https://doi.org/10.1016/j.jretai.2011.02.006

Lin, W. S., & Wang, C. H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: a contingency framework based on models of information system success and task-technology fit. *Computers & Education, 58*(1), 88-99. https://doi.org/10.1016/j.compedu.2011.07.008

Lu, H. P., & Yang, Y. W. (2014). Toward an understanding of the behavioral intention to use a social networking site: an extension of task-technology fit to social-technology fit. *Computers in Human Behavior, 34,* 323-332. https://doi.org/10.1016/j.chb.2013.10.020

Martin, N. M. (2002). Task-technology fit: brick and mortar beware? *Journal of Academy of Business, 1*(2), 278-281.

Moore, A. (2012). *Teaching and Learning Pedagogy, Curriculum and Culture* (2nd ed.). Routledge.

Mukul, E., & Büyüközkan, G. (2023). Digital transformation in education: A systematic review of education 4.0. *Technological Forecasting and Social Change, 194,* 122664. https://doi.org/10.1016/j.techfore.2023.122664.

Noh, M. J., & Lee, K. T. (2016). An analysis of the relationship between quality and user acceptance in smartphone apps. *Information Systems and e-Business Management, 14*(2), 273-291.

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

O'Cass, A., & French, T. (2003). Web retailing adoption: exploring the nature of internet users web retailing behavior. *Journal of Retailing and Consumer Services, 10*(2), 81-94.

Padgett, D., & Allen, D. (1997). Communicating Experiences: A Narrative Approach to Creating Service Brand Image. *Journal of Advertising, 26*(4), 49-62. https://doi.org/10.1080/00913367.1997.10673535

Peter, P. J., & Olson, J. C. (2010). *Consumer Behavior and Marketing Strategy* (1st ed.). McGraw-Hill Irwin.

Petter, S., & McLean, E. R. (2009). A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level. *Information & Management, 46,* 159-166. https://doi.org/10.1016/j.im.2008.12.006

Polonsky, M. J., & Waller, D. S. (2015). *Designing and Managing a Research Project: A Business Student's Guid*e. SAGE Publications.

Ramlall, I. (2016). Applied Structural Equation Modelling for Researchers and Practitioners: Using R and Stata for Behavioural Research. *Research Gate, 1*(2), 1-10. https://doi.org/10.1108/9781786358820

Roca, J. C., Chiu, C. M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: an extension of the technology acceptance model. *International Journal of Human-Computer Studies, 64*(8), 683-696. https://doi.org/10.1016/j.ijhcs.2006.01.003

Roni, M., Margaret, M., & Julia, M. (2020). Conducting Quantitative Research in Education, *Research Gate, 10,* 1-10.

Rutberg, S., & Bouikidis, C. (2018). Exploring the Evidence: Quantitative and Qualitative Research. *Nephrology Nursing Journal, 45*(2), 1-10.

Saeed, K. A., Hwang, Y., & Mun, Y. Y. (2003). Toward an integrative framework for online consumer behavior research: a meta-analysis approach. *Journal of End User Computing, 15*(4), 1-26. https://doi.org/10.4018/joeuc.2003100101

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27-50). Nova Science Publishers.

Solimun, A., & Fernandes, A. (2017). Investigation of instrument validity: Investigate the consistency between criterion and unidimensional in instrument validity (case study in management research). *International Journal of Law and Management, 59*(6), 1203-1210. https://doi.org/10.1108/ijlma-09-2016-0076

Stangor, C., & Walinga, J. (2014). *Introduction to Psychology* (1st ed.). Psychology.

Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research, 11,* 342-365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Wang, Q., & Li, S. (2019). The relationship between task motivation and L2 motivation: An empirical study. In Z. Wen & M. Ahmadian (Eds.), *Researching L2 task performance and pedagogy: In honour of Peter Skehan* (pp. 67-92). John Benjamins.

Wang, Y. S., Li, C. R., Yeh, C. H., Cheng, S. T., Chiou, C. C., Tang, Y. C., & Tang, T. I. (2016). A conceptual model for assessing blog-based learning system success in the context of business education. *The International Journal of Management Education, 14*(3), 379-387. https://doi.org/10.1016/j.ijme.2016.09.002

Yen, D. C., Wu, C. S., Cheng, F. F., & Huang, Y.-W. (2010). Determinants of users' intention to adopt wireless technology: an empirical study by integrating TTF with TAM. *Computers in Human Behavior, 26*(5), 906-915. https://doi.org/10.1016/j.chb.2010.02.005

Yu, T. K., & Yu, T. Y. (2010). Modelling the factors that affect individuals' utilization of online learning systems: an empirical study combining the task technology fit model with the theory of planned behavior. *British Journal of Educational Technology, 41*(6), 1003-1017. https://doi.org/10.1111/j.1467-8535.2010.01054.x