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Factors Impacting Behavioral Intention and Use Behavior of Undergraduate Students to Use English Learning Apps in Kunming, China

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Abstract

Purpose: This study investigates the factors influencing the behavioral intention and use behavior of English learning apps among higher education students in Kunming, China. The conceptual framework incorporates variables such as perceived ease of use, perceived usefulness, attitude, perceived behavioral control, social influence, behavioral intention, and use behavior. **Research design, data, and methodology:** The target population consists of 500 undergraduate students from the top three universities in Kunming, China. The research employed a quantitative approach, utilizing a questionnaire as the primary data collection tool. Sampling techniques included judgmental, stratified random, and convenience sampling. To ensure validity and reliability, a pilot test involving 50 participants was conducted, assessing the item-objective congruence (IOC) index for validity and Cronbach's alpha for reliability. The data collected were analyzed using confirmatory factor analysis (CFA) and structural equation modeling (SEM) as the main statistical analyses for this study. **Results:** Perceived ease of use significantly impacts attitude and perceived usefulness. Perceived usefulness significantly impacts attitude. Behavioral intention is significantly impacted by attitude, perceived behavioral control, and social influence. Furthermore, behavioral intention has a significant impact on use behavior. **Conclusions:** The results are valued to entrepreneurs or developers of English learning apps who are looking for opportunities in mobile education.

Keywords : Attitude, Behavioral Intention, Use Behavior, English Learning Apps, Higher Education

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With the continuous development of China's economy, college students have a wider range of learning and need more and more time to study independently. In today's technological age, many language-learning apps can help them learn more effectively. Language learning apps can encourage them to form good learning habits and make college students' learning methods more liberal. Educational technology can be divided into hardware, software, and teaching methods. Modern educational technology is an educational technology that includes information technology. Modern science and technology achieve the goal of teaching modernization through optimizing education (Wang et al., 2010).

Chen et al. (2017) considered that in this era of continuous development of society, people's per capita income is also increasing, so people's requirements for life have also increased. For example, in terms of the network, there are many applications of the network not only in the family but also in the school. Many schools give the children homework after class to use the computer, and some schools require each student to use a tablet in class.

Digital learning is mainly based on the theory of

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constructivism, which focuses on the learners' self-construction process. Compared to the traditional teaching method, such as chalk, or blackboard, its principal feature is the main learning process. Inverted classrooms mainly focused on the out-of-class; however, the class course was mainly used to solve the problems in learning (Sun, 2019).

English learning apps were gaining significant popularity in China. The increasing demand for English language proficiency, driven by globalization and the importance of English in international business and education, has led to the widespread adoption of digital learning platforms. Some popular English learning apps in China are Duolingo, HelloTalk, Babbel, Memrise, ABCmouse, etc. (Qimai, n.d.).

The learning process changed from simple classroom learning to multi-dimensional and fragmented learning, which required a full utilization of tools and resources for formal and informal learning. Higher education institutions, particularly universities emphasizing face-to-face education, were forced to adjust. Research has shown that online courses fully meet these needs, and schools must develop and deliver shorter, more personalized courses (Hill, 2012).

To fill the research gap in the limited study on the student's behavioral intention and use behavior of English learning apps in China, this study investigates the factors influencing the behavioral intention and use behavior of English learning apps among higher education students in Kunming, China. The conceptual framework incorporates perceived ease of use, usefulness, attitude, perceived behavioral control, social influence, behavioral intention, and use behavior.

2. Literature Review

2.1 Perceived Ease of Use

Davis (1989) considered perceived ease of use as the degree to which individuals believed using a particular system would be easy or simple. When it comes to online education, perceived ease of use is the extent of ease related to using some specific system (Venkatesh et al., 2003). Alternatively, it was the degree to which an individual thought that using some system would not require great effort (Lee, 2006). When a potential adopter believes a particular technology or system has a higher ease of use, their intention of using it would be strong. Conversely, the higher the perceptual usefulness, the more positive the attitude toward using the technology (Beyari, 2018). In TAM theory, perceived usefulness (PU) and perceived ease of use (PEOU) were two major factors of acceptance of technology (Lee, 2006). These two factors affect attitudes toward usability (Davis, 1989). Escobar-Rodriguez and Monge-Lozano (2012) investigated the relationship between perceived ease of use and perceived usefulness during the study of the usage of Moodle platform, and the results show that there is a significant positive relation between perceived ease of use and perceived usefulness. Accordingly, the following hypotheses proposed based on the above studies:

H1: Perceived ease of use has a significant impact on attitude.

H3: Perceived ease of use has a significant impact on perceived usefulness.

2.2 Perceived Usefulness

Perceived usefulness is defined as a user thinking that using some specific systems can improve their job performance (Chen et al., 2017). When it is to education, perceived usefulness is the extent of an individual thinking that using some specific technology would help them to get better academic performance (Akbar, 2013; Venkatesh et al., 2003) or the level to which a user believes that it would enhance their learning performance. Hu et al. (2015) study shows that perceived usefulness significantly affects attitude, and the students' perceived usefulness will positively influence their attitude toward m-library apps. Regarding information systems, according to Lee (2010), perceived usefulness affects a user's attitude toward the usage. Thus, a hypothesis is stated as follows:

H2: Perceived usefulness has a significant impact on attitude.

2.3 Perceived Behavior Control

Perceived behavior control could be explained as the perceived difficulty level when an individual performs a behavior (Ajzen, 1991). Wu (2023) believed that perceived behavior control, an individual ability to control required opportunities and resources when acting, represents the degree to which a person can control his/her behavior practice. Indeed, it is a concept very similar to self-efficacy, which is defined as a person's confidence that he or she can accomplish some access in a particular domain (Bandura, 1997). Ilyas and Zaman (2020) showed that students´ perceived behavioral control affects their persistence intentions positively. Alain et al. (2006) investigated the impact of entrepreneurship education programs and found that perceived behavioral control is one of the positive predictors of behavior. Therefore, the next hypothesis is indicated:

H4: Perceived behavioral control has a significant impact on behavioral intention.

2.4 Attitude

Kim and Woo (2016) indicated that attitude was characteristic of pleasant or unpleasant distinguish objects, people, events, institutions, or others' worlds. It was also an

extent to which a person thought some system was interesting and wanted to use it (Bajaj & Nidumolu, 1998). David believed that attitude was how a person felt about using the same technology or system (Davis, 1989). Ajzen (1991) thought that attitude toward behavior affected career intentions. In the other article by Ajzen and Fishbein (1980), the researchers showed that attitudes could predict intentions. In the research of Alain et al. (2006), intention formation depends upon attitudes toward behavior, subjective norms, and perceived behavioral control in the theoretical framework. Therefore, the next hypothesis is indicated:
H5: Attitude has a significant impact on behavioral intention.

2.5 Social Influence

Social influence is described as people in the same group giving others the belief of using or not using some technology (Ukut, 2018). It was also defined as the extent of a person who thinks it is important that others believe he or she should use the system (Sánchez & Hueros, 2010). Social influence was one of the important factors in prognosis technology use behavior and intention to use (Venkatesh & Davis, 2000). Several studies (Calisir et al., 2014; Karaali et al., 2011; Terzis et al., 2012) have shown the closed relation between social influence and the perceived usefulness of the usage of some technology. Social influence significantly impacts students' behavioral intention to adopt LMSs (Akbar, 2013; Hsu, 2012; Sumak et al., 2010). Accordingly, a hypothesis examined in this work is as follows:
H6: Social influence has a significant impact on behavioral intention.

2.6 Behavioral Intention

The behavioral intention was defined as the possibility that an individual would use some technology or system (Ukut, 2018). According to Davis (1989), behavioral intention explains some preparation to adopt or use some system. Zhong et al. (2022) stated that when people think about their ability to use a particular system or technology, a stronger behavioral intention to use it is presented. The studies showed that behavioral intention was very influenced by perceived usefulness and user satisfaction (Lee & Lehto, 2013). Yu and Huang (2020) found that consumers' intent to use smart libraries will positively and directly impact their behavior. Gunasinghe et al. (2020) showed that behavioral intention influences academicians' use of e-learning. Therefore, a hypothesis is proposed:
H7: Behavioral intention has a significant impact on use behavior.

2.6 Use Behavior

Use behavior was defined as the frequency and purpose of use (Ukut, 2018). It also meant how and when people used the system or technology (Attuquayefio & Addo, 2014). Regarding e-learning, use behavior was defined as the students' actual behavior using the online system to complete their study tasks (Gunasinghe et al., 2020). The technology acceptance model (TAM) is the most widely used information system to find factors like use behavior and adopting new technologies (Davis, 1989). This model was widely accepted as an instrument that could measure the relationship between attitude and use behavior of information systems (Lee, 2010; Yu & Huang, 2020; Zhong et al., 2022).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this study was developed based on three previous studies. Chao and Yu (2019) adopt the(perceived behavioral control, attitude towards social influences, and behavioral intention to explain Taiwanese students' usage behavior for weblog learning. Camarero et al. (2012) investigated the relationship between perceived ease of use, perceived usefulness, attitude, and behavioral intention to evaluate the use and effectiveness of online discussion forums. Yu and Huang (2020) studied consumers' intent to use smart libraries to examine the effect of perceived usefulness on use attitude, behavioral intention, and behavioral intention toward behavior. The study emphasizes several important constructs, namely perceived ease of use, perceived usefulness, attitude, perceived behavioral control, social influence, behavioral intention, and use behavior, as presented in Figure 1.

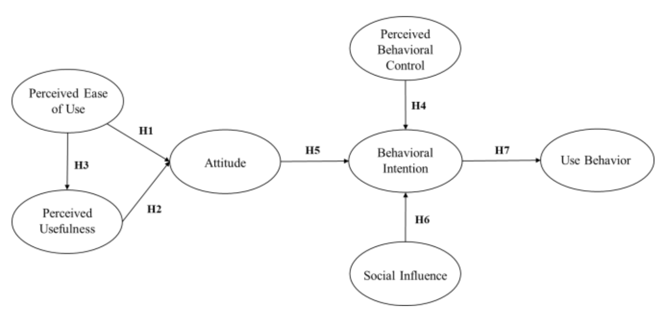

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on attitude.
H2: Perceived usefulness has a significant impact on attitude.
H3: Perceived ease of use has a significant impact on perceived usefulness.
H4: Perceived behavioral control has a significant impact on behavioral intention.
H5: Attitude has a significant impact on behavioral intention.
H6: Social influence has a significant impact on behavioral intention.
H7: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

This study applied quantitative methods to the data with a questionnaire. The questionnaire utilized in this research consists of three sections. The first part comprises screening questions to ensure the eligibility of participants. The second part includes five-point Likert scale items that measure respondents' opinions, attitudes, or perceptions of the research topic. Lastly, the questionnaire concludes with a section dedicated to collecting demographic information from participants. Data collection in Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) involves gathering information from participants to estimate and validate the proposed models.

The Index of Item-Objective Congruence (IOC) is a numerical value that falls within the range of -1 to +1. Positive IOC values indicate a positive relationship between the item and the overall measure. In this study, three experts with Ph.D. titles or high-level management positions evaluated the IOC. The results of the IOC analysis, shown in Appendix A, were compared to a minimum acceptable score of 0.6 and above to assess the content validity of the items (Streiner & Norman, 2008).

To apply Cronbach's Alpha during pilot testing, researchers typically collect responses from a pilot sample consisting of 50 participants. The collected data includes participants' responses to the items within the scale or questionnaire being tested. Cronbach's Alpha ranges from 0 to 1, with higher values indicating greater internal consistency or reliability of the scale. Researchers interpret Cronbach's Alpha value to assess the scale's reliability. The statement mentions a threshold of 0.70 as a generally accepted criterion for acceptable internal consistency (Nunnally & Bernstein, 1994).

3.3 Population and Sample Size

The target population for this study consists of undergraduate students who have experienced using English Learning Apps at top three universities in Kunming, China. Based on Soper's (2023) guidelines, the minimum required sample size is 425. However, to ensure efficient data analysis for structural equation modeling (SEM), the researcher collected a total of 500 participants.

3.4 Sampling Technique

In this study, the sampling techniques are probability and nonprobability, encompassing judgmental, stratified random, and convenience sampling. To serve this study's objectives, the researcher considers applied judgmental sampling to select students from the top three universities in Kunming, China. The stratified random sampling method ensures a proportional representation of different subgroups within the population and can improve the precision and representativeness of the sample (Lohr, 2019). The researcher applied stratified random sampling, as shown in Table 1. For convenience sampling, this research collected the data through administered questionnaires to students from the top three universities in Kunming, China, who have experienced the use of English learning apps. The online survey was distributed via email and the WeChat application.

Table 1: Sample Units and Sample Size

Universities	Undergraduate	Sample Size (n=500)
University A	31,447	202
University B	16,330	105
University C	30,000	193
Total	**77,777**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 reveals the demographic information of 500 participants. Among the respondents, 52.8% were male, and 47.2% were female. This shows a relatively balanced gender distribution among users of English learning platforms in the sample population. The data indicates that the majority of respondents are in their third year of undergraduate study, comprising 32.2% of the sample. The second-year students follow closely at 27.0%, while the first-year and fourth-year students make up 22.2% and 18.6% of the sample, respectively. This suggests that English learning platforms are being utilized by students from various academic levels. Around 16.6% of the respondents reported using English learning platforms for one year or less. A significant majority, 64.2%, had been using these platforms for 2 to 4 years. Additionally, 19.2% of respondents had more extensive experience, using English learning platforms for 5 years or longer. This indicates a high level of long-term engagement with English learning apps and platforms among the respondents.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	264	52.8%
	Female	236	47.2%
Undergraduate's Year of Study	First Year	111	22.2%
	Second Year	135	27.0%
	Third Year	161	32.2%
	Fourth Year	93	18.6%
Experience use of English learning platform	1 year or below	83	16.6%
	2-4 years	321	64.2%
	5 years or above	96	19.2%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is utilized in this study to examine the measurement model, evaluating the connections between observed variables and underlying constructs. Table 3 displays the CFA results, demonstrating that Cronbach's Alpha values, used to assess the scale's reliability, surpass the generally accepted threshold of 0.70 as established by Nunnally and Bernstein (1994). The factor loading criteria were set at 0.5, and the P-value coefficients were required to be less than 0.05.

Additionally, in accordance with the guidelines outlined by Fornell and Larcker (1981), Composite Reliability (CR) and Average Variance Extracted (AVE) were used to determine the cutoff points. The CR was set at 0.7, and the AVE was set at 0.5. By adhering to these criteria, the CFA model confirms the convergent and discriminant validities of this study.

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
1. Perceived Ease of Use (PEOU)	Thi et al. (2023)	4	0.914	0.816-0.885	0.915	0.730
2. Perceived Usefulness (PU)	Venkatesh et al. (2003)	5	0.888	0.729-0.864	0.891	0.623
3. Attitude (ATT)	Singh and Tewari (2021)	4	0.907	0.821-0.889	0.908	0.712
4. Perceived Behavioral Control (PBC)	Al-Mamary et al. (2023)	3	0.920	0.855-0.919	0.920	0.794
5. Social Influence (SI)	Singh and Tewari (2021)	3	0.851	0.772-0.841	0.852	0.657
6. Behavioral Intention (BI)	Liaw (2008)	4	0.918	0.832-0.877	0.918	0.737
7. Use Behavior (UB)	Al-Mamary et al. (2023)	3	0.858	0.799-0.846	0.859	0.670

The measurement model is a crucial component of structural equation modeling (SEM) that specifies the relationships between latent variables (unobserved constructs) and their observed indicators (measured variables). Model fit assessment is a critical step in evaluating the adequacy of the model, resulting in CMIN/DF = 2.116, GFI = 0.919, AGFI = 0.898, NFI = 0.939, CFI = 0.967, TLI = 0.961, and RMSEA = 0.047.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	≤ 5.00 (Marsh et al., 2004)	588.252/278 = 2.116
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.919
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.898
NFI	≥ 0.80 (Wu & Wang, 2006)	0.939
CFI	≥ 0.80 (Bentler, 1990)	0.967
TLI	≥ 0.80 (Sharma et al., 2005)	0.961
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.047
Model summary		**In harmony with empirical data**

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 = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index and RMSEA = Root mean square error of approximation

The assessment of discriminant validity, as proposed by Fornell and Larcker (1981), involved calculating the square root of each Average Variance Extracted (AVE). In this study, the computed discriminant validity value exceeded all inter-construct or factor correlations, thus supporting the discriminant validity. The study successfully demonstrated both convergent and discriminant validity, providing sufficient evidence to establish the construct validity conclusively.

Table 5: Discriminant Validity

	PBC	PEOU	ATT	SI	UB	BI	PU
PBC	**0.891**						
PEOU	0.595	**0.854**					
ATT	0.555	0.516	**0.844**				
SI	0.393	0.368	0.391	**0.811**			
UB	0.608	0.411	0.497	0.362	**0.818**		
BI	0.576	0.456	0.453	0.475	0.437	**0.859**	
PU	0.512	0.559	0.523	0.389	0.456	0.441	**0.789**

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

4.3 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is employed to evaluate the adequacy of the structural model in fitting the observed data (Byrne, 2016). The study's findings reveal the following fit indices: CMIN/DF = 3.677, GFI = 0.858, AGFI = 0.830, NFI = 0.888, CFI = 0.916, TLI = 0.906, and RMSEA = 0.073. Based on these results, it is evident from Table 6 that the modified SEM model has successfully met the acceptable fit criteria.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	≤ 5.00 (Marsh et al., 2004)	1073.747/292 = 3.677
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.830
NFI	≥ 0.80 (Wu & Wang, 2006)	0.888
CFI	≥ 0.80 (Bentler, 1990)	0.916
TLI	≥ 0.80 (Sharma et al., 2005)	0.906
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.073
Model summary		**In harmony with empirical data**

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 = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index and RMSEA = Root mean square error of approximation

4.4 Research Hypothesis Testing Result

In Table 7, the significance of each variable was evaluated by analyzing its standardized path coefficient (β) and t-value. The results indicate that all the hypotheses in this study are supported, with a significance level of $p<0.05$.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→ATT	0.327	6.126*	Supported
H2: PU→ATT	0.341	6.226*	Supported
H3: PEOU→PU	0.559	11.012*	Supported
H4: PBC →BI	0.449	9.935*	Supported
H5: ATT →BI	0.190	4.427*	Supported
H6: SI →BI	0.296	6.429*	Supported
H7: BI→ UB	0.435	8.592*	Supported

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

H1: Perceived Ease of Use (PEOU) significantly influences Attitude (ATT), with a standardized path coefficient (β) of 0.327 and a t-value of 6.126*, thus supporting the hypothesis.

H2: Perceived Usefulness (PU) significantly affects Attitude (ATT), with a standardized path coefficient (β) of 0.341 and a t-value of 6.226*, indicating that the hypothesis is supported.

H3: Perceived Ease of Use (PEOU) significantly influences Perceived Usefulness (PU), with a standardized path coefficient (β) of 0.559 and a t-value of 11.012*, providing support for the hypothesis.

H4: Perceived Behavioral Control (PBC) significantly impacts Behavioral Intention (BI), with a standardized path coefficient (β) of 0.449 and a t-value of 9.935*, thus supporting the hypothesis.

H5: Attitude (ATT) has a significant effect on Behavioral Intention (BI), with a standardized path coefficient (β) of 0.190 and a t-value of 4.427*, indicating support for the hypothesis.

H6: Social Influence (SI) significantly influences Behavioral Intention (BI), with a standardized path coefficient (β) of 0.296 and a t-value of 6.429*, supporting the hypothesis.

H7: Behavioral Intention (BI) significantly influences Use Behavior (UB), with a standardized path coefficient (β) of 0.435 and a t-value of 8.592*, providing support for the hypothesis.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study delved into the factors influencing the behavioral intention and use behavior of English learning apps among higher education students in Kunming, China. The findings revealed significant relationships among various variables.

Firstly, perceived ease of use was found to have a significant impact on attitude and perceived usefulness (Beyari, 2018). Students who perceived the apps as user-friendly and easy to navigate tended to have a more positive attitude towards using them and perceived them as useful tools for their language learning journey (Lee, 2006).

Secondly, perceived usefulness was shown to significantly influence attitude, as aligned with previous assumptions (Akbar, 2013; Venkatesh et al., 2003). When students perceived the apps as beneficial and valuable for improving their English skills, their overall attitude towards using the apps became more favorable.

Thirdly, behavioral intention was found to be significantly impacted by attitude, perceived behavioral control, and social influence (Alain et al., 2006; Calisir et al., 2014; Karaali et al., 2011; Terzis et al., 2012), Students' intention to use the English learning apps was influenced by their attitude towards the apps, their perceived ability to control their usage, and the influence of social factors, such as peer recommendations or teachers' encouragement.

Lastly, the study revealed that behavioral intention had a significant impact on use behavior. Students who had a strong intention to use the English learning apps were more likely to translate that intention into actual usage behavior, demonstrating the role of behavioral intention as a key predictor of app adoption and usage (Lee & Lehto, 2013; Yu & Huang, 2020).

These findings underscore the importance of user perceptions and attitudes in determining the adoption and use of English learning apps among higher education students in Kunming, China. The study sheds light on the factors that can promote successful implementation and integration of such educational technology in language learning contexts. Educators, app developers, and policymakers can utilize these insights to design and implement more effective English learning apps tailored to the needs and preferences of students, ultimately enhancing language learning outcomes in the region. However, it is crucial to acknowledge that individual differences, cultural factors, and other contextual variables may also play a role in shaping students' behavioral intentions and use behavior, warranting further research and consideration in future studies.

5.2 Recommendation

Based on the findings of the study, here are some recommendations for improving the adoption and use of English learning apps among higher education students in Kunming, China:

Developers of English learning apps should focus on creating user-friendly and intuitive interfaces. By simplifying navigation and making the apps easy to use, students are more likely to have positive attitudes towards them and perceive them as useful tools for language learning.

App developers and educators should emphasize the benefits and practical applications of using the English learning apps. Showcasing how these apps can help improve language skills and enhance academic and career prospects will increase students' perceived usefulness, leading to a more positive attitude towards app adoption.

Institutions and educators can play a crucial role in supporting students' use of English learning apps. Offer training sessions or workshops that introduce the apps' features and functionalities and provide guidance on how to maximize their potential for language learning.

Social influence was found to impact behavioral intention. Therefore, educators can encourage a positive learning environment by promoting peer interaction and collaboration. Students who see their peers using the apps and benefiting from them are more likely to develop a favorable intention to use the apps themselves.

Recognize the diverse learning needs and preferences of students. Customizing the app's content and features to cater to individual learning styles can increase students' engagement and motivation to use the app regularly.

Consider implementing incentives or rewards for app usage and engagement. This can be in the form of virtual badges, points, or certificates to acknowledge students' progress and accomplishments, fostering a sense of achievement and motivation to continue using the app.

Regularly assess the app's performance and user feedback. Incorporate updates and improvements based on user suggestions to ensure the app remains relevant, effective, and engaging over time.

Collaborate with educational institutions to integrate English learning apps into the curriculum. Incorporating app-based activities and assignments can make the learning experience more interactive and meaningful for students.

Address any technical issues or bugs promptly to ensure a seamless and frustration-free user experience. Technical difficulties can deter students from using the app regularly.

Create strategies to maintain students' long-term engagement with the app. Provide new and challenging content regularly, organize contests, or set goals and milestones to keep students motivated and committed to using the app over an extended period.

By implementing these recommendations, educators, app developers, and policymakers can enhance the effectiveness and impact of English learning apps among higher education students in Kunming, China, ultimately contributing to improved language proficiency and academic success.

5.3 Limitation and Further Study

The study's sample may have been limited to specific higher education institutions or departments in Kunming, which may not fully represent the diversity of students' language learning experiences across the region. Future studies could aim for more diverse and representative samples to ensure broader generalizability of findings. Additionally, the study's findings may have been limited to the specific English learning apps and constructs examined in this particular context. Further research could explore a broader range of English learning apps and other relevant factors that may influence app adoption and usage. Lastly, the study examined direct relationships between variables, but there could be underlying mediating or moderating factors that influence the relationships between perceived ease of use, perceived usefulness, attitude, behavioral intention, and use behavior. Future research could explore these potential mediating and moderating variables.

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