INVESTIGATION ON THE USE BEHAVIOR OF MOBILE VIDEO APPS AMONG GEN Z STUDENTS IN CHONGQING, CHINA

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Abstract

Mobile video applications have a second opportunity because of their convenience, real-time, and distance-free features. This research explores the factors that influence the use behavior of mobile video apps among generation Z in Chongqing, China. These factors are determined by perceived ease of use, usefulness, social influence, habit, facilitating conditions, behavioral intention, and user behavior. The researchers used quantitative research methods and non-probabilistic sampling as sampling tools. A total of 500 science college students studying and using mobile video apps in Chongqing, China, were invited to participate in the study. In this research, structural equation models (SEM) and confirmatory factor analysis (CFA) were used to model fit, reliability, and validity. The results show that perceived ease of use, and habit significantly affect the behavioral intention towards use behavior. Perceived ease of use significantly affects perceived usefulness. Additionally, behavioral intention and facilitating conditions significantly affect use behavior. Nevertheless, perceived usefulness and social influence has no effect on behavioral intention.

Keywords: Mobile Video Application, Generation Z, Science Students, Behavioral Intention, Use Behavior

Introduction

Mobile video applications have begun to gain a firm foothold in China. With the convenience of mobile phones, online video can be played regardless of time, space and mode. With the help of applications, users can demand programs in various situations, fully reflecting videos' information and entertainment value (Tjondronegoro et al., 2007). The current generation of young people, generally defined as those born after 1995, is known as Generation Z (Chillakuri & Mahanandia, 2018), accounting for 32% of the global population (Miller & Lu, 2019). Generation Z is a group of people who enter society and maintain a strong interest in the interest and use of technology (Ryback, 2016). They were born in the era of the Internet technology explosion. By the end of December 2020, Internet users aged 10 to 29 accounted for 31.3 percent of China's total Internet users. Students account for 21.9 percent of the occupational structure of Chinese netizens, making them the largest category among netizens. Generation Z plays a crucial role in China's Internet and has a major influence on the future development trend of the Internet. Generation Z, as the heavy Internet users today, will also become the main user group of mobile video applications. Science students pay more attention to education and training in mathematics, physics, logical thinking, and rational analysis. This kind of education mode significantly impacts the thinking mode and emotional cognition of this group, which is quite different from liberal arts students. Studying the factors that influence their choice of mobile video applications is an interesting and valuable topic.

Literature Review

1. Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is that the user's belief determines the attitude toward using the system, and the attitude develops into the intention of using the system, which directly affects the decision-making of the actual use of technology. This causal relationship has been widely used and studied (Chen et al., 2002). Venkatesh et al. (2003) deleted attitude from TAM because it did not affect the overall difference in use. Many studies have proved that TAM has greatly explored users' behavioral intentions and actual use. It describes the antecedents of technology use through "perceived ease of use" and "perceived usefulness," thus explaining users' adoption of technology (Davis, 1989).

1.1. Perceived ease of use

Perceived ease of use refers to a user's view of how simple and comfortable it is to use technology (Gao & Bai, 2014). Perceived ease of use was a crucial factor influencing user behavior intention and was one of the primary aspects of the technology adoption model (Zhong et al., 2022). Perceived ease of use was deemed a key driver of behavioral intention in many earlier research studies (Davis, 1989). However, other research has shown that perceived ease of use indirectly influences behavioral intention via perceived usefulness (Joo et al., 2016). According to Venkatesh et al. (2003), if it is difficult to use, users may not use it. When users felt that the technology could be used easily, the technology would be used more frequently. Hence, hypotheses are set:

H1: Perceived ease of use has a significant effect on perceived usefulness.

H2: Perceived ease of use has a significant effect on behavioral intention.

1.2. Perceived usefulness

The primary variable in new technology adoption was perceived usefulness (Dahlberg et al., 2015). The degree to which users believed that technology helped them enhance performance was perceived usefulness (Akbar, 2013). According to Fishbein and Ajzen (1975), perceived usefulness was defined as the subjective likelihood that users would improve their performance by utilizing a certain technology or system. The relationship between perceived usefulness and behavioral intention was validated by Al-Emran and Teo

(2020). Thus, a hypothesis is indicated:

H3: Perceived usefulness has a significant effect on behavioral intention.

2. Extend Unified Theory of Acceptance and Use of Technology (UTAUT2)

Extend Unified Theory of Acceptance and Use of Technology (UTAUT2) provides an established framework with a higher predictive ability for the use and adoption of technology from the perspective of consumers' hedonic background (Venkatesh et al., 2012). Four elements influence individuals' intentions to embrace and adopt technology in UTAUT. Performance expectations, social influence, effort expectations, and facilitating conditions are the factors to consider (Venkatesh et al., 2003). UTAUT2 improves it by adding three new variables: hedonic motivation, habit, and price sensitivity (Baptista & Oliveira, 2016).

2.1. Social Influence

Individuals' decision to employ technology would favorably influence their self-perception in social circumstances (Min et al., 2022). When individuals believe that their surrounding groups approve of their use of technology or that it improves their social image, they are more inclined to utilize it (José Liébana-Cabanillas et al., 2014). San Martín and Herrero (2012) pointed out that reference people were generally the groups valued by users, such as family members, friends, teachers, and classmates. Social influence could directly or indirectly influence users' behavior intention (Venkatesh et al., 2003). Therefore, a hypothesis is proposed:

H4: Social influence has a significant effect on behavioral intention.

2.2. Habit

The habit is defined as the perceptual structure reflecting experience results (Venkatesh et al., 2012). Limayem et al. (2007) believed that people tended to automatically participate in specific behaviors through past learning, which was habit. It was related to automaticity (Kim et al., 2005). In all domains, the habit was the most powerful predictor of actual consumption. It plays a significant role in behavior intention, and it was established that habit and behavior intention significantly impact user behavior (Baptista & Oliveira, 2017). Thereby, the following hypothesis is derived:

H5: Habit has a significant effect on behavioral intention.

2.3. Behavioral Intention

Li et al. (2020) considered that behavioral intention referred to an individual's subjective judgment of future behavior. Behavioral intention is one of the key elements determining human behavior, according to Venkatesh et al. (2003), and behavioral intention might be utilized to anticipate action. Ajzen (1991) held that behavioral intention strongly determines subsequent action. Use behavior and desire to utilize technology were strongly influenced by perceived usefulness and perceived ease of use. Thus, a proposed hypothesis is set:

H6: Behavioral intention has a significant effect on use behavior.

2.4. Facilitating Conditions

Brown et al. (2015) considered that facilitating conditions were the resources needed for adopting new technologies, the advantages, and disadvantages of infrastructure, or the support provided by other technologies. Teo et al. (2007) defined facilitating conditions as environmental elements influencing an individual's motivation to undertake an activity. Many studies have found that facilitating conditions had a favorable influence on not just the intention to use technology but also the actual behavior of utilizing technology (Dwivedi et al., 2011). Accordingly, a hypothesis is conducted:

H7: Facilitating conditions has a significant effect on use behavior.

2.5. Use behavior

The actual frequency of technology use could be used to measure the level of user behavior. The duration of interaction between individuals and specific technology could also be used to evaluate user behavior (Venkatesh et al., 2008). Research and technology models suggest that user behavior can best predict how consumers utilize technology. The user behavior of some network technologies was positively affected by facilitating conditions and behavior intention (Deng et al., 2011). Behavior intention was regarded as a powerful indicator of the actual use behavior of Internet mobile technology.

Research Framework

This conceptual framework combines TAM and UTAUT2 from previous literature (Chua et al., 2018; Dhiman et al., 2019; Hu & Lai, 2019; Samsudeen & Mohamed, 2019). Seven variables can construct the conceptual framework of this study: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Social Influence (SI), Habits (HB), Behavioral Intention (BI), Facilitating Conditions (FC), and Use Behavior (UB).

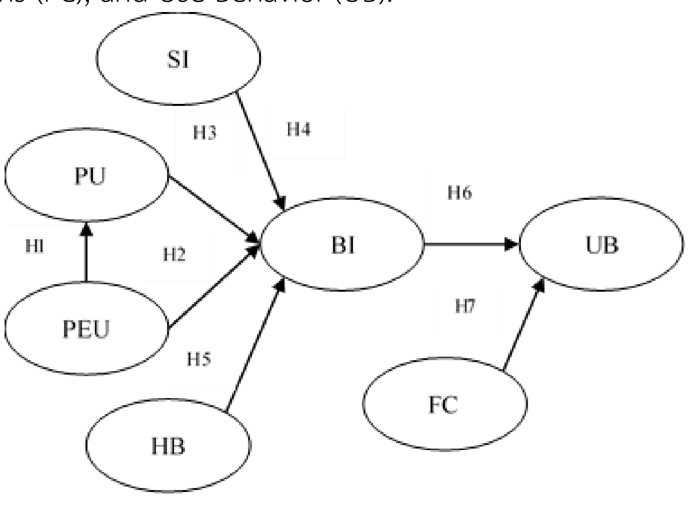

Figure 1 Conceptual Framework

Research Methodology

The research is a quantitative study using online and offline questionnaires as data collection tools and statistical procedures for analysis. Data were collected mainly through WJX, an online questionnaire website. The questionnaire consists of 2 screening questions to identify target respondents, five demographic questions to classify the population statistically, and 25 measurement items through a five-point Likert scale (1 = strongly disagree to 5 - strongly agree).

1. Population and Sample Size

The target population of this study are science students who are generation Z in two selected universities in Chongqing, China, and have been experiencing the use of mobile video apps. The study determines minimum sample size by inputting the effect size of 0.2, the recommended statistical power of 0.8, the probability level of 0.05, 7 potential variables and 25 observation variables, and the minimum sample size recommended by the Calculator of 425. The sample size aims to 500 to achieve better research results.

2. Sampling Techniques

This study applied judgmental, quota, and convenience sampling. The judgmental sampling is to select generation Z students, majoring science from two selected universities in Chongqing, China, and have been experiencing the use of mobile video apps. The quota sampling divides 250 students per university. Online and offline questionnaire distribution was employed according to convenience sampling.

Results and Discussion

1. Demographic Information

The demographic results of 500 target respondents are shown in Table 1. Female students account for 23.6% (118) and male students for 76.4% (382). In terms of age, 18-22 years old is the majority group, accounting for 87.2% (436). Most of them have 4-6 years' use experience, accounting for 43% (215). Among the respondents, 87.2% (436) were studying at universities for their bachelor's.

Table 1 Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	382	76.4
	Female	118	23.6
Age	Below 18 years	15	3
	18 – 22 years	436	87.2
	23 – 25 years	31	6.2
	More than 25 years	18	3.6
Mobile Video Apps Experience	Below 1 year	35	7
	1 – 3 years	167	31.4
	4 – 6 years	215	43
	More than 6 years	83	16.6
Study for degree	Bachelor's Degree	436	87.2
	Master's Degree	51	10.2
	Doctorate Degree	13	2.6

2. Confirmatory Factor Analysis (CFA)

This research used confirmatory factor analysis (CFA) to assess the correlation of variables within the project and measure the degree of adaptation of the model. According to Table 2, the greater the factor load value, the higher the reliability of the project (Hair et al., 2010). In this study, the factor loads of every single item were greater than 0.50, mostly above 0.70, ranging from 0.659 to 0.857. According to Fornell and Larcker (1981), composite reliability (CR) and average variance extracted (AVE) values of 0.7 and 0.4 or higher are acceptable. In this study, CR was higher than the threshold. The range is 0.790 - 0.866. AVE values were all greater than 0.4, ranging from 0.499 to 0.648.

Table 2 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEU)	Lee et al., 2012	4	0.824	0.659-0.748	0.799	0.499
Perceived Usefulness (PU)	Davis et al., 1989	4	0.866	0.722-0.792	0.836	0.561
Social Influence (SI)	Chun et al., 2012	3	0.705	0.723-0.857	0.846	0.648
Habit (HB)	Venkatesh et al., 2012	3	0.725	0.754-0.829	0.842	0.641

Table 2 continue

Latent Variables	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Facilitating Conditions (FC)	Venkatesh et al., 2003	5	0.906	0.662-0.807	0.866	0.565
Behavioral intention (BI)	Davis et al., 1989	3	0.738	0.686-0.799	0.790	0.557
Use Behavior (UB)	Davis et al., 1989	3	0.861	0.726-0.774	0.799	0.570

Source: Created by the author

Confirmatory factor analysis was used to evaluate the measurement model to determine the fitting degree of the model. Therefore, this study does not need to modify the measurement model because the original model already has model fitting, as shown in Table 3.

Table 3 Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Awang, 2012)	514.592/254 or 2.026
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.921
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.898
NFI	≥ 0.80 (Wu & Wang, 2006)	0.925
CFI	≥ 0.80 (Bentler, 1990)	0.961
TLI	≥ 0.80 (Sharma et al., 2005)	0.953
RMSEA	< 0.08 (Pedroso et al., 2016)	0.045
Model summary		**Unacceptable Model Fit**

Note: 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, RMSEA = Root mean square error of approximation.

From Table 4, the method of determining validity is to confirm that AVE's square root is greater than any corresponding structure coefficient (Fornell & Larcker, 1981). The AVE square root of all structures on the diagonal is greater than the inter-scale correlation, and the discriminant validity is guaranteed.

Table 4 Discriminant Validity

	PEU	PU	SI	HB	FC	BI	UB
PEU	**0.706**						
PU	0.625	**0.748**					
SI	0.285	0.448	**0.804**				
HB	0.480	0.444	0.410	**0.800**			
FC	0.554	0.501	0.404	0.625	**0.751**		
BI	0.593	0.502	0.373	0.665	0.674	**0.746**	
UB	0.483	0.428	0.357	0.661	0.680	0.711	**0.754**

Note: The diagonally listed value is the AVE square roots of the variables.

3. Structural Equation Model (SEM)

In this study, the structural equation model (SEM) was used to evaluate the structural models, to determine the causal relationship between model fitness and variables, and to determine the factors that affect the user behavior of science students in Chongqing universities on mobile video applications. Structural models can show direct or indirect relationships between potential variables (Byrne, 2010). From Table 5, the structural model is modified by the correlation between the measurement errors of the constructs. The goodness of fit index was recalculated according to the modified structural model. As shown in Table 5, the statistical values are CMIN/DF =4.152, GFI = 0.852, AGFI = 0.809, NFI=0.848, CFI = 0.880, TLI = 0.857, and RMSEA = 0.079. The fitting of the structural model is verified.

Table 5 Goodness of Fit for Measurement and Structural Model

Index	Acceptable Values	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Awang, 2012)	1223.130/268 or 4.564	1046.305/252 or 4.152
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.830	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.794	0.809
NFI	≥ 0.80 (Wu & Wang, 2006)	0.823	0.848
CFI	≥ 0.80 (Bentler, 1990)	0.855	0.880
TLI	≥ 0.80 (Sharma et al., 2005)	0.838	0.857
RMSEA	< 0.08 (Pedroso et al., 2016)	0.085	0.079
Model summary		**Not in harmony with empirical data**	**In harmony with empirical data**

Note: 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, RMSEA = Root mean square error of approximation.

4. Hypothesis Testing Result

The magnitude of the correlation between the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients (β).

Table 6 Hypothesis Results of the Structural Equation Model

Hypothesis	(β)	t-value	Result
H1: PEU → PU	0.766	12.296*	Supported
H2: PEU → BI	0.390	4.705*	Supported
H3: PU → BI	0.093	1.166	Not Supported
H4: SI → BI	0.084	2.263	Not Supported
H5: HB → BI	0.649	13.183*	Supported
H6: BI → UB	0.722	11.382*	Supported
H7: FC→ UB	0.448	8.252*	Supported

Note: *** p<0.001

Source: Created by the author

H1: Perceived ease of use significantly affects perceived usefulness, with a standardized path coefficient of 0.766 and a t-value of 12.296.

H2: There is a significant effect of perceived ease of use on behavioral intention, with a standardized path coefficient of 0.390 and a t-value of 4.705.

H3: Behavioral intention is not affected by perceived usefulness, with the standardized path coefficient of 0.093 and t-value at 1.166.

H4: The relationship between social influence and behavioral intention is not supported. Among the factors that significantly influence behavioral intention, with the standardized path coefficient of 0.084 and t-value at 2.263.

H5: There is the greatest influence between habit and behavioral intention, with the standardized path coefficient of 0.649 t-value at 13.183.

H6: Both behavioral intention and facilitating conditions significantly influence user behavior, and behavioral intention has the greatest influence on user behavior—the standardized path coefficient of 0.722 and the t-value of 11.382.

H7: Facilitating conditions significantly affects use behavior, reflecting the standardized path coefficient of 0.448 and t value at 8.252.

Conclusions, Recommendations, Limitations and Future Research

1. Conclusions

In order to form the conceptual framework of the research, the researchers collected relevant theories and studies on the subject through the study of previous theoretical models and literature. This study mainly adopts two core theories: the Technology Acceptance Model (TAM) and the Unified Theory of Extended Technology Acceptance and Use (UTAUT2). According to the research, habits have the most significant influence on the behavioral intention of the respondents. The literature of Dhiman et al. (2019) demonstrates this relationship, and users' long-term fixed use of technology will significantly improve their willingness to use it. Perceived ease of use plays a dual role in influencing users' behavioral intentions. The research results of Hu and Lai (2019) supports their relationship. Users will judge the difficulty of using this technology, which will directly lead to whether they have behavioral intentions. This study also demonstrates the positive impact of facilitating conditions on user behavior, and it is verified by Samsudeen and Mohamed (2019) that behavioral intention cannot be translated into actual behavior without preconditions supporting the development and use of technology. Finally, Chua et al. (2018) believed that behavioral intention had the most significant impact on user behavior, which was also confirmed in the results of this study. The intensity of users' intentions determines the actions they take. People's behavior is the ultimate embodiment of their ideas, and strong intentions will be realized through behavior. In conclusion, the research results show that perceived ease of use, habit, and behavioral intention are positively correlated, and facilitating conditions and behavioral intention positively impact user behavior.

2. Recommendations

This research shows that the key influencing factors of science students’ behavioral intention and use behavior of mobile video applications in Chongqing are habit, perceived ease of use, and facilitating conditions. Therefore, if we want to improve and promote the usage rate of mobile video applications in this population range, we need to start from these factors to achieve better results. This research also reflects the main influencing factors that Z generation people studying in colleges and universities under science education will be affected by when choosing mobile video applications. From the research data, habit is the most significant factor affecting the behavioral intention of groups, and users' addiction to technology makes them form long-term behavior patterns. Increasing the engagement between the user and the application technology is one of the primary considerations for application technology developers. Users can emotionally connect with the technology to enhance its attractiveness and interactivity (Dhiman et al., 2019). For example, big data can be used to understand the subscription types of such users and push the content they are interested in every day to form a habit similar to watching the news every day. To provide users with a creative platform and communication platform, users create images to get more feedback, encourage creators to create behavior, and let the application technology become a fixed platform for their image content publication.

In improving user-friendliness, technology developers need to start from various aspects to meet the technical needs of such young users and ensure the convenience of technology applications (Hew et al., 2015). Today's users are no longer satisfied with using a single platform for applications. In pursuit of technological innovation, they will use newer and faster smartphones or systems. This makes it imperative for app developers to keep up with The Times and adapt their technology to new platforms. The sooner an application occupies the commanding heights of a platform, the sooner it can capture the attention of this audience. In addition, application developers and managers must address usability issues outside the technology. While most generation Z people in China have smartphones and access to the Internet via WI-FI, mobile data is also needed at special times. Apps can sign joint agreements with mobile traffic companies to reduce the amount of data generated while using the app and make users more likely to choose the app for information access.

3. Limitations and Future Research

This study selected science students from two representative universities in Chongqing. This approach cannot fully reflect differentiation. Future research should expand the sample and target selection range from Chongqing to other regions or countries. Next, researchers can use qualitative methods to collect data, such as face-to-face and in-depth interviews, to obtain more in-depth information from respondents. Finally, other factors that may influence people's behavior when using mobile video apps, such as attitude, performance expectations, effort expectations, etc., can be added to make the study more accurately reflect the behavior of users.

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