pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
https://assumptionjournal.au.edu/index.php/Scholar

Exploring the Impact of Mobile Apps on English Vocabulary Learning Intentions Among Gen X Adults Learners in Chengdu, China

Zhenzhen Wang*

Received: June 5, 2024. Revised: July 29, 2024. Accepted: Frebuary 18, 2025.

Abstract

Purpose: The purpose of this study is to investigate the impact of Gen X users in Chengdu, China, on their English learn ing behavior intention by using the most popular English word learning Applications in China among system quality, info rmation quality, service quality, perceived usefulness, attitude, technology characteristics, task characteristics, task-technolo gy fit and behavior intention. **Research design, data, and methodology:** The researchers conducted the study based on q uantitative research methods. The data were collected from 500 Gen X living in Chengdu who have used the top three E nglish word-learning Applications in China to learn English. This study focuses on confirmatory factor analysis and struct ural equation modeling as statistical tools to test data, model accuracy, and key variables' influence. **Results:** The results show that behavioral intention has the most influence on the use attitude. In addition, system quality, information quality, service quality, attitude, technical characteristics, task characteristics, and personal perception are statistically significant an d impact the behavioral intention. Nevertheless, technology characteristics has no significant impact on task-technology fit. **Conclusions:** Developers and educators can create more engaging, effective, and user-friendly English word learning appl ications that cater to the needs of Gen X users in Chengdu, China, which does not only enhance user satisfaction but als o improve learning outcomes and foster a more positive attitude towards using mobile applications for language learning.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The widespread use of smartphones has become an important phenomenon that has changed the interaction between people. Alexander Graham Bell, the father of the telephone was the first to invent a new technology to replace the telegraph. At present, the mobile phone revolution has gone through three generations. The first phase of mobile phones is designed for organizational purposes. However, the first smartphone was made public during this period - Simon of IBM in 1993. The second generation of mobile phones began with the launch of the iPhone in 2007, and Google launched the Android operating system at the end of 2007. After 2008, the third generation of smartphones began to rise. Smartphones are widely used all over the world to provide customers with a variety of choices. Customers have obtained sufficient direct revenue through highly competitive advantages in the market (Sarwar & Soomro, 2013).

With the extensive expansion of the smartphone market. Its core function is to make phone calls, send text messages, and focus on the way of life and learning. Smartphone manufacturers integrate powerful technologies into a device called a handheld computer (Pan et al., 2015). With the continuous iterative innovation of science and technology, customers more easily accept technological innovation. Smartphones and tablets are no longer just ordinary communication devices but Internet access, entertainment, information, and access to educational resources. With the continuous growth of the

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

Internet, mobile platforms quickly replace desktops and laptops and become the best choice for end users to access information (Ventura, 2019).

This study holds particular significance as it examines the impact of English mobile learning software, a technology widely used in China, on adults' English learning behavior intention.

Behavioral intent, a key concept in this study, is influenced by several factors, including compatibility, perceived usability, perceived cost, perceived risk, perceived usefulness, and personal innovation (Kazemi et al., 2013; Lewis, 2010). Understanding these factors is crucial in determining the actual use of mobile learning software.

Kim et al. (2008) refers to the frequency and usage period. Straub (2009) states that actual use could be determined as a will to accept or reject the technology. In addition, behavioral intention is described as the possibility of specific action by specific individuals. Many experiments proved that behavioral intent had an important effect on actual use. For example, the factors that influence the use of the accountant by the enterprise. This study examines the hypothesis that there is a causal relationship between behavioral intent and actual use. The study on online banking in Taiwan investigated how individual beliefs, attitudes, subjective norms, and perceived behavior control dominate action intentions. Two variables in the original technology acceptance model (TAM) proposed by Davis (1989) played an important role in the innovation acceptance model, i.e., ease of use and perceptual usefulness (PU). Based on TAM, perceived usefulness has had the greatest impact on information technology (Davis, 1989). PU was described as a range of thought that using certain innovations would improve his work (Davis, 1989). PU is also interpreted as a range where users are expected to interact online to improve their work performance (Barry & Jan, 2018). Many studies demonstrated that perceived usefulness positively and significantly affected behavioral intentions (Davis et al., 1992).

Venkatesh (2000) uses usability to predict the intention to act using Venkatesh's new information technology, supported by another research. Eze (2011) stated that the consciousness of use significantly correlated with the intention of action. Ease of use refers to how much people and users understand the effort. It is easy to adopt the new technology (Barry & Jan, 2018). Venkatesh and Davis (2000) found that ease of use responded to behavioral intentions and perceived usefulness. In addition, reliability and tastes in online shopping were investigated, and perceived usefulness positively correlated with perceptual usefulness.

In addition, personal innovation refers to the tendency to take on personal risks (Agarwal & Prasad, 1998). Based on Fagan et al. (2012), this study aims to examine students' ease of use, the usefulness of innovative technologies, and personal innovation. Through extended technology acceptance and the application of unified theory (UTAUT 2) and other variables (self), determinants of smartphone application, self-efficacy, and personal innovation ability were investigated. As a result, it was shown that individual innovation ability was the most important determinant of the action intention.

2. Literature Review

2.1 System Quality

System quality involves multiple aspects, including system querying, file transfer, response speed, and hardware and software access speeds (DeLone & McLean, 1992). Users are more likely to trust the system if they perceive the network quality as good and secure. System quality also encompasses interactivity, navigation, access methods, hyperlinks, and the innovative and entertainment experience (Deb & Agrawal, 2017; Lin & Hsieh, 2011; O'Cass & Carlson, 2012).

Lin et al. (2011) believes that if users find the system's quick query function responsive, they will perceive the system as useful. It suggests that ease of use is related to aspects of system quality such as support, reliability, security, and accessibility. Spreng and MacKoy (1996) Argue that the perception of system quality is more important than satisfaction and value.

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

2.2 Information Quality

Information quality means information output correctness and satisfaction and provides information for learning (Ahn et al., 2007; Roca et al., 2006). Online and application learning information is the latest, comprehensive, accurate, detailed, and classified (Halonen et al., 2009). The quality of information is an important aspect of determining whether the user is satisfied and used (Aparicio et al., 2017).

In academic settings, effectively managing adult students in universities and junior colleges involves improving online and mobile learning systems. Providing support and sharing positive online learning experiences can increase student confidence (Cho et al., 2011).

Davis (1989) identified the critical role of 'perceived ease of use' in information systems, suggesting that technological improvements can simplify system use, thus lessening user stress. Equally important, Cheng (2012) observed that quality course materials are instrumental in enhancing both the perceived usefulness and ease of use of these systems.

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

2.3 Service Quality

Service quality usually includes the following aspects: tangibility, reliability, acceptability, assurance, communication, and interactivity (Lin et al., 2011). At the same time, service quality also impacts satisfaction (Oktal et al., 2016) and practical effect (Roca et al., 2006). Therefore, connectivity services contribute to "the moment of truth" and give meaning to it (Cho & Menor, 2012; Davis et al., 1992)

In university mobile learning, Al-Mushasha and Hassan (2009) introduced a model to evaluate service quality and its impact on learner satisfaction and future behavioral intentions. This model emphasizes the importance of the reliability and usability of mobile software interfaces and the significance of bidirectional information in enhancing the mobile learning experience.

Furthermore, Abbas (2016) delved into the concept of behavioral intentions within the context of e-learning, providing valuable insights into the factors that influence user engagement with online learning platforms. His findings have significant practical implications for educators and professionals in the field.

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

2.4 Perceived Usefulness

In academic analysis, perceived usefulness is a key determinant of user behavior intention. This study defines the perceived usefulness of mobile software in education as the users' belief in its ability to enhance learning efficiency. Furthermore, user attitudes toward system usage are influenced by perceived usefulness, aligning with the theory of planned behavior (Lee, 2010).

Davis (1989), through the Technology Acceptance Model (TAM), emphasized that perceived usefulness is about users' desire to improve efficiency in accessing specific information. Cheng (2012) elaborated that, within this model, external factors influence user behavior intentions toward new products through perceived usefulness and ease of use.

H4: Perceived usefulness has a significant impact on attitude.

2.5 Technology Characteristics

In the field of network application software learning, the technical characteristics, notably the reliability of technology, play a pivotal role. Richard et al. (2009) stress that the reliability of technology, its capacity to transmit accurate information, and its adaptability to user needs, significantly elevate users' expectations of technology. This reliability is particularly impactful in software applications, as it supports both software and hardware used in the learning process, thereby meeting the practical needs of users. Goodhue and Thompson (1995) highlight that technical characteristics include instrumental elements like service expenditures and the hardware and software required to execute specific tasks. Roni et al. (2020) points out, these characteristics directly influence the outcomes of technology usage.

H5: Technology characteristics has a significant impact on task-technology fit.

2.6 Task Characteristics

In application systems, task characteristics such as task diversity and feedback play a motivational role, while social identity is more concerned with group connections and self-categorization in social contexts. These factors are largely independent, as highlighted by Lin et al. (2011), who note that individuals may appreciate their tasks but not necessarily the organization they work for due to managerial constraints. Consumer attitude towards online shopping refers to the psychological state of individuals when making purchases over the Internet. In marketing, attitude is defined as an individual's overall evaluation of a concept (Peter & Olson, 2010). Peter and Olson (2010) define it, consumer attitude is a composite of beliefs, feelings, and behavioral intentions that individuals hold towards a specific object within the marketing context.

Task characteristics could also affect performance and result in technical characteristics, which may affect usage results (Goodhue & Thompson, 1995).

Although many other factors are related to task characteristics, such as task autonomy, diversity, and timely feedback, task variability and importance are more worth studying (Hackman & Oldham, 1980).

H6: Task characteristics has a significant impact on task-technology fit.

2.7 Task-Technology Fit

Task-Technology Fit (TTF) assesses how well technology, with its network functionalities like hardware and software, aligns with task requirements and individual skills. This alignment plays a crucial role in network usability, essentially determining the effectiveness of technology in aiding task completion (D'Ambra & Wilson, 2004). TTF's significance lies in its impact on information systems' practical performance and efficiency, as it bridges the gap between technology features and task characteristics (Goodhue & Thompson, 1995).

Task-Technology Fit (TTF) is a key framework used to evaluate various information technologies, including internet usage (D'Ambra & Wilson, 2004), educational computing (Teo, 2009), mobile internet learning systems (Lin & Wang, 2012), and social networking sites (Lu & Yang, 2014). It is also applied in assessing user preferences in mobile services, learning (Liu et al., 2010a, 2010b), finance (Zhou et al., 2010), and commerce.

H7: Task-technology fit has a significant impact on behavior intention.

2.8 Attitude

Generally, attitude consists of three parts: emotion, behavior, and cognition. Olson and Kendrick (2008) proposed that satisfaction is representative of attitude. Emotion is a kind of emotional feedback that involves the user's feelings and emotions for an object (Breckler, 1984). According to the theory of planned behavior, the intention of writing is influenced by the attitude from behavior and social norms and the perceived behavior control (Ajzen, 1991). Fishbein and Ajzen (1975) believed that the attitude to things would impact the realization of behavior and intention. High satisfaction with computer systems was related to the positive attitude of users (Igersheim, 1976; Lucas, 1978).

H8: Attitude has a significant impact on behavior intention.

2.9 Behavior Intention

Behavioral intention refers to the result-oriented decision-making individuals consciously make (Ajzen, 1991). Due to the strong relationship between the utility of technology and the use of behavioral intent, behavior tended to use more techniques (Teo, 2009). The intention to use technological innovations is crucial in technology studies, as identified by Venkatesh et al. (2003), with various studies linking behavioral intentions to technology usage across different contexts (Park, 2009)

3. Research Methods and Materials

3.1 Research Framework

The study shows that the conceptual framework uses five research models. This study also describes the relationship between the research and conceptual frameworks. This research framework is based on an existing theoretical model so researchers can help develop conceptual and previous research frameworks. The previous empirical research is shown in Figure 1. This study aims to investigate the user's perceived usefulness and attitude under system quality, information quality, and service quality. This conceptual framework proposes five variables that will be used in this study. These theories allow one to study behavioral intent, usability, and attitude. For the previous research framework, Hu and Zhang (2016) presided over the first research framework. It uses D & M and TAM. Moreover, it includes the effects of system, information, and service quality on perceived usefulness and attitudes.

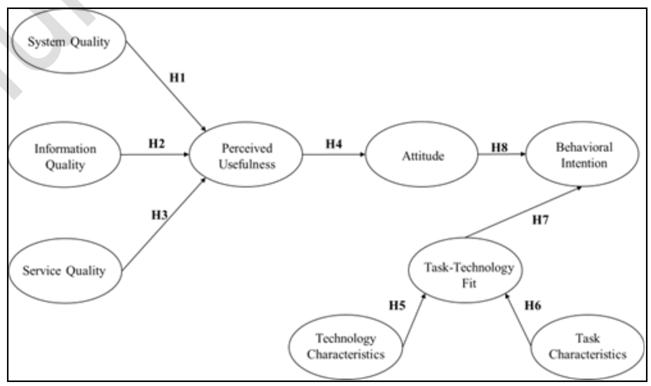

Figure 1: Conceptual Framework

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

This study adopts a quantitative research method. Quantitative research is a method to establish and test theory (Roni et al., 2020). DeCuir-Gunby and Schutz (2017) also classified two traditional research methods. A new research framework is presented based on the previous research. Quantitative research is defined as a method involving digital measurement forms (Clark-Carter, 2010). Hair et al. (2006) defined quantification as a measurement considering numbers directly used to represent the characteristics of elements. In addition, Cooper and Schindler (2001) pointed out that quantitative research is the way to measure consumer behavior, views, knowledge, and attitudes. It is also a way to answer the frequency, quantity, amount, time, and HR-related questions. In addition, the quantitative method is considered coding and classification data for statistical analysis.

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 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 line with Nunnally and Bernstein's (1994) guidelines. Following data collection, confirmatory factor analysis and structural equation modeling were used to analyze data accuracy and the impact of key variables.

3.3 Population and Sample Size

The population is the users age range of personal mobile application users, 41 to 55 (Generation X, born in 1966 to 1980). The individual must have experience in using mobile devices. The application users must use China's top three mobile English learning software. This study focuses on their experience-based views. The sample size is 500 participants.

3.4 Sampling Technique

The researchers of this study adopted purposive sampling to target the population in the age range of personal mobile application users, 41 to 55 (Generation X, born in 1966 to 1980). The individual must have experience in using mobile devices. The application users must use China's top three mobile English learning software. The quota sampling is proportionate per Table 1. The convenience sampling is conducted to faculty members in three selected universities.

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 (48.1%) and female respondents (51.9%). 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 41-50 years old, accounting for 52.4%, while respondents 51-55 years old account for 47.6%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	217	48.1%
	Female	234	51.9%
Age	41-50 years old	262	52.4%
	51-55 years old	238	47.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is frequently utilized to examine the variables proposed by researchers in hypothetical models and the relationships between these variables (Brown & Moore, 2012). Confirmatory factor analysis (CFA) focuses on observing the relationships between variables or indicator variables. It can test the fit between the hypothesized factor structure model proposed by researchers and the actual observed data (Donaldson, 1983). Suppose the fit of the measurement model could be better with the data. Some observed variables may be unreliable in that case, hindering researchers from proceeding with path model analysis. Therefore, it is recommended that the higher the fit between the model and the measurement model, the better the fit of the model, leading to better results in the path analysis stage.

Table 3 shows the results of the analysis. According to the calculation of JAMOVI, all variables are above 0.7, so it is acceptable in Cronbach's alpha test. The value is greater than 0.9, reaching "excellent." Some variables, such as more than 0.8, reach "very good."

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	0.790-0.830	0.850	0.660
Information Quality (IQ)	Ahn et al. (2007)	4	0.911	0.740-0.980	0.920	0.800
Service Quality (SQ)	Lin et al. (2011)	4	0.927	0.850-1.000	0.970	0.890
Perceived Usefulness (PU)	Venkatesh (2000)	4	0.941	0.950-0.970	0.980	0.910
Technical Characteristics (TC)	Goodhue and Thompson (1995)	3	0.949	0.910-0.970	0.950	0.870
Task Characteristics (TAC)	Peter and Olson (2010)	2	0.874	0.850-0.890	0.860	0.760
Task-Technology Fit (TTF)	D'Ambra and Wilson (2004)	3	0.910	0.750-0.790	0.820	0.600
Attitude (AT)	Davis (1989)	4	0.909	0.960-0.990	0.990	0.960
Behavioral Intention (BI)	Ajzen (1991)	3	0.925	0.830-0.890	0.900	0.760

Hair et al. (2010) confirmed that the value of goodness of fit must be less than 3. Bagozzi and Yi (1988) stipulated that the GFI value must be equal to or greater than 0.9. According to Sica and Ghisi (2007), the AGFI value must be equal to or greater than 0.85. For CFI, Hu and Bentler (1999) suggested that the value be equal to or greater than 0.95. For NFI, Arbuckle (1995) assumes that the value should be equal to or greater than 0.95. Hu and Bentler (1999) say the RMSEA value should be less than 0.08.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3 (Hair et al., 2010)	1.745
GFI	>0.90 (Bagozzi & Yi, 1988)	0.918
AGFI	>0.85 (Sica & Ghisi, 2007)	0.896
NFI	> 0.95 (Arbuckle, 1995)	0.963
CFI	>0.95 (Hu & Bentler, 1999)	0.984
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.041
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

Discriminant validity refers to the distinctiveness of measurements across different concepts. Discriminant validity is satisfied when the square root of the average variance extracted (AVE) for any given construct is greater than the correlation coefficients associated with other constructs (Fornell & Larcker, 1981). Hair et al. (2006) state that discriminant validity is supported when the AVE exceeds the squared inter-construct correlations. According to Fornell and Larcker (1981), the discriminant validity testing wase valuated by calculating the square root of each AVE.

Table 5: Discriminant Validity

	SSQ	IQ	SQ	PU	TC	TAC	TTF	AT	BI
SSQ	**0.66**								
IQ	0.40	**0.80**							
SQ	0.34	0.28	**0.89**						
PU	0.31	0.26	0.27	**0.91**					
TC	0.30	0.13	0.00	0.24	**0.87**				
TAC	0.35	0.16	0.26	0.67	0.21	**0.76**			
TTF	0.12	0.12	0.20	0.11	-0.27	0.19	**0.60**		
AT	0.34	0.30	0.34	0.27	0.07	0.19	0.20	**0.96**	
BI	0.49	0.42	0.39	0.60	0.27	0.62	0.35	0.45	**0.76**

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

4.3 Structural Equation Model (SEM)

The SEM (Structural Equation Modeling) is a theory multivariate method that produces two models, i.e., CFA (Confirmatory Factor Analysis) and SEM (Structural Equation Modeling) or path analysis (Ho, 2014). Ullman (2001) mentioned that SEM was a statistical technique combining actor and regression analyses (multivariate models). Furthermore, SEM and path analysis allowed the researcher to test the relationship between dependent and independent variables simultaneously (Byrne, 2010; Ho, 2014).

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3 (Hair et al., 2010)	1.800
GFI	>0.90 (Bagozzi & Yi, 1988)	0.910
AGFI	>0.85 (Sica & Ghisi, 2007)	0.900
NFI	> 0.95 (Arbuckle, 1995)	0.980
CFI	>0.95 (Hu & Bentler, 1999)	0.980
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.040
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

In this path, the researcher will discuss the path analysis result of the SEM, which also shows the hypothesis testing result of a proposed model. The results used the regression and standardized regression weights to consider whether the proposed hypotheses were supported. the summary table of the result of the hypothesis testing is presented below:

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SSQ→PU	0.24	4.230***	Supported
H2: IQ→PU	0.329	5.476*	Supported
H3: SQ→PU	0.11	2.110*	Supported
H4: PU→AT	0.15	3.110**	Supported
H5: TC→TTF	0.107	2.229	Not Supported
H6: TAC→TTF	0.23	5.100***	Supported
H7: TTF→BI	-0.39	-7.900***	Supported
H8: AT→BI	0.28	6.000***	Supported
H9: TTF→AT	2.83	5.600***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

According to the analysis results in Table 7, these nine hypotheses are supported. Therefore, researchers can summarize as follows:

H1: The standardized path coefficient between System Quality and Perceived Usefulness (0.24, t-value = 4.23***) suggests a significant positive relationship, supporting H1.

H2: The standardized path coefficient between Information Quality and Perceived Usefulness (0.11, t-value = 2.11*) suggests a significant positive relationship, supporting H2.

H3: Similarly, the standardized path coefficient between Service Quality and Perceived Usefulness (0.15, t-value =3.11**) suggests a significant positive relationship, supporting H3.

H4: The positive relationship between Perceived Usefulness and Attitude (0.23, t-value = 5.10***) supports H4.

H5: The positive relationship between Technology Characteristics and Task-Technology fit (-0.39, t-value =-7.90***) supports H5.

H6: Task Characteristics also significantly relate to Task-Technology fit (standardized path coefficient: 0.28, t-value = 6.00***), supporting H6.

H7: Task-Technology fit significantly influences Behavior Intention (standardized path coefficient: 2.83, t-value = 5.60***), supporting H7.

H8: Attitude significantly predicts Behavior Intention (standardized path coefficient: 0.23, t-value = 6.70***), supporting H8.

H9: Lastly, Task-Technology fit significantly affects Attitude (standardized path coefficient: 0.16, t-value = 3.20**), supporting H9.

5. Conclusion and Recommendation

5.1 Conclusion

The findings of this study provide important insights into the factors influencing Gen X users in Chengdu, China, regarding their intention to learn English using popular English word learning applications. The study's results highlight several key points that warrant further discussion.

First, the significant influence of behavioral intention on the attitude towards using mobile applications for English word learning underscores the importance of understanding user motivation and commitment. This finding suggests that efforts to enhance behavioral intention, such as through personalized learning experiences and motivational features, can positively impact users' attitudes and increase their engagement with the applications.

System quality, information quality, and service quality were all found to significantly impact behavioral intention. This highlights the critical role of these quality dimensions in shaping user perceptions and intentions. High system quality ensures that the application is reliable and easy to use, information quality ensures that the content is relevant and accurate, and service quality ensures that users receive adequate support and assistance. Developers and providers of English learning applications should focus on these areas to enhance user satisfaction and encourage continued use.

The significant impact of attitude on behavioral intention suggests that users' positive attitudes towards the applications are crucial for their intention to use them. This finding aligns with the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use influence users' attitudes towards technology, subsequently affecting their behavioral intention. Efforts to improve user attitudes, such as through user-friendly interfaces and demonstrating the benefits of the application, can therefore enhance behavioral intention.

Interestingly, while technology characteristics were found to significantly impact behavioral intention, they did not have a significant impact on task-technology fit. This discrepancy indicates that while users may appreciate the technological features of the applications, these features alone do not necessarily align with their specific learning tasks. This suggests a need for better integration of technological features with educational content to ensure that the applications effectively support users' learning objectives.

The findings also highlight the importance of task characteristics and personal perception in influencing behavioral intention. Task characteristics refer to the specific demands of the learning task, and their alignment with the application's features can enhance user satisfaction and intention to use the application. Personal perception, including factors such as self-efficacy and perceived control, also plays a significant role in shaping behavioral intention. This suggests that applications should be designed to support users' individual needs and perceptions, providing tailored experiences that boost confidence and motivation.

Overall, this study provides valuable insights into the factors influencing Gen X users' behavioral intention to learn

English using mobile applications in Chengdu, China. By understanding these factors, developers and educators can create more effective and engaging learning experiences that cater to the specific needs and preferences of this demographic. Future research could further explore the interplay between these factors and investigate additional variables that may influence technology adoption in educational contexts.

5.2 Recommendation

Based on the findings of this study, several key recommendations can be made to enhance the effectiveness of English word learning applications for Gen X users in Chengdu, China. The implementation of these recommendations can significantly improve user engagement, satisfaction, and learning outcomes.

Firstly, enhancing system, information, and service quality is paramount. System quality is a critical factor that influences user experience. Ensuring that the application is reliable, easy to navigate, and free from technical glitches is essential. Regular updates and maintenance are necessary to provide a smooth user experience and to fix any bugs or issues that may arise. Information quality is equally important; providing accurate, relevant, and up-to-date learning content keeps users engaged and ensures that the learning material is useful and effective. Incorporating a variety of learning materials, including videos, quizzes, and interactive exercises, can cater to different learning preferences and enhance the overall learning experience. Service quality also plays a significant role. Offering robust customer support to assist users with any issues they encounter can greatly improve user satisfaction. This can include live chat support, comprehensive FAQs, and tutorial videos to help users navigate the application effectively.

Improving user attitude and behavioral intention is another crucial aspect. Integrating features that boost motivation, such as gamification elements, personalized learning paths, and progress tracking, can make the learning process more enjoyable and engaging. Gamification elements, such as rewards and badges, can motivate users to complete tasks and achieve their learning goals. Personalized learning paths tailored to individual user performance and preferences can keep users engaged by providing content that is appropriately challenging and relevant. Additionally, designing a user-friendly interface that is intuitive and visually appealing can enhance the overall user experience. Simplifying the onboarding process is also important to ensure that new users can start using the app effectively without feeling overwhelmed.

Aligning technology with learning tasks is essential to maximize the effectiveness of the application. Ensuring that the technological features of the application are well-aligned with the specific learning tasks can significantly enhance user satisfaction and learning outcomes. For example, features like speech recognition for pronunciation practice, spaced repetition systems for vocabulary retention, and contextual learning scenarios can provide practical and relevant learning experiences. Incorporating real-life scenarios and practical applications of the English language can make learning more meaningful and engaging for users, helping them see the relevance of their learning to their daily lives.

Personalizing learning experiences is another important recommendation. Using adaptive learning technologies to tailor content and difficulty levels based on individual user performance and preferences can help maintain user engagement and motivation. Providing personalized feedback on user performance and allowing customization options can also enhance the learning experience. Users should be able to set their learning goals and preferences, which can help them stay motivated and engaged with the application.

Fostering positive attitudes through demonstrated usefulness is also crucial. Highlighting the practical benefits of learning English through the application, such as career advancement, travel opportunities, and personal growth, can motivate users to engage with the application. Success stories and testimonials from other users can also be persuasive and help demonstrate the value of the application. Ensuring that the application is easy to use from the very beginning is also important. Offering tutorials and guided tours can help new users understand the features and how to use them effectively, which can improve their initial experience and encourage continued use.

Lastly, conducting further research and continuous improvement is essential for the long-term success of the application. Regularly collecting and analyzing user feedback can help identify areas for improvement and ensure that the application continues to meet user needs and preferences. User reviews, surveys, and focus groups can provide valuable insights into what users like and dislike about the application. Staying updated with the latest trends and advancements in educational technology is also important to continuously enhance the application's features and content.

In conclusion, by implementing these recommendations, developers and educators can create more engaging, effective, and user-friendly English word learning applications that cater to the needs of Gen X users in Chengdu, China. This approach will not only enhance user satisfaction but also improve learning outcomes and foster a more positive attitude towards using mobile applications for language learning.

5.3 Limitation and Further Study

Despite the insightful findings of this study on Gen X users in Chengdu, China, regarding their behavioral intention to use English word learning applications, there are several limitations that must be acknowledged. Firstly, the study employed nonprobability sampling techniques, including quota and convenience sampling, which may limit the generalizability of the results to the broader population. Additionally, the reliance on self-reported data through network self-administered questionnaires could introduce response bias, as participants may provide socially desirable answers. The study's focus on only the top three English word-learning applications may also overlook other potentially influential applications, limiting the comprehensiveness of the findings. Furthermore, the cross-sectional design of the study captures a single point in time, thus failing to account for changes in user behavior and attitudes over time. Lastly, while confirmatory factor analysis and structural equation modeling provided robust statistical tools for data analysis, they are based on the assumption that the model fits the data well, and any deviations might affect the validity of the results. Future research should consider longitudinal designs, a broader range of applications, and more diverse sampling techniques to address these limitations.

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

Agarwal, R., & Prasad, J. (1998). A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology. *Information Systems Research, 9,* 204-224. http://dx.doi.org/10.1287/isre.9.2.204

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

Al-Mushasha, N., & Hassan, S. (2009). A Model for Mobile Learning Service Quality in University Environment. *International Journal of Mobile Computing and Multimedia Communications, 1*(1), 70-91. https://doi.org/10.4018/jmcmc.2009010105

Aparicio, M., Bacao, F., & Oliveira, T. (2017). Grit in the path to e-learning success. *Computers in Human Behavior, 66*(1), 388-399. https://doi.org/10.1016/j.chb.2016.10.009

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

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

Barry, M., & Jan, M. T. (2018). Factors Influencing the use of M-Commerce: An Extended Technology Acceptance Model Perspective. *Research Gate, 26*(1), 157-183.

Breckler, S. J. (1984). Empirical validation of affect, behavior, and cognition as distinct components of attitude. *Journal of Personality and Social Psychology, 47*(6), 1191-1205. https://doi.org/10.1037//0022-3514.47.6.1191

Brown, T. A., & Moore, M. T. (2012). Confirmatory Factor Analysis. In R. H. Hoyle (Ed.), *Handbook of Structural Equation Modeling* (pp. 361-379). Guilford Publications.

Byrne, B. M. (2010). *Structural Equation Modeling with Amos: Basic Concepts, Applications, and Programming* (2nd ed.). Taylor and Francis Group.

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

Cho, J., Park, I., & Michel, J. W. (2011). How does leadership affect information systems success? The role of transformational leadership. *Information and Management, 48*(7), 270-277. https://doi.org/10.1016/j.im.2011.07.003

Cho, Y. K., & Menor, L. J. (2012). Towards a Provider-based View on the Design and Delivery of Quality E-service Encounter. *Journal of Service Research, 13*(1), 83-95. https://doi.org/10.1177/1094670509350490

Clark-Carter, D. (2010). *Quantitative Psychological Research: The Complete Student's Companion* (1st ed.). Psychology Press-Taylor & Francis.

Cooper, D., & Schindler, P. (2001). *Business Research Methods* (7th ed.). McGraw-Hill.

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

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

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (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

Deb, M., & Agrawal, A. (2017). Factors impacting the adoption of m-banking: understanding Brand India's potential for financial inclusion. *Journal of Asia Business Studies, 11*(1), 22-40. https://doi.org/10.1108/jabs-11-2015-0191

DeCuir-Gunby, J. T., & Schutz, P. A. (2017). Developing a Mixed Methods Proposal: A Practical Guide for Beginning Researchers. *Research gate, 1*(2), 1-10. https://doi.org/10.4135/9781483399980

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

Donaldson, G. (1983). Confirmatory factor analysis models of information processing stages: An alternative to difference scores. *Psychological Bulletin, 94*(1), 143-151. https://doi.org/10.1037/0033-2909.94.1.143

Eze, J. F. (2011, February 2-3). *Entrepreneurship Education for Self-Reliance and Implications for the Millennium Development Goals.* The Sixth International Conference on Development Studies, Benue State University, Makurdi, Nigeria.

Fagan, C., Lyonette, C., Smith, M., & Saladana-Tejeda, A. (2012). The Influence of Working Time Arrangements on Work-life Integration or 'Balance': A Review of the International Evidence. *International Labor, 2*(2), 1-10.

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research* (1st ed.). Addison-Wesley.

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

Hackman, J. R., & Oldham, G. R. (1980). *Work Redesign* (1st ed.). Addison-Wesley.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis* (6th ed). Pearson Prentice Hall.

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

Halonen, R., Acton, T., Golden, W., & Conboy, K. (2009). DeLone & McLean success model as a descriptive tool in evaluating a virtual learning environment. *International Conference on Organizational Learning, Knowledge and Capabilities, Amsterdam, 16,* 1-10.

Ho, Y. S. (2014). Highly cited articles in the education and educational research category in the social science citation Index: A bibliometric analysis. *Education Review, 2*(4), 1-10.

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

Igersheim, R. H. (1976). Managerial response to an information system. *AFIPS Conference Proceedings National Computer Conference, 45,* 877-882. https://doi.org/10.1145/1499799.1499918

Kazemi, S. A., Cruz, A., de Hulster, E., Hebly, M., Palmqvist, E. A., & Olsson, L. (2013). Long-term adaptation of Saccharomyces cerevisiae to the burden of recombinant insulin production. *Biotechnol Bioeng, 110*(10), 2749-2763. https://doi.org/10.1002/bit.24927

Kim, D., Ferrin, D., & Rao, H. (2008). A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents. *Decision Support Systems, 44*(2), 544-564. https://doi.org/10.1016/j.dss.2007.07.001

Lee, M. (2010). Explaining and predicting users' continuance intention toward e-learning: an extension of the expectation-confirmation model. *Computers & Education, 54*(2), 506-516. https://doi.org/10.1016/j.compedu.2009.09.002

Lewis, B. K. (2010). Social Media and Strategic Communication: Attitudes and Perceptions among College Students. *Public Relations Journal, 4,* 1-23.

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

Liu, Y., Han, S., & Li, H. (2010). Understanding the factors driving m-learning adoption: a literature review. *Campus-Wide Information Systems, 27*(4), 210-226. https://doi.org/10.1108/10650741011073761

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

Lucas, H. C. (1978). Empirical evidence for a descriptive model of implementation. *MIS Quarterly, 2*(2), 27-41. https://doi.org/10.2307/248939

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

O'Cass, A., & Carlson, J. (2012). An e-retailing assessment of perceived website-service innovativeness: implications for website quality evaluations, trust, loyalty, and word of mouth. *Australasian Marketing Journal, 20*(3), 28-36. https://doi.org/10.1016/j.ausmj.2011.10.012

Oktal, O., Alpu, O., & Yazici, B. (2016). Measurement of internal user satisfaction and acceptance of the e-justices: EBSCOhost. *Aslib Journal of Information Management, 68*(6), 716-735. https://doi.org/10.1108/ajim-04-2016-0048

Olson, M. A., & Kendrick, R. V. (2008). Origins of attitudes, book: attitudes and attitude change. In W. D. Crano & R. Prislin (Eds.), *Attitudes and Attitude Change.* Psychology Press.

Pan, X., M. Chin, R., Gautam, H., Bian, D., Kim, P. R., Colarco, T. L., Diehl, T., Takemura, L., Pozzoli, K., Tsigaridis, S. B., & Bellouin, N. (2015). A multi-model evaluation of aerosols over South Asia: Common problems and possible causes. *Atmos. Chem. Phys., 15,* 5903-5928. https://doi.org/10.5194/acp-15-5903-2015

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding University students' behavioral intention to use e-learning. *Dinamika Pendidikan, 12*(1), 150-162.

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

Richard, P., Devinney, T., Yip, G., & Johnson, G. (2009). Measuring Organizational Performance: Towards Methodological Best Practice. *Journal of Management, 35,* 718-804. https://doi.org/10.1177/0149206308330560

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.

Sarwar, M., & Soomro, T. (2013). Impact of Smartphone's on Society. *European Journal of Scientific Research, 98*(2), 1-10.

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.

Spreng, R. A., & MacKoy, R. D. (1996). An Empirical Examination of a Model of Perceived Service Quality and Satisfaction. *Journal of Retailing, 72,* 201-214. https://doi.org/10.1016/S0022-4359(96)90014-7

Straub, E. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research, 79,* 625-649. https://doi.org/10.3102/0034654308325896

Teo, T. (2009). Modeling Technology Acceptance in Education: A Study of Pre-Service Teachers. *Computers & Education, 52,* 302-312. http://dx.doi.org/10.1016/j.compedu.2008.08.006

Ullman, J. B. (2001). Structural equation modeling. In: B. G. Tabachnick, & L. S. Fidell (Eds.), *Using multivariate statistics.* Pearson Education.

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., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46,* 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

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

Ventura, M. J. (2019). Prosecuting Starvation under International Criminal Law: Exploring the Legal Possibilities. *Journal of International Criminal Justice, 17*(4), 781-814. https://doi.org/10.1093/jicj/mqz043

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior, 26*(4), 760-767. https://doi.org/10.1016/j.chb.2010.01.013