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# Predicting Significant Factors of Postgraduate Students to Use English Learning Apps in Kunming, China

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## Abstract

**Purpose:** This research delves into the determinants that shape the behavioral intention and use behavior of English learning apps among postgraduate students in Kunming, China. The conceptual framework encompasses elements like the perceived simplicity of use, perceived utility, attitude, perceived control over behavior, social impact, behavioral intent, and use behavior. **Research design, data, and methodology:** The target population encompasses 500 postgraduate students from the top three universities located in Kunming, China. Employing a quantitative methodology, the research engaged a questionnaire as the principal means of data collection. The sampling methodologies employed judgmental, stratified random, and convenience sampling. A preliminary assessment was carried out with 50 participants, analyzed by Cronbach's alpha. The data were analyzed with confirmatory factor analysis (CFA) and structural equation modeling (SEM). **Results:** Perceived usefulness significantly impacts attitude. Behavioral intention has a significant impact on use behavior. Behavioral intention is significantly impacted by attitude, but isn't impacted by perceived behavioral control, and social influence. Additionally, perceived ease of use did not significantly impact attitude and perceived usefulness. **Conclusions:** The insights gained pave the way for more targeted strategies to enhance app adoption and effective use, with implications for educational institutions, app designers, and policymakers seeking to optimize technology integration in education.

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

**JEL Classification Code**: E44, F31, F37, G15

## 1. Introduction

With the development of information technology, the use of mobile devices in learning is becoming more and more popular. Mobile learning has made remarkable progress and has attracted widespread attention worldwide. In the context of big data and the Internet, using mobile devices for education has become familiar in people's daily lives (Luo et al., 2022). After the new crown pneumonia epidemic outbreak, nearly 300 million people across the country suspended classes and learned at home, and mobile learning has become increasingly important (Wu, 2023).

The success of online learning is inseparable from the assistance of learning APP resources. As of the end of 2015, the domestic mobile learning APP has a market size of more than 1.5 billion yuan. Many mobile learning apps cover many fields, such as foreign language learning, exam training, and early childhood education (Hu et al., 2015). The growth of internet penetration laid the foundation for the online education market. More and more people had access to the Internet. Thus, online education has become a broad market foundation. With the rapid development of infrastructures, such as the promotion of 5G, Artificial Intelligent, big data, and other technologies, all have been widely used for online education. China's internet users have grown recently (Qadir et al., 2023).

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In recent years, the adoption of English learning apps has witnessed a significant surge in China, driven by factors such as the increasing importance of English proficiency in the global job market and the convenience offered by mobile technology. These apps allow learners to enhance their language skills at their own pace and convenience. Apps like "VIPKid," which connects Chinese students with English-speaking teachers for one-on-one online lessons, have gained immense popularity. According to a report by Technavio, the online English learning market in China, including using such apps, was projected to grow significantly (Qimai, n.d.).

Furthermore, integrating advanced technologies like artificial intelligence (AI) into English learning apps has allowed personalized learning experiences. Apps can now analyze students' performance and tailor lessons to their needs, providing targeted practice and feedback. However, the effectiveness of these apps in achieving substantial language proficiency has been a topic of discussion. While they offer convenience and supplementary learning, the lack of in-person interaction and practice can sometimes fully limit their ability to develop communication skills (Qimai, n.d.).

In response to the existing research void concerning student behavioral intent and usage patterns of English learning apps in China, this investigation aims to bridge the gap by exploring the determinants that shape behavioral intent and usage behaviors among higher education students in Kunming, China. The conceptual framework encompasses variables such as perceived ease of use, perceived usefulness, attitude, perceived behavioral control, social influence, behavioral intention, and usage behavior.

## 2. Literature Review

### 2.1 Perceived Ease of Use

Perceived ease of use is the degree to which individuals believe using a particular system would be easy or simple (Davis, 1989). It was the degree to which an individual thought using some system would require little effort (Lee, 2006). Perceived ease of use means the ease with which they can access the system (Amoako-Gyampah, 2007). Frey and Osborne (2017) believed that when people thought learning some system was not difficult, they would be more likely to use it. Zheng and Tsai (2019) said that if a person thought some system was easy to learn, they would also think that it would help them finish more work and improve job performance with the same efforts they made. Perceived ease of use meant higher control influencing their attitude toward using the technology or system (Chao & Yu, 2019).

Tajudeen Shittu et al. (2011) investigated students' attitudes and intentions to use social software in higher institutions of learning in Malaysia, and they proved that perceived ease of use affects students' attitudes toward social software usage. Sánchez et al. (2013), perceived ease of use has a positive influence on the perceived usefulness of WebCT. The investigation of Yu and Huang (2020) proves that perceived ease of use directly affects 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 referred to the degree to which a person considers adopting some system could enhance their performance (Davis, 1989). Perceived usefulness has two dimensions: for the individual, the benefit of using some technology was improved performance; for the organization, it was from possible better product quality and savings in teaching costs (Robey & Farrow, 1982). According to Moes and Vliet (2017), if some technology or system could reduce the time to complete the potential adopters' tasks or offer timely information, they would see it useful.

Perceived usefulness was a predictor of the intention to use some applications in various contexts (Avci & Askar, 2012). Studies have also identified it as a robust predictor of people's behavioral intentions (Hsu, 2012). The study of Tajudeen Shittu et al. (2011) revealed that compared to perceived ease of use, perceived usefulness is not such a strong factor that affects those students' usage of social software. The study of Stoel and Lee (2003) also shows the positive role of perceptions of usefulness on attitude. 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). Some studies showed that an individual's intention to use a particular system or technology is strongly related to the influence of attitude and perceived behavior control towards the technology (Salleh, 2015). When people thought some system was easy to study, they would have a more positive attitude towards this system. It also said that perceived ease of use, perceived behavior control, and self-efficacy could impact the attitude toward the technology or system.

Chao and Yu (2019) indicated that an individual's behavioral intention is also affected by opportunities, resources, and his or her ability to control her behavior. Salleh (2015) studied the influence of teachers' beliefs

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towards technology integration in the classroom, and his conceptual framework shows that perceived behavioral control (PBC) had a positive effect on intention. The investigation of Yu and Huang (2020) described that perceived behavioral control had a positive and direct impact on consumers' intent to use smart libraries. Therefore, the next hypothesis is indicated:

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

## 2.4. Attitude

Attitude also reflects a person's beliefs towards a system technology (Bock et al., 2005; Hassandoust et al., 2011). 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). Individuals who perceive a system with much ease of use are more inclined to believe in its usefulness (Robey & Farrow, 1982). It was evident that certain social norms form their attitude and personal belief (Hsu, 2012).

Ajzen and Fishbein (1980) 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. In the theoretical TRA, attitude is an independent determinant of intention (Hassandoust et al., 2011). Therefore, the next hypothesis is indicated:

**H5:** Attitude has a significant impact on behavioral intention.

## 2.5 Social Influence

Social influence is defined as people in the same group giving others the belief of using or not using some technology (Ukut, 2018). It could also be considered the level to which a person thought his or her environment needed him or her to use the technology or system (Venkatesh et al., 2012). Social influence refers to external factors, such as companions or supervisory and encouragement from others, that influence the intention to e-Learning (Gunasinghe et al., 2020). Eckhardt et al. (2009) demonstrated that the source (peer groups) and sink (adopters and non-adopters) of the system could explain the impact of social influence.

Teo et al. (2019) found that sometimes social influence was more related to students' intention to use some system than perceived usefulness. Studies based on the UTAUT model have shown that social influence will be one of the conditions of behavioral intentions (Attuquayefio & Addo, 2014). The study by Ukut (2018) showed that according to students' performance, social influence significantly impacted behavioral intention. Accordingly, a hypothesis examined in this work is as follows:

**H6:** Social influence has a significant impact on behavioral intention.

## 2.6 Behavioral Intention

Lu (2018) defined intention as a potential adopter's willingness to precede specific behavior. It was also considered as the intention to make a certain response to the attitude object, and it was a state of preparation before acting in the behavior (Salleh, 2015). Furthermore, intention was the most important predictor of perceived behavior (Krueger et al., 2000). Besides, several studies explored users' technology readiness and predicted their behavioral intention (Parasuraman, 2000). Ukut (2018) found that behavioral intention significantly impacts use 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 is affected by behavioral intention. If a potential adopter's intention to use some technology or system is strong, he or she is likely to use it more frequently (Lu, 2018). Compeau and Higgins (1995) declared that technical support positively influenced technology usage. Numerous empirical studies pointed out that perceived usefulness was the most important predictor of information technology usage (Davis, 1989). Nevertheless, in some studies, behavioral intention meant almost the same as use behavior, which was the actual usage of the technology (Camarero et al., 2012). 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).

# 3. Research Methods and Materials

## 3.1 Research Framework

The underlying framework for this study draws inspiration from three preceding research works. Chao and Yu (2019) employed perceived behavioral control, attitude towards social influences, and behavioral intention to elucidate the usage patterns of Taiwanese students in weblog learning. Camarero et al. (2012) scrutinized the interplay between perceived ease of use, perceived usefulness, attitude, and behavioral intention to assess the efficacy and

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adoption of online discussion forums. Yu and Huang (2020) delved into consumers' inclination to utilize smart libraries, investigating the impact of perceived usefulness on attitudes, behavioral intentions, and behavioral intentions regarding behavior. The study places particular emphasis on key constructs, namely perceived ease of use, perceived usefulness, attitude, perceived behavioral control, social influence, behavioral intention, and usage behavior, as depicted in Figure 1.

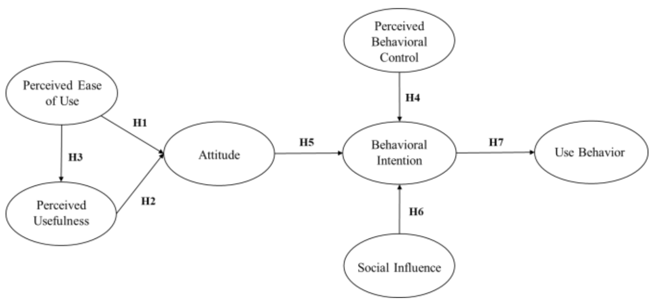


**Figure 1:** Conceptual Framework

**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

Quantitative methodologies were employed in this study, utilizing a structured questionnaire for data collection. The questionnaire was designed with three distinct sections. The initial segment encompassed screening questions aimed at verifying participant eligibility. The subsequent portion comprised items rated on a five-point Likert scale, intended to gauge respondents' viewpoints, attitudes, or perceptions regarding the research subject. Lastly, demographic information was gathered from participants in the concluding section.

Data collection for Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) entailed the acquisition of participant data to estimate and validate the proposed models.

The Index of Item-Objective Congruence (IOC) is a numerical value spanning from -1 to +1, with positive values signifying a favorable relationship between the item and the overall measure. To evaluate the content validity of the items, three experts holding Ph.D. titles or high-level management positions assessed the IOC values. The outcomes of the IOC analysis, presented in Appendix A, were juxtaposed with a minimum acceptable score of 0.6 and above, aligning with established standards for content validity (Streiner & Norman, 2008).

Incorporating Cronbach's Alpha during the pilot phase typically necessitates gathering responses from a pilot sample comprising 50 participants. Collected data encompasses participants' item responses within the scale or questionnaire under examination. Cronbach's Alpha, a metric ranging from 0 to 1, signifies higher internal consistency or reliability as values increase. Researchers interpret the Cronbach's Alpha coefficient to evaluate scale reliability. The text alludes to a benchmark of 0.70, widely recognized as a criterion for acceptable internal consistency (Nunnally & Bernstein, 1994).

## 3.3 Population and Sample Size

This study focuses on postgraduate students from the leading three universities in Kunming, China, who have practical experience with English Learning Apps. In accordance with Soper's (2023) recommendations, the specified target sample size was set at a minimum of 425 participants. However, with the aim of facilitating effective data analysis for structural equation modeling (SEM), the researcher opted to gather a total of 500 participants.

## 3.4 Sampling Technique

This study employs a combination of probability and nonprobability sampling techniques, encompassing judgmental, stratified random, and convenience sampling. To fulfill the study's objectives, the researcher has chosen to use judgmental sampling to select postgraduate students from the leading three universities in Kunming, China. To ensure balanced representation across various population subgroups and enhance the sample's precision and inclusiveness, the researcher opted for the stratified random sampling method (Lohr, 2019), as illustrated in Table 1. For the convenience sampling aspect, data collection was executed through administered questionnaires distributed among students from the prominent universities in Kunming, China, who possess firsthand experience with English learning apps. The online survey was disseminated via email and the WeChat application.

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**Table 1:** Sample Units and Sample Size

| Universities | Postgraduate | Sample Size (n=500) |
|---|---|---|
| **University A** | 11,143 | 126 |
| **University B** | 14,903 | 170 |
| **University C** | 18,000 | 204 |
| **Total** | **44,046** | **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, 40.4% were male, and 59.6% 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 Master's Degree program, comprising 79.8% of the sample. Around 11.2% of the respondents reported using English learning platforms for one year or less. A significant majority, 59.6%, had been using these platforms for 2 to 4 years. Additionally, 29.2% 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 | 202 | 40.4% |
| | Female | 298 | 59.6% |
| **Post Graduate's Program** | Master's Degree | 399 | 79.8% |
| | Doctorate Degree | 101 | 20.2% |
| **Experience use of English learning platform** | 1 year or below | 56 | 11.2% |
| | 2-4 years | 298 | 59.6% |
| | 5 years or above | 146 | 29.2% |

## 4.2 Confirmatory Factor Analysis (CFA)

Prior to conducting a Structural Equation Model (SEM), Confirmatory Factor Analysis (CFA) was employed. The CFA results revealed the significance of all items within each variable, supported by their factor loadings, thus confirming discriminant validity. Stevens (1992) established that item loadings greater than 0.40 with a p-value lower than 0.05 are considered satisfactory for Confirmatory Factor Analysis. Additionally, in accordance with the recommendations put forth by Fornell and Larcker (1981), even if the Average Variance Extracted (AVE) falls below 0.5, as long as the Composite Reliability (CR) exceeds 0.6, the construct's convergent validity remains adequate, as shown in Table 3.

**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 | 0.836 | 0.681-0.799 | 0.837 | 0.563 |
| 2. Perceived Usefulness (PU) | Venkatesh et al. (2003) | 5 | 0.763 | 0.481-0.741 | 0.777 | 0.416 |
| 3. Attitude (ATT) | Singh and Tewari (2021) | 4 | 0.834 | 0.679-0.832 | 0.839 | 0.567 |
| 4. Perceived Behavioral Control (PBC) | Al-Mamary et al. (2023) | 3 | 0.881 | 0.826-0.865 | 0.881 | 0.711 |
| 5. Social Influence (SI) | Singh and Tewari (2021) | 3 | 0.800 | 0.649-0.830 | 0.803 | 0.579 |
| 6. Behavioral Intention (BI) | Liaw (2008) | 4 | 0.857 | 0.734-0.842 | 0.858 | 0.602 |
| 7. Use Behavior (UB) | Al-Mamary et al. (2023) | 3 | 0.881 | 0.600-0.993 | 0.901 | 0.761 |

Within the framework of structural equation modeling (SEM), the measurement model holds paramount significance as it delineates the interconnections between latent variables (unobserved constructs) and their manifest indicators (measured variables). Evaluating the model's appropriateness is a pivotal phase, leading to the following fit indices: CMIN/DF = 1.380, GFI = 0.944, AGFI = 0.929, NFI = 0.942, CFI = 0.983, TLI = 0.980, and RMSEA = 0.028.

**Table 4:** Goodness of Fit for Measurement Model

| Fit Index | Acceptable Criteria | Statistical Values |
|---|---|---|
| **CMIN/DF** | ≤ 5.00 (Marsh et al., 2004) | 383.670/278 = 1.380 |
| **GFI** | ≥ 0.85 (Sica & Ghisi, 2007) | 0.944 |
| **AGFI** | ≥ 0.80 (Sica & Ghisi, 2007) | 0.929 |
| **NFI** | ≥ 0.80 (Wu & Wang, 2006) | 0.942 |
| **CFI** | ≥ 0.80 (Bentler, 1990) | 0.983 |
| **TLI** | ≥ 0.80 (Sharma et al., 2005) | 0.980 |
| **RMSEA** | ≤ 0.08 (Pedroso et al., 2016) | 0.028 |
| **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

As per the guidelines outlined by Fornell and Larcker (1981), the assessment of discriminant validity involved the computation of the square root for each Average Variance Extracted (AVE). In the context of this study, the calculated discriminant validity value surpasses all inter-construct/factor correlations, affirming its presence. Both convergent and discriminant validity have been demonstrated, thus providing ample substantiation for the establishment of construct validity.

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**Table 5:** Discriminant Validity

| | PBC | PEOU | ATT | SI | UB | BI | PU |
|---|---|---|---|---|---|---|---|
| **PBC** | **0.843** | | | | | | |
| **PEOU** | -0.044 | **0.750** | | | | | |
| **ATT** | 0.052 | 0.074 | **0.753** | | | | |
| **SI** | 0.464 | -0.040 | 0.032 | **0.761** | | | |
| **UB** | -0.088 | 0.058 | 0.101 | -0.109 | **0.872** | | |
| **BI** | 0.110 | 0.069 | 0.733 | 0.071 | 0.109 | **0.776** | |
| **PU** | 0.088 | 0.013 | 0.545 | 0.056 | 0.077 | 0.498 | **0.645** |

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

## 4.3 Structural Equation Model (SEM)

Employing Structural Equation Modeling (SEM), an evaluation is conducted to gauge the appropriateness of the structural model's representation of the observed data, following the framework set forth by Byrne (2016). The results of this examination reveal the subsequent fit measures: CMIN/DF = 1.667, GFI = 0.929, AGFI = 0.915, NFI = 0.927, CFI = 0.969, TLI = 0.966, and RMSEA = 0.037. Derived from these findings, it becomes apparent, as illustrated in Table 6, that the modified SEM model has effectively met the predefined criteria for a satisfactory fit.

**Table 6:** Goodness of Fit for Structural Model

| Index | Acceptable | Statistical Values |
|---|---|---|
| **CMIN/DF** | ≤ 5.00 (Marsh et al., 2004) | 486.803/292 = 1.667 |
| **GFI** | ≥ 0.85 (Sica & Ghisi, 2007) | 0.929 |
| **AGFI** | ≥ 0.80 (Sica & Ghisi, 2007) | 0.915 |
| **NFI** | ≥ 0.80 (Wu & Wang, 2006) | 0.927 |
| **CFI** | ≥ 0.80 (Bentler, 1990) | 0.969 |
| **TLI** | ≥ 0.80 (Sharma et al., 2005) | 0.966 |
| **RMSEA** | ≤ 0.08 (Pedroso et al., 2016) | 0.037 |
| **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

Table 7 presents an evaluation of the significance of each variable through the examination of its standardized path coefficient (β) and t-value. The findings affirm the support for all hypotheses in this study, achieving a significance level of $p<0.05$. Overall, the analysis indicates that hypotheses H2, H5, and H7 are supported, while hypotheses H1, H3, H4, and H6 are not supported.

**Table 7:** Hypothesis Results of the Structural Equation Modeling

| Hypothesis | (β) | t-Value | Result |
|---|---|---|---|
| H1: PEOU→ATT | 0.070 | 1.490 | Not Supported |
| H2: PU→ATT | 0.563 | 8.940* | Supported |
| H3: PEOU→PU | 0.013 | 0.241 | Not Supported |
| H4: PBC →BI | 0.065 | 1.635 | Not Supported |
| H5: ATT →BI | 0.743 | 13.183* | Supported |
| H6: SI →BI | 0.020 | 0.487 | Not Supported |
| H7: BI→ UB | 0.114 | 2.376* | Supported |

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

H1: The observed result was a coefficient of 0.070 with a t-value of 1.490, leading to the conclusion that this hypothesis is not supported.

H2: With a coefficient of 0.563 and a significant t-value of 8.940*, this hypothesis is supported.

H3: The coefficient of 0.013 and a t-value of 0.241 indicate that this hypothesis is not supported.

H4: The coefficient of 0.065 and a t-value of 1.635 suggest that this hypothesis is not supported.

H5: A substantial coefficient of 0.743 and a significant t-value of 13.183* provide support for this hypothesis.

H6: The coefficient of 0.020 and a t-value of 0.487 lead to the conclusion that this hypothesis is not supported.

H7: With a coefficient of 0.114 and a significant t-value of 2.376*, this hypothesis is supported.

# 5. Conclusion and Recommendation

## 5.1 Conclusion and Discussion

In the context of English learning apps among postgraduate students in Kunming, China, several key determinants have emerged as influential factors shaping both behavioral intention and use behavior. The findings underscore the significance of perceived usefulness in influencing individuals' attitudes towards these apps. This suggests that when students perceive English learning apps as valuable tools for their educational pursuits, they are more likely to develop positive attitudes towards using them.

Furthermore, the study establishes a notable connection between behavioral intention and use behavior. This implies that students who express a strong intent to utilize these apps are more likely to translate this intention into actual use.

Interestingly, the impact of attitude on behavioral intention is pronounced, highlighting the pivotal role that positive attitudes play in motivating individuals to intend to use English learning apps. However, contrary to expectations, perceived behavioral control and social influence were found to have no significant impact on behavioral intention. This nuanced insight into the interplay of factors underscores the

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need for a comprehensive understanding of the dynamics at play.

A somewhat unexpected outcome pertains to the perceived ease of use, which did not exhibit a significant impact on attitude and perceived usefulness. This suggests that, in this context, the perceived ease of using these apps may not be a primary driver of students' attitudes or their perception of usefulness. This outcome prompts further exploration into the specific factors that do contribute to attitude and perceived usefulness

The study's outcomes shed light on the complex landscape of determinants that influence the behavioral intentions and use behavior of English learning apps among postgraduate students in Kunming, China. The prominent role of perceived usefulness aligns with the broader technology acceptance literature, indicating that when individuals perceive a tool as beneficial, their attitudes and subsequent intentions towards using it are positively influenced.

The strong connection between behavioral intention and use behavior reaffirms the notion that intention can serve as a reliable predictor of actual behavior. This insight is particularly relevant for educators and app developers aiming to encourage consistent and meaningful usage among students.

The intriguing finding that perceived behavioral control and social influence do not significantly impact behavioral intention prompts deeper exploration. Cultural and contextual factors specific to the study's locale may contribute to this outcome. Future research could delve into the cultural dynamics at play, investigating how individual autonomy and social factors intersect with technology adoption.

The unexpected relationship between perceived ease of use and attitude/perceived usefulness suggests a need for a more nuanced investigation into the user experience of these apps. Factors beyond ease of use, such as the apps' functionality, content relevance, and alignment with learning goals, might be stronger drivers of users' attitudes and perceptions of usefulness.

In conclusion, this study advances our understanding of the determinants shaping the use of English learning apps among postgraduate students in Kunming, China. The insights gained pave the way for more targeted strategies to enhance app adoption and effective use, with implications for educational institutions, app designers, and policymakers seeking to optimize technology integration in education. Further research is encouraged to explore the intricate interplay of cultural, psychological, and contextual variables within this domain.

## 5.2 Recommendation

Incorporating recommendations can contribute to a more comprehensive approach for promoting the effective use of English learning apps among postgraduate students in Kunming, China. By addressing the identified gaps and building on the factors that influence attitudes and usage behavior, institutions and app developers can optimize the integration of technology in language learning and enhance students' overall learning outcomes

Educational institutions and app developers should focus on clearly communicating the various ways in which English learning apps can be beneficial to postgraduate students. Highlighting specific features that cater to their academic needs, such as vocabulary building, language proficiency enhancement, or subject-specific resources, can bolster perceived usefulness and, consequently, attitudes towards app usage.

While perceived ease of use may not be a significant driver in this context, it is still important to ensure that English learning apps are user-friendly and intuitive. Incorporating features that simplify navigation, provide personalized learning pathways, and offer real-time progress tracking can contribute to a more positive user experience.

Institutions and app developers should actively engage students through well-designed content, interactive exercises, and collaborative learning opportunities. This engagement can foster positive attitudes by making the learning process enjoyable, relevant, and rewarding.

Further research is needed to understand the specific cultural and contextual factors that influence perceived behavioral control and social influence in this context. Institutions can consider organizing workshops, seminars, or peer-led activities that emphasize the benefits of app usage and provide guidance on effective usage strategies.

Identify influential figures within the student community who can serve as advocates for English learning apps. Their positive endorsement and success stories can have a persuasive impact on their peers, potentially addressing the gap in social influence observed in this study.

Emphasize the practical applications of English learning skills in students' academic and professional lives. Showcasing how proficiency in the language can open doors to research opportunities, international collaborations, and career advancement can enhance perceived usefulness and encourage app adoption.

Periodically assess students' experiences and gather feedback regarding app usage. This iterative approach allows for continuous improvement based on user preferences and needs, ensuring that the app remains aligned with students' expectations.

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Customize app content and features to cater to the specific requirements and interests of postgraduate students. This personalization can make the app more relevant and valuable, thus boosting both perceived usefulness and attitudes.

Collaborate closely with educators to integrate app usage seamlessly into the curriculum. Facilitate training sessions for teachers to effectively incorporate app-based learning activities into their teaching strategies, enhancing the overall learning experience.

Develop strategies to encourage sustained and consistent app usage over an extended period. Implementing gamification elements, offering incentives tied to usage milestones, or providing certificates for achieving language proficiency can motivate students to continue using the app.

### 5.3 Limitation and Further Study

This study focused on postgraduate students in Kunming, China. Future research could explore how cultural variations across different regions within China or in other countries might influence the identified determinants. Cross-cultural comparisons could provide deeper insights into the generalizability of the findings. While quantitative methods provide valuable insights, qualitative research techniques such as interviews or focus groups could offer richer insights into the underlying motivations, perceptions, and experiences of postgraduate students using English learning apps. Furthermore, the study focused on specific determinants such as perceived usefulness, attitude, and social influence. Future studies could incorporate additional external variables such as individual learning styles, technological literacy, and self-regulation, which might interact with the identified determinants.

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