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The Assessment of Liberal Arts Students' Behavioral Intention and Use Behavior of Mobile Video Apps in Chongqing, China

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Abstract

Purpose: Generation Z people are reported to be main users of Internet and mobile video applications. Thus, this study aims to assess the influencing factors of behavioral intention and use behavior towards mobile video apps, using a case of Gen Z students in liberal arts in Chongqing, China. **Research design, data and methodology:** The researchers used quantitative research methods and nonprobability sampling techniques including purposive, quota and convenience samplings for the data collection. 500 college students in liberal arts program who have been using mobile video apps in Chongqing, China, were invited to participate in the study. Item Objective Congruence (IOC) Index and Cronbach's Alpha reliability were approved before the data collection process. Afterwards, structural equation model (SEM) and confirmatory factor analysis (CFA) were used for the data analysis and results. **Results:** Perceived ease of use, social influence, habit and facilitating conditions have a significant affect behavioral intention. Furthermore, behavioral intention significantly affects use behavior. On the other hand, perceived usefulness has no significant effect on behavioral intention. **Conclusions:** This study validates factors impacting Gen Z's adoption on mobile video editing applications which mobile developers are recommended to emphasize this major group of user's use behavior for the better development of the apps.

Keywords: Mobile Video Applications, Generation Z, Students, Behavioral Intention, Use behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The COVID-19 epidemic has brought fundamental change to human life on a global scale. In the early days of the outbreak, people were isolated in the places where they lived and banned from social activities to prevent the spread of the virus (Wilder & Friedman, 2020). Chinese society was the first to suffer the baptism of COVID-19 (Haroon & Rizvi, 2020). During periods of isolation, people need to receive external information, and in order to relieve negative emotions, they also need entertainment (Bradbury-Jones & Isham, 2020). As the most intuitive carrier of information transmission, network video has been widely used by individual users, enterprises and governments.

Governments, businesses and individuals have all accelerated the digital transformation of society. From the perspective of individuals, isolation measures make individuals more inclined to use Internet tools, and promote

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the formation of users' online intentions and habits (Nagel, 2020). During the epidemic, online business models such as online office work and online trading have provided technical support for normal operation of enterprises. Special periods promote digital operation transformation of enterprises (Beland et al., 2020). By the end of 2020, the COVID-19 epidemic in China had been basically under control, and society will enter the post-epidemic era and gradually restore social order (Qin, 2020). Meanwhile, measures to prevent a recurrence of COVID-19 are still in place in 2022. By 2020, the last year of the 13th Five-Year Plan, China's Internet infrastructure will be fully covered and the number of Internet users will continue to grow steadily (China Internet Network Information Center, 2021).

Information links between the Internet and mobile phones have stimulated the popularity of the Internet and mobile Internet in China. The mobile Internet has opened up to the masses as the mobile phone has transformed from a luxury to a communication tool. Mobile devices bring entertainment and productivity to users through mobile applications (Hew et al., 2015). This brings more business opportunities to the mobile phone industry. Mobile games, mobile phone business, mobile phone marketing, mobile phone video and so on emerge at the historic moment (Liu & Li, 2009). At present, the scale of Mobile Internet users in China is gradually expanding and reaching saturation. Mobile networks dominate the Internet in China. Mobile phones have become the main mobile Internet access device in China and are used by the vast majority of Internet users.

In this context, with the maturity of streaming media technology, online video has gradually become the main channel of information transmission, and mobile video applications have begun to gain a firm foothold in China. Combined 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 the information and entertainment value of videos (Tjondronegoro et al., 2006). In June 2020, the popularity of 5G technology improved the speed of network information transmission, and the scale of Internet video users made a breakthrough in this context. There were nearly 100 million more users in March 2020 (after the outbreak) than in June 2019 (before the outbreak), and the number of users has maintained a steady upward trend since the outbreak. China had 927 million online video users by the end of December 2020, accounting for 93.7 percent of all Internet users, an increase of about 76 million from March of the same year (China Internet Network Information Center, 2021).

The current generation of young people, generally defined as those born after 1995, is known as Generation Z (Chillakuri & Mahanandia, 2018; Lanier, 2017), 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 and use of technology (Ryback, 2016). They were born in the era of 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 users of the Internet today, will also become the main user group of mobile video applications.

The group of college students who have received higher education and have not graduated in China is mainly between 18 and 25 years old, and they all belong to Generation Z who were born after 1995 (Bassiouni & Hackley, 2014). In 2020, there were nearly 49.25 million college students in China (National Bureau of Statistics, 2020), including undergraduates, junior college students, postgraduates and doctoral students. Compared with other Generation Z, college students have a certain economic foundation and tend to be adults psychologically. They have the ability to think and take responsibility for their choices and actions. This group will become the mainstay of society after graduation and employment.

However, there are differences among college students because of the problems of educational planning. The education system of separating arts and sciences has been implemented for a long time in China. It divides the types of instruction into arts and sciences, and educates students according to their choice. Although this system is gradually being replaced, the liberal arts and science education model still exists in higher education. Liberal arts students pay more attention to the education and cultivation of humanities, society, literature and history, which has a significant impact on the thinking mode and emotional cognition of this group and is different from science students. It is an interesting and worthwhile topic to study the factors that influence their choice of mobile video applications.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is adapted from the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980), it is better than TPB in explaining the behavioral intention of using technology and system (Chau & Hu, 2001;

Huh et al., 2009). TAM is similar to TRA in that the user's belief determines the attitude of 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; Morris & Dillon, 1997; Suh & Han, 2002; Teo et al., 1999). Taylor and Todd (1995) found that attitude was not a significant predictor of intention to use in TAM. Venkatesh and Davis (2000) and Venkatesh et al. (2003) deleted attitude from TAM because it did not affect the overall use. A large number of studies have proved that TAM has made great achievements in exploring users' behavioral intention and actual use. It describes the antecedents of technology use through "perceived ease of use" and "perceived usefulness", explaining users" adoption of technology (Davis, 1989). Perceived ease of use refers to the extent to which people believe that the use of this technology can be effortless, and the extent to which people believe that the use of this technology will improve their performance is perceived usefulness. They are important determinants of the use of systems and technologies in TAM (Davis et al., 1989). Venkatesh et al. (2012) noted that additional variables, such as the opinions of influential individuals, will impact users' adoption of technology. Schierz et al. (2010) also pointed out that TAM should be expanded according to the research technology to achieve its effectiveness.

2.2 Extend Unified Theory of Acceptance and Use of Technology (UTAUT2)

Extend Unified Theory of Acceptance and Use of Technology (UTAUT2) provides an established framework, which has a higher predictive ability for the use and adoption of technology from the perspective of consumers' hedonic background (Venkatesh et al., 2012). Individuals' intentions to embrace and adopt technology are influenced by four elements in UTAUT which are performance expectancy, social influence, effort expectancy and facilitating conditions (Venkatesh et al., 2003). UTAUT2 improves it by adding three new variables, namely hedonic motivation, habit and price sensitivity (Baptista & Oliveira, 2016; Kumar et al., 2012; Venkatesh et al., 2012). Compared with the structure of UTAUT, UTAUT2 contains hedonic variables (Lua et al., 2016). Through these seven factors, UTAUT2 can explain the user's intention to use a technology. UTAUT2 has been used in a number of research to predict mobile apps adoption in various scenarios (Chopdar et al., 2018; Gupta et al., 2018). According to Huang and Kao (2015), the model may successfully explain and assess people's acceptance behavior of new IT product technology. In this sense, UTAUT2 model has been applied to the prediction of media technology (Mütterlein et al., 2019).

2.3 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). It is mainly reflected in the user's efforts in using a certain function (Lee et al., 2012), as well as the level of effort required to make technology simple to use (Venkatesh & Davis, 2000). Perceived ease of use is a crucial factor influencing users' behavior intention and is one of the primary aspects of the technology adoption model. Perceived ease of use is deemed a key driver of behavioral intention in a great number of earlier studies (Davis, 1989). However, other researches have shown that perceived ease of use has an indirect influence on behavioral intention via perceived usefulness (Joo et al., 2016). According to Venkatesh et al. (2003), perceived ease of use has a significant impact on perceived usefulness of innovative technology. If a technology is difficult to use, users may perceive it cannot provide benefits as they expected. In addition, when users feel that the technology can be easily used, they have intentions to use it. Consequently, a following hypotheses are developed:

H1: Perceived ease of use has a significant effect on perceived usefulness of mobile video apps among liberal arts students.

H2: Perceived ease of use has a significant effect on behavioral intention to use mobile video apps among liberal arts students.

2.4 Perceived Usefulness

Another primary variable in new technology adoption is perceived usefulness (Dalhberg et al., 2015). One of the most essential fundamental components in the technology adoption paradigm is how users think that it can be beneficial (Davis et al., 1989). The degree to which users believe that employing a technology can enhance their performance is referred to perceived usefulness (Akbar, 2013). Perceived usefulness, according to Fishbein and Ajzen (1975), is 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). In the model of innovation diffusion theory, motivation theory, and social cognitive theory, perceived usefulness is considered as a major component (Venkatesh et al., 2003). Individuals perceive technology's usefulness has a substantial effect on their behavioral intention, and consequently on actual usage (Adams et al., 1992). If the convenience of technology or system exists, the perceived usefulness of users is affected (Lai, 2013). Based

on previous studies' evidences, a hypothesis is proposed:
H3: Perceived usefulness has a significant effect on behavioral intention to use mobile video apps among liberal arts students.

2.5 Social Influence

Social influence can be understood as external social factors influencing behavior, which could be divided into self-perception in social situations (Chun et al., 2012) and societal conventions (Hsu & Lu, 2004). An individual's decision to employ technology favorably influences by self-perception in social circumstances. When an individual believes that his or her surrounding groups approve of his or her use of technology, or that using technology improves the individual's social image, he or she more inclines to utilize it (Liébana-Cabanillas et al., 2014). Users can be impacted by their societal conventions (Arrieta et al., 2019). Martin and Herrero (2012) pointed out that reference people are generally the groups valued by users, such as family members, friends, teachers and classmates. In other words, users consider the expectations of this group of people, and tend to implement these expected behaviors. Social influence could directly or indirectly influence users' behavioral intention through others' feelings, thoughts and actions (Venkatesh et al., 2003). One of the most important aspects that influence consumers' behavior is when it comes to using a mobile apps is driven by social influence (Arrieta et al., 2019; Hew et al., 2015). It is easier for people to accept technology when people who are important to them recommend it (Bagozzi & Lee, 2002). The role of social influence is more important in the early stages of consumers' usage of technology (Thompson et al., 1994). As a result, an indicated hypothesis is properly stated:
H4: Social influence has a significant effect on behavioral intention to use mobile video apps among liberal arts students.

2.6 Habit

Habit is defined as the perceptual structure reflecting the past experience (Venkatesh et al., 2012). Limayem et al. (2007) believed that people tend to automatically participate in specific behaviors through past learning, which calls habit. It is related to automaticity (Kim et al., 2005), which requires long-term experience and accumulation of knowledge (Alalwan et al., 2015). In all domains, habit is the most powerful predictor of actual consumption. It has a significant role to behavioral intention, and it is established that habit and behavioral intention have a significant impact on use behavior (Baptista & Oliveira, 2017). Convenient, adaptable and reusable technology can enhance users to be addicted and forms their habits (Huili & Chunfang, 2011). Dhir et al. (2018) posited that habit is a strong driving factor of young people to use social networks. Consequently, understanding users' behaviors is crucial in order to improve technology adoption rate. Subsequently, previous studies produce a hypothesis:
H5: Habit has a significant effect on behavioral intention to use mobile video apps among liberal arts students.

2.7 Facilitating Conditions

The degree to which users feel that the technological infrastructure and organizational support of the system's functions exist is explained as facilitating conditions (Venkatesh et al., 2003). It is also defined as the appropriate education and training supplied to users in the promotion of new technologies, which may allude to the compatibility of new technology (Teo & Noyes, 2014). Brown et al. (2015) considered that facilitating conditions are the resources that are required for the adoption of new technologies, the advantages and disadvantages of infrastructure or the support provided by organizations. Teo et al. (2008) defined facilitating conditions as environmental elements that influence an individual's motivation to undertake an activity. Many studies found that facilitating conditions have a favorable influence on not just the intention to use technology, but also on the use behavior (Dwivedi et al., 2011). The facilitating conditions are necessary requirements for the adoption of new technologies. It does not only aid people in learning how to use a new technology in a short time, but it also lessens the number of difficulties they possibly encounter (Huang, 2015). Accordingly, H6 is set.
H7: Facilitating conditions have a significant effect on behavioral intention to use mobile video apps among liberal arts students.

2.8 Behavioral Intention

The behavioral intention is termed as how strong a person's intention is at the start of a certain activity (Davis et al., 1989), and can also be used as an evaluation of an individual's motivation to take action (Ajzen & Fishbein, 1980). Li et al. (2020) considered that behavioral intention refers to an individual's subjective judgment of future behavior. Yi et al. (2016) acknowledged behavioral intention as the subjective probability of usage behavior. Behavioral intention is one of the key elements determining human behavior (Venkatesh et al., 2003). Ajzen (1991) held that behavioral intention is a strong determinant of subsequent action. Use behavior comes from a desire to use a technology or behavioral intention. The assumptions lead to a proposed hypothesis:
H6: Behavioral intention has a significant effect on use behavior of mobile video apps among liberal arts students.

2.9 Use Behavior

Use behavior is usually defined as the degree of technology being used by people (Venkatesh et al., 2003). The use behavior refers to the number of times rather than deliberately of users to use it in their daily life. The actual frequency of technology use can measure the level of use behavior. The duration of interaction between individual and specific technology can be used to evaluate the use behavior (Venkatesh et al., 2008). The technology acceptance model can explain about how people utilize technology (Davis et al., 1989). Many researchers and technology models suggest that use behavior can best predict how consumers would actually utilize technology. The use behavior of some network technologies is positively affected by facilitating conditions and behavior intention (Deng et al., 2011). Behavior intention is regarded as a powerful indicator of the actual use behavior of Internet mobile technology. De Haan et al. (2018) found that the popularity of mobile network also improves the use behavior of mobile devices and technologies.

3. Conceptual Framework

The conceptual framework is built under the combination of TAM, and UTAUT2. To understand the behavioral intention and use behavior of college students to use mobile video applications, various research and frameworks related to the mobile network applications were reviewed. Four previous studies provide valid results in the development of research model including Chua et al. (2018), Hu and Lai (2019), Dhiman et al. (2020), and Samsudeen and Mohamed (2019). To develop seven hypotheses, seven variables involve Perceived Ease of Use (PEU), Perceived Usefulness (PU), Social Influence (SI), Habits (HB), Behavioral Intention (BI), Facilitating Conditions (FC), and Use Behavior (UB).

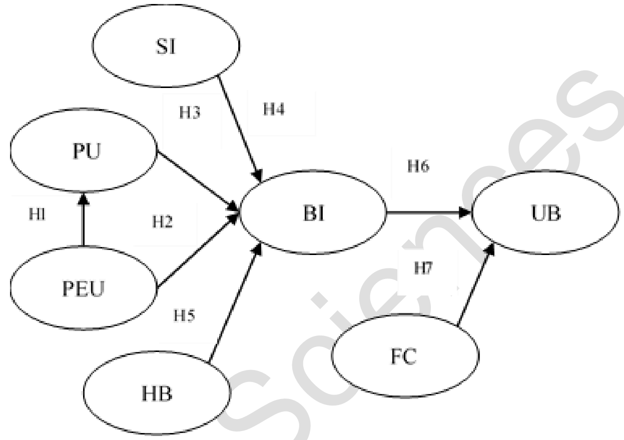

Figure 1: Conceptual Framework
Source: Created by the author.

H1: Perceived ease of use has a significant effect on perceived usefulness of mobile video apps among liberal arts students.
H2: Perceived ease of use has a significant effect on behavioral intention to use mobile video apps among liberal arts students.
H3: Perceived usefulness has a significant effect on behavioral intention to use mobile video apps among liberal arts students.
H4: Social influence has a significant effect on behavioral intention to use mobile video apps among liberal arts students.
H5: Habit has a significant effect on behavioral intention to use mobile video apps among liberal arts students.
H6: Behavioral intention has a significant effect on use behavior of mobile video apps among liberal arts students.
H7: Facilitating conditions have a significant effect on behavioral intention to use mobile video apps among liberal arts students.

4. Research Methods and Materials

4.1 Research Methodology

Per the research objective to assess the influencing factors of behavioral intention and use behavior towards mobile video apps, using a case of liberal arts students in Chongqing, China, this quantitative study was conducted to collect the quantitative data which are offline survey via the offices of student affairs and online survey via “Wen Juan Xing" website and other social medias. The questionnaire consists of 2 screening questions to identify target respondents, 5 demographic questions to classify the population statistically, and 25 measurement items of fivepoint Likert scale to measure factors influencing the behavioral intention and use behavior. The Likert-scale consists of 5 scales, 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree). In this research, the demographic information was statistically analyzed. Item Objective Congruence (IOC) Index were approved before the data collection process by four experts at the score equal or above 0.5. Cronbach's alpha results were that each item was accepted coefficient value greater than or equal to 0.60 (Sekaran, 1992). After the completion of data collection, skewness and kurtosis results were used to prove the normality of the data. Confirmatory factor analysis (CFA) and structural equation model (SEM) were used to assess measurement and structural models.

4.2 Population and Sample Size

The purpose of this study is to assess influencing factors of behavioral intention and use behavior of Gen Z towards mobile video apps, using a case of liberal arts students in Chongqing, China. Therefore, this study selects the top two universities in Chongqing. Sample size is crucial to most empirical research (Taherdoost, 2017). In this study, Soper (2022) recommended the minimum sample size by the calculator of 425. To minimize the risk of data error and gain the most reliable statistical results, the sample size of 500 participants was determined.

4.3 Sampling Techniques

Researchers carried out purposive, quota and convenience as sampling techniques. Firstly, purposive sampling was to select liberal arts students of two selected universities in Chongqing, China, who were born after 1995, considering as Gen Z, and have been using mobile video apps. Secondly, quota sampling was applied by the calculation of sample size in two subgroups. Finally, convenience sampling was used for the distribution of questionnaires offline via the offices of student affairs, and online survey via “Wen Juan Xing" website and other social medias from November 2021 to March 2022.

5. Results and Discussion

5.1 Demographic Information

The demographic results present that females account for 75% (375) and males of 25% (125). In terms of age, 18-22 years old was the majority, accounting for 88.4% (442), followed by 23-25 years old, accounting for 8.4% (42), less than 18 years old and more than 25 years old, accounting for 1.8% (9) and 1.4% (7) respectively. From the use experience of mobile video apps, most of them have 4-6 years’ use experience, accounting for 36.6% (183), 1-3 years of 35.4% (177), more than 6 years of 26.6% (113), and less than 1 year of 5.4% (27). Among the respondents, 90.4% (452) are bachelor’s degree students, while 8.8% (44) of respondents are master’s degree, and 0.8% (4) are doctor’s degree.

Table 1: Demophraphic Profile

Demographic Factors	Frequency	Percentage (%)
Gender		
Male	125	25%
Female	375	75%
Age		
Below 18 years	9	1.8%
18 – 22 years	442	88.4%
23 – 25 years	42	8.4%
More than 25 years	7	1.4%
Experience of mobile video apps		
Below 1 year	27	5.4%
1 – 3 years	177	35.4%
4 – 6 years	183	36.6%
More than 6 years	113	22.6%
Study for degree		
Bachelor’s	452	90.4%
Master’s	44	8.8%
Doctor’s	4	0.8%

Source: Created by the author.

5.2 Confirmatory Factor Analysis (CFA)

This research used confirmatory factor analysis (CFA) to assess the correlation of variables within the measurement model. From Table 2, the greater the factor loadings value, the higher the reliability of the model (Hair et al., 2010). The acceptable threshold for factor loadings is 0.5 or higher (Hair et al., 1998). In this study, Cronbach's alpha results were that each item was accepted coefficient value greater than or equal to 0.60 (Sekaran, 1992). Factor loadings of each item were all greater than 0.50, ranging from 0.595 to 0.858. According to Fornell and Larcker (1981), composite reliability (CR) is accepted at the value of equal or greater 0.7, and average variance extraction (AVE) is acceptable at 0.4 or higher. In this study, CR was higher than threshold, ranging from 0.784 to 0.883. AVE values were all greater than 0.4, ranging from 0.421 to 0.715. Goodness of fit indices were used to evaluate the fit of the measurement model as of Table 3. The fit measures are Chi-square statistics (CMIN/ DF), the Goodness of Fit Index (GFI), the Adjusted Goodness of Fit Index (AGFI), Normative Fit Index (NFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI) and the Root Mean Square Error of Approximation (RMSEA). As a results of this study, all values are within the acceptable criteria, which means acceptable model fit.

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

Variable	Source of Questionnaire (Measurement Indicator)	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEU)	Chua et al. (2018)	4	0.824	0.652-0.782	0.806	0.512
Perceived Usefulness (PU)	Chua et al. (2018)	4	0.866	0.678-0.779	0.826	0.543
Social Influence (SI)	Hu and Lai (2019)	3	0.705	0.736-0.858	0.838	0.634
Habit (HB)	Hu and Lai (2019)	3	0.725	0.823-0.870	0.883	0.715
Facilitating Conditions (FC)	Hu and Lai (2019)	5	0.906	0.595-0.706	0.784	0.421
Behavioral intention (BI)	Chua et al. (2018)	3	0.738	0.714-0.770	0.796	0.565
Use Behavior (UB)	Chua et al. (2018)	3	0.861	0.727-0.796	0.812	0.590

Source: Created by the author.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria
CMIN/DF	< 5.00 (Awang, 2012)
GFI	≥ 0.85 (Sica & Ghisi, 2007)
AGFI	≥ 0.80 (Sica & Ghisi, 2007)
NFI	≥ 0.80 (Wu & Wang, 2006)
CFI	≥ 0.80 (Bentler, 1990)
TLI	≥ 0.80 (Sharma et al., 2005)
RMSEA	< 0.08 (Pedroso et al., 2016)

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, and RMSEA = Root mean square error of approximation.

From Table 4, the method of determining validity is to confirm that the square root of AVE is greater than the coefficient of any interrelated structure (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	**0.715**						
PU	0.620	**0.736**					
SI	0.548	0.487	**0.796**				
HB	0.491	0.511	0.504	**0.845**			
FC	0.441	0.448	0.491	0.560	**0.648**		
BI	0.654	0.553	0.606	0.638	0.556	**0.751**	
UB	0.534	0.476	0.533	0.657	0.620	0.747	**0.778**

5.4 Structural Equation Model (SEM)

Goodness of fit index is used to evaluate the fit of structural model. The fitting index is the same as confirmatory factor analysis (CFA), Chi-square statistics (CMIN/ DF), the Goodness of Fit Index (GFI), the Adjusted Goodness of Fit Index (AGFI), Normative Fit Index (NFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI) and the Root Mean Square Error of Approximation (RMSEA). The fitting degree of the model was evaluated by indicators, and the statistical value of the indicators was compared with the acceptable value of goodness of fit in Table 5. The statistical values of each index were CMIN/DF = 4.033, GFI = 0.838, AGFI = 0.804, NFI=0.836, CFI = 0.870, TLI = 0.855 and RMSEA = 0.078, respectively. Before an adjustment, GFI index is not qualified. Therefore, the structural model needs to be modified by correlation between the measurement errors of the constructs. The statistical values after the model's adjustment are CMIN/DF = 3.761, GFI = 0.850, AGFI = 0.809, NFI=0.854, CFI = 0.888, TLI = 0.868, RMSEA = 0.074. Consequently, the fitting of the structural model is verified.

Table 5: Goodness of Fit for Structural Model

Index	Acceptable Criteria	Statistical Values	
		Before Adjustment	After Adjustment
CMIN/DF	< 5.00	1080.742/268 or 4.033	958.931/255 or 3.761
GFI	≥ 0.85	0.838	0.850
AGFI	≥ 0.80	0.804	0.809
NFI	≥ 0.80	0.836	0.854
CFI	≥ 0.80	0.870	0.888
TLI	≥ 0.80	0.855	0.868
RMSEA	< 0.08	0.078	0.074
Model summary		**Unacceptable Model Fit**	**Acceptable 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, and RMSEA = Root mean square error of approximation.

5.5 Research 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. As shown in Table 6, six of the seven hypotheses proposed in this research are supported. The use behavior of mobile video applications is most influenced by behavioral intention, followed by facilitating conditions. The behavioral intention of mobile video applications is significantly influenced by perceived ease of use, habit and social influence. On the other hand, perceived usefulness has no significant effect on behavioral intention.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypotheses	Standardized path coefficient (β)	t-value	Testing result
H1: Perceived ease of use has a significant effect on perceived usefulness.	0.760	12.624*	Supported
H2: Perceived ease of use has a significant effect on behavioral intention.	0.571	6.528*	Supported
H3: Perceived usefulness has a significant effect on behavioral intention.	-0.064	-0.789	Not Supported
H4: Social influence has a significant effect on behavioral intention.	0.392	8.435*	Supported
H5: Habit has a significant effect on behavioral intention	0.532	10.958*	Supported
H6: Behavioral intention has a significant effect on use behavior.	0.775	10.974*	Supported
H7: Facilitating conditions have a significant effect on behavioral intention.	0.382	6.969*	Supported

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

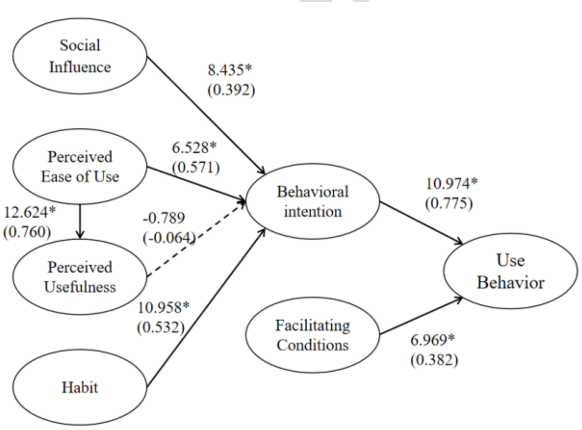

Figure 2: SEM diagram
Note: * p<0.05
Source: Created by the author.

H1 confirms that perceived ease of use has a significant effect on perceived usefulness of mobile video apps among liberal arts students with standardized path coefficient of 0.760 and t-value at 12.624.

H2 supports the significant effect of perceived ease of use on behavioral intention to use mobile video apps among liberal arts students with standardized path coefficient of 0.571 and t-value at 6.528.

H3 points out that perceived usefulness has no significant effect on behavioral intention to use mobile video apps among liberal arts students with standardized path coefficient of -0.064 and t-value at -0.789.

H4 shows social influence has a significant effect on behavioral intention to use mobile video apps among liberal arts students with standardized path coefficient of 0.392 and t-value at 8.435.

H5 proves that habit has a significant effect on behavioral intention to use mobile video apps among liberal arts students with standardized path coefficient of 0.532 and t-value at 10.958.

H6 presents that behavioral intention has the strongest significant effect on use behavior of mobile video apps among liberal arts students with standardized path coefficient of 0.775 and t-value at 10.974.

H7 approves the support relationship between facilitating conditions and behavioral intention to use mobile video apps among liberal arts students with standardized path coefficient of 0.382 and t-value at 6.969.

6. Conclusions and Recommendation

6.1 Conclusion

The COVID-19 has promoted the market transformation of media platforms in various economies, and has brought new development opportunities to mobile video applications. With the intervention of mobile Internet as the basic condition, the number of users has further increased. As the leading group of the current Internet and future technology development, the use and views of generation Z, who are currently studying in universities, also influence the development of various technologies, and mobile video application technology is no exception. The difference of educational institutions in the training mode of college students will also affect their differences in concept, and the difference will also be reflected in the choice of technology. Therefore, this research focuses on the factors that influence the behavior intention and use behavior of liberal arts students in universities in Chongqing, China. Statistical programs were used to conduct confirmatory factor analysis and the structural equation model. The factor analysis and correlation regression analysis were used to draw following conclusions.

In order to form the conceptual framework of the research, the researchers collected relevant theories and studies based on the research subject. This study mainly adopts two core theories which are Technology Acceptance Model (TAM) and the Extended Unified Theory of Extended Technology Acceptance and Use (UTAUT2). According to the findings, habits have the most significant influence on the behavioral intention of the respondents. The literature of Dhiman et al. (2020) demonstrates this relationship, and users' long-term use of technology significantly improves their willingness to use it. Social influence plays a significant role in influencing users' behavioral intentions, and perceived ease of use plays the third role in influencing users' behavioral intentions as supported by the report of Hu and Lai (2019). Users are more likely to be influenced by social and environmental factors before they engage in behavioral intentions of using technology. Users make choices based on their judgment of the social environment. When users feel that using technology will enhance their social acceptance, or they are attracted by social influence, they will have behavioral intention to use technology. Users also judge the difficulty in using a technology, which directly lead to their tendency to use or not use it.

This study also demonstrates the significant effect of facilitating conditions on use 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 use behavior, which was also confirmed in the results of this study. The intensity of users' intention determines the actions they take. People's behavior is the ultimate embodiment of their ideas, and strong intentions will be realized through behavior. In contrary, the relationship between perceived usefulness and behavioral intention is not supported which contradicts with many scholars that degree to which users believe that employing a technology can enhance their performance is subject the behavioral intention (Akbar, 2013). The reason would be that the benefits of using mobile video apps are not clear in the user's mind. In conclusion, the results of this research show that perceived ease of use, social influence, habit and facilitating conditions have a significant affect behavioral intention. Furthermore, behavioral intention significantly affects use behavior. On the other hand, perceived usefulness has no significant effect on behavioral intention.

6.2 Recommendation

This research shows that the key influencing factors of liberal arts students' behavioral intention and use behavior of mobile video application in Chongqing are habit, social influence, 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 generation Z people who are studying in colleges and universities under the category of liberal arts education will be affected by when choosing mobile video applications.

What we know from the research is that habits are the most influential factor in the group's behavioral intentions, which suggests that they are not just using the technology at random but forming a long-term behavior pattern. To keep users using the app for a long time, application developers need to increase the stickiness between the user and the app. Therefore, it is suggested that application developers should focus on developing attractive and interactive technologies, so that customers can emotionally connect with the application (Dhiman et al., 2020), and the application can keep pace with the times to add new content, while also providing users with space for creation so that they can become the creators of images while absorbing the information of images. Mobile video applications are becoming a bridge for users to communicate with each other and a part of their daily lives.

Social influence plays an important role in this process, which means that social environment, public opinion and personal influence can influence the choice of college students in liberal arts. Therefore, application developers should introduce more social influence factors into application technology, and provide users with a platform for communication, whether during or after watching, so that users can communicate more and promote mutual influence. It can also provide a better platform for high-quality information publishers to expand their advantages. Compared with other information sources, recommended groups are considered to be more reliable and excellent, which will maximize the advantages brought by social influence.

Modern technology brings people a convenient and interactive life mode. From the perspective of user experience, the operation interface should be properly simplified to make people clear and easy to understand. The detailed and tedious operation interface will make the young generation unwilling to make further attempts. The young people who grow up in the Internet environment prefer to go straight to the theme to achieve the purpose of a fast pace of life. Therefore, at the technical design level, attention should be paid to the relevant role of perceived ease of use.

Although young users are considered to be relatively more capable in technology application, application developers still need to improve the user friendliness of technology from all aspects to ensure the facilitating conditions of application (Hew et al., 2015). For example, through data observation, the user's history of watching video information can be understood, the user's preference in selection can be analyzed and similar video information can be pushed to help them make a choice. Application developers can also study which features can be integrated into the application by observing users' daily usage. In addition, managers also need to address ease of use from outside to inside view of users on the use of technology. While the majority of Gen Z in China now have smartphones and access to the Internet via WIFI and Internet technologies, there are times when mobile data is needed. The mobile video apps' companies could sign a joint agreement with a mobile traffic company to reduce the amount of data users incur when using the app and make them more willing to choose the app for information access.

Through this research, we have a basic understanding of the user portraits of the group of liberal arts students in universities in Chongqing, China. They grew up in the era of modern world under the background of Internet technology and are accustomed to rapid and concise behavior patterns. They believe that technological development and innovation should revolve around their compact lifestyle. They have also become accustomed to using technology to get information and voice opinions, and want to rely on it to become opinion leaders in various fields. Internet-related technologies have become an integral part of their lives, and learning to master emerging technologies and models has become one of their essential skills.

6.3 Limitation and Further Study

In this research, two representative universities' liberal arts students in Chongqing were selected as the research objects, and the data were mainly derived from electronic questionnaire online survey. This method may lead to the relative assimilation of the target groups, and the population characteristics cannot reflect sufficient differentiation. Future research should expand the sample selection range and expand the target selection beyond Chongqing to other regions or countries. In addition, generation Z group is not the future generation, so it is still necessary to conduct further research to other younger generations. In the future, researchers can collect data in qualitative method, such as face-to-face and in-depth interviews, so as to obtain more in-depth information from the subjects. Additionally, other factors that may affect people's behavior of using mobile video applications, such as attitude, performance expectation, effort expectation, etc., can be added, so that the research can more accurately reflect users' behavior.

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