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Short Video Platforms for Learning: What Drives Undergraduates' Satisfaction and Continued Use in Chengdu

Guo Xinyi*

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Abstract

Purpose: This study develops a structural model to examine factors influencing student satisfaction and continuance intention in using short video platforms for educational purposes. Given the rapid growth of the short video industry, the research provides a reference framework for understanding technology adoption in digital learning. **Research design, data and methodology:** A quantitative approach was adopted using an online questionnaire distributed to 500 liberal arts students at Geely University in Chengdu, China. Non-probability sampling included judgment, quota, and convenience methods. Confirmatory Factor Analysis (CFA) assessed reliability and model fit, while Structural Equation Modeling (SEM) examined relationships among constructs. **Results:** SEM analysis confirmed all six hypotheses. Perceived usefulness ($\beta = 0.284$), perceived enjoyment ($\beta = 0.168$), product novelty ($\beta = 0.155$), and privacy protection behavior ($\beta = 0.224$) significantly affected satisfaction. Satisfaction ($\beta = 0.348$) and informational social influence ($\beta = 0.223$) positively influenced continuance intention. **Conclusions:** The findings offer practical guidance for educators, platform designers, and content developers. Enhancing content usefulness, enjoyment, novelty, and privacy measures can significantly improve learner satisfaction. Moreover, fostering a socially supportive learning environment encourages sustained engagement with short video platforms, ultimately improving digital learning outcomes.

Keywords: Satisfaction, Informational Social Influence, Continuous Intention, Short Video Platforms, Learning Tools

JEL Classification Code: A22, I23, L86, O30

1. Introduction

The advent of the big data era has led to an abundance of information, the rise of new media, and the proliferation of mobile micro-resources. As an emerging form of media, short video platforms have experienced rapid growth due to their rich content, ease of use, and powerful communication capabilities (Andrews et al., 2016; Wu & Hsiao, 2017). They have gradually become central to modern social interactions and students' daily lives, making them an indispensable component of contemporary society (Sheng, 2021). In the educational context, short video platforms offer unique benefits, such as supporting microlearning, promoting autonomous and personalized study, and enhancing students' motivation and retention through visual and interactive content. As such, they demonstrate great potential and offer broad application prospects in both formal and informal learning environments.

Short video refers to video content that typically ranges from a few seconds to under 15 minutes, distinguishing it from traditional long-format content such as films, television series, and variety shows (Zhang et al., 2023). This format delivers information, entertainment, and educational content in a concise, intuitive, and easily consumable manner, making it particularly well-suited for mobile device viewing (Hu & Nian, 2022). A short video platform is an online service or application that facilitates short video production, publishing, sharing, and viewing over the Internet (Chen & Geng, 2023). As a new form of Internet media, these platforms provide users with an engaging and interactive social video experience, allowing them to share achievements, insights, and creative ideas

[1]*Guo Xinyi, Geely University of China. Email : sl729227528@gmail.com

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(Zhang & Liang, 2023). They also feature user-friendly interfaces that support engagement functions such as liking, commenting, sharing, and following (Sheng, 2021). Driven by advanced algorithms and data analytics, these platforms curate personalized content recommendations based on users' interests, browsing history, and social interactions, thereby reshaping how people communicate and exchange information (He & Li, 2024).

The NMC Higher Education Horizon Report highlights key trends in higher education related to mobility (Johnson et al., 2012) and openness (Johnson et al., 2013). Short video platforms contribute to knowledge dissemination through their rich educational resources (Chen et al., 2019), personalized recommendations (Omar & Dequan, 2020), quick and accessible learning opportunities (Kaye et al., 2020), and flexible learning schedules (Sakibayev, 2022). These capabilities not only support diverse learning styles but also extend educational access to under-resourced or time-constrained learners. Moreover, they help bridge the gap between formal education and everyday learning experiences, making education more integrated into students' digital lives. These features, combined with immediacy and interactivity (Kumar & Chand, 2019), generate educational value beyond traditional teaching methods. As a result, conventional education models face challenges and transformations driven by the Internet and mobile technology, with short video platforms emerging as influential tools in reshaping knowledge production and dissemination.

The Research Report on the Development of China Online Audio-Visual, widely regarded as a benchmark in China's online audio-visual industry, was released in Chengdu. According to the report, the number of short video users in China had reached 1.012 billion, accounting for 94.8% of total Internet users, making short videos a primary driver of growth in the online audio-visual industry. Notably, 72.1% of Internet users under the age of 30 regularly consume short video content, highlighting its widespread adoption among younger audiences.

Chengdu, the research site of this study, serves as the capital of Sichuan Province and is a key metropolitan center in Southwest China. The city is home to several top-tier universities and a large student population, many of whom actively engage with short video content as part of their daily communication, learning, and entertainment routines. Liberal arts students, in particular, represent a demographic with frequent exposure to media-rich content and reflective engagement with social and cultural trends, making them an ideal group for examining educational adoption patterns. Therefore, this study focuses on liberal arts students at Geely University in Chengdu, addressing the gap in empirical research on the factors influencing satisfaction and continuance intention in the use of short video platforms for learning purposes. The objective is to develop and validate a structural model that explains these factors and offers practical guidance for future educational technology integration.

2. Literature Review

2.1 Factors Affecting Satisfaction and Continuous Intention

Perceived usefulness refers to users' belief that a technology enhances efficiency, effectiveness, and overall performance (Davis, 1989). It is a key determinant of technology acceptance, satisfaction, and continued use across various domains, including mobile commerce (Faqih & Jaradat, 2015), educational technology (Teo, 2011), artificial intelligence (Saavedra et al., 2023), and financial technology (Shiau et al., 2020). Within the Technology Acceptance Model (TAM), perceived usefulness directly predicts user satisfaction and behavioral intent (Venkatesh et al., 2003).

Perceived enjoyment is the intrinsic pleasure derived from using technology beyond its functional value (Lee et al., 2005). The Unified Theory of Acceptance and Use of Technology (UTAUT) recognizes it as a factor influencing technology adoption (Xu & Thien, 2024). Enjoyment comprises emotional, cognitive, and behavioral dimensions (Nabi & Krcmar, 2004), where users experience positive emotions, skill development, and deep engagement in technology-based activities (Johnston & Taylor, 2018). It plays a key role in user engagement, entertainment, and satisfaction across social platforms (Huotari & Hamari, 2017) and educational tools (Xu & Thien, 2024).

Product novelty refers to a product's uniqueness, originality, and innovative features that differentiate it in the market (Wells et al., 2010). It includes design, functionality, and technological advancements that attract users and enhance their experience (Rubera et al., 2010). Novelty stimulates excitement, curiosity, and exploration, which drive satisfaction and engagement (Solomon, 2018). Maintaining novelty requires continuous interface optimization and algorithm improvements to sustain user interest (Ottum & Moore, 1997).

Privacy protection behavior involves users' proactive efforts to safeguard personal data in digital environments (Belanger et al., 2002). Privacy concerns stem from security risks in online interactions, leading users to engage in protective actions such as adjusting settings and limiting data sharing (Young & Quan-Haase, 2013). Ensuring privacy fosters trust and user retention (Mosteller & Poddar, 2017). As digital interactions expand, privacy protection remains a key factor in user confidence and sustained engagement (Jain et al., 2021).

Informational social influence refers to individuals conforming to others' behaviors based on perceived accuracy and reliability of shared information (Wang & Lin, 2011). Social influence plays a critical role in technology adoption, as individuals seek validation from peers, influencers, and online communities (Ebrahim, 2020). In uncertain situations, users rely on social networks to mitigate risks associated with adopting new technologies (Burkhardt & Brass, 1990).

Satisfaction is the extent to which a product or service meets user expectations and needs (Oliver, 1980). It is a key predictor of post-adoption behavior within the Expectation Confirmation Model (ECM) (Hsu & Lin, 2015). In digital platforms, satisfaction is influenced by user experience, perceived value, and platform functionality (Deng et al., 2010). High satisfaction levels drive loyalty, positive word-of-mouth, and continued use (Oliver & DeSarbo, 1988).

Continuous intention refers to a user's willingness to persist in using a product, service, or technology over time (Limayem et al., 2007). It reflects long-term engagement, shaped by satisfaction, perceived value, and prior experiences (Kim et al., 2013). In digital environments, continued use depends on factors such as usability, trust, and sustained relevance (Ambalov, 2021). Understanding and fostering continuous intention is crucial for retaining users and achieving business sustainability (Bhattacherjee, 2001).

2.2 Research Hypothesis and Relationship between Variables

2.2.1 Relation between Perceived Usefulness and Satisfaction

The relationship between perceived usefulness and satisfaction has been extensively studied across various fields, including information systems (Kang & Lee, 2010), technology acceptance (Bhattacherjee, 2001), and consumer behavior (Jung et al., 2009). Evidence consistently shows that perceived usefulness has a strong and significant impact on user satisfaction. In the original Technology Acceptance Model (TAM), Davis (1989) identified perceived usefulness as a primary determinant of user satisfaction and system adoption, assuming that users who find a system beneficial are more likely to be satisfied, leading to continued use. Al-Sabawy et al. (2011) further expanded this concept, integrating perceived usefulness into the Information System Success Model, where it is often associated with system quality and information quality. They found that when users perceive a system as valuable for enhancing job performance or decision-making, their satisfaction significantly increases.

Recent studies in digital and mobile learning environments (e.g., Gonzalez, 2022; Vázquez-Cano et al., 2023) confirm that perceived usefulness enhances learner satisfaction by improving accessibility and self-paced learning. However, in less structured settings like short video platforms, the perception of usefulness may vary depending on content quality and learner intent, highlighting a potential gap in existing research. Based on the literature review, this study proposes the following research hypothesis:

H1: Perceived usefulness has a significant influence on satisfaction when using short video platforms for learning.

2.2.2 Relation between Perceived Enjoyment and Satisfaction

Perceived enjoyment, defined as the extent to which an activity is pleasurable or intrinsically rewarding, significantly impacts user satisfaction across various contexts (Nabi & Krcmar, 2004). In hedonic information systems, Van der Heijden (2004) identified perceived enjoyment as a key determinant of user satisfaction. Similarly, Venkatesh and Brown (2001), in the Unified Theory of Technology Acceptance and Use (UTAUT2), emphasized hedonic motivation as a crucial factor influencing satisfaction and continued use. Their model suggests that the more users enjoy a technology, the more satisfied they become, fostering long-term engagement.

Perceived enjoyment plays a vital role in user satisfaction across various fields. In e-commerce and online shopping, it is a key driver of customer satisfaction (Kim et al., 2021). In mobile Internet services, Thong et al. (2006) highlighted its significant impact on satisfaction. In online gaming, Hsu and Lu (2004) found that perceived enjoyment is the primary determinant of satisfaction, influencing user loyalty. In online learning, Lee et al. (2005) demonstrated that students who find learning enjoyable report higher satisfaction with educational technology.

However, recent findings (e.g., Chang & Hsu, 2022) suggest that in goal-oriented digital learning, perceived enjoyment may have a weaker influence compared to perceived usefulness or self-efficacy. This raises questions about its role in learning-driven short video platforms, which may serve both hedonic and utilitarian purposes. More context-specific investigation is needed. Based on the literature review, this study proposes the following research hypothesis:

H2: Perceived enjoyment has a significant influence on satisfaction when using short video platforms for learning.

2.2.3 Relation between Product Novelty and Satisfaction

Novelty is linked to emotional experiences such as surprise, making products feel more valuable, exciting, and unique, which enhances user satisfaction (Gonzalez-Cutre & Sicilia, 2019). Research shows that product novelty—the

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extent to which a product offers new, unique, or innovative features—significantly influences user satisfaction (McLean & Wilson, 2019).

In consumer behavior, consumers actively seek novel experiences, which enhance satisfaction (Casalo et al., 2018). In consumer electronics, Jin and Xu (2021) found that innovative features lead to higher satisfaction, as users appreciate uniqueness and advanced functionalities. Similarly, in e-commerce, Kang et al. (2023) demonstrated that novel and distinctive products significantly improve customer satisfaction, as consumers value innovation and differentiation. Casalo et al. (2018) further confirmed that product novelty enhances consumer satisfaction and repeat purchase intentions by offering a fresh and unique shopping experience.

In the education context, Chen et al. (2021) and Lee and Jeong (2023) observed that novel learning formats such as short videos stimulate curiosity and engagement. However, they also caution that novelty effects may diminish over time if content is not continuously refreshed or updated, suggesting a temporal limitation in its impact on satisfaction. This highlights a gap in understanding sustained novelty effects in educational media. Based on the literature review, this study proposes the following research hypothesis:

H3: Product novelty has a significant influence on satisfaction when using short video platforms for learning.

2.2.4 Relation between Privacy Protection Behavior and Satisfaction

Research shows that privacy protection behaviors, practices implemented by companies, platforms, or individuals to safeguard user information, significantly impact user satisfaction (Liang et al., 2014). Effective privacy protection enhances trust, user experience, and overall satisfaction (Kim et al., 2009). This relationship has been explored across various sectors, including online services, e-commerce, and social media.

In mobile banking, Ketema and Selassie (2020) found a strong correlation between privacy security and customer satisfaction. Users who perceive a service as a threat to their personal data security often express anger and dissatisfaction (Tran, 2020). Similarly, Cheng and Jiang (2020) demonstrated that clear and transparent privacy policies positively influence user satisfaction, as users feel more secure when platforms clearly communicate data protection measures and provide them with control over their personal information.

Recent studies in digital education platforms (e.g., Alghizzawi et al., 2022; Kang & Lee, 2021) also reveal that students expect platforms to safeguard personal data. While most findings affirm the positive impact of privacy protection on satisfaction, some researchers suggest its effect may be mediated by perceived control or platform trust, indicating a need for further model testing. Based on the literature review, this study proposes the following research hypothesis:

H4: Privacy Protection Behavior has a significant influence on satisfaction when using short video platforms for learning.

2.2.5 Relation between Satisfaction and Continuous Intention

Research consistently shows that satisfaction plays a crucial role in shaping continuous intention, the user's willingness to continue using a product, service, or technology over time (Kalinic et al., 2020; Tsai et al., 2018). Bhattacherjee (2001) introduced Expectation-Confirmation Theory (ECT) in the context of information systems, stating that satisfaction is a key determinant of continuous intention. If a product or service meets or exceeds user expectations, users are more likely to continue using it. Empirical research confirms that higher satisfaction leads to stronger long-term system usage.

Similarly, Reichheld and Schefter (2000) found that customer satisfaction strongly predicts loyalty behaviors, including repeat purchases and continued engagement with brands or services. In mobile applications, Zhou (2013) demonstrated that satisfaction with an app's performance, functionality, and usability significantly predicts continuous intention, as satisfied users are more likely to retain the app, an essential factor for its long-term success.

More recent work (Rodríguez-Abitia & Bribiesca-Correa, 2021) highlights the increasing importance of emotional and interactive satisfaction components, particularly in mobile and remote learning environments. While overall consensus supports this relationship, further studies are needed to examine how satisfaction influences continuous use in informal and hybrid learning models such as short video platforms. Based on the literature review, this study proposes the following research hypothesis:

H5: Satisfaction has a significant influence on continuous intention when using short video platforms for learning.

2.2.6 Informational Social Influence and Continuous Intention

Research suggests that informational social influence—where individuals conform to the views or actions of others based on the belief that others possess more accurate information—significantly impacts continuous intention (Dumpit & Fernandez, 2017). This effect is particularly strong when users rely on peer opinions and actions to decide whether to continue using a product or service (Arpaci, 2016).

Informational social influence is a behavior-based social interaction, where individuals follow others' actions,

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particularly in learning environments where network-based learning adoption becomes a norm (Wang & Lin, 2011). Observable behaviors of the majority influence individual decisions, as people tend to assume commonly adopted behaviors are wise (Elek et al., 2006).

In the Technology Acceptance Model (TAM) extension, Venkatesh and Davis (2000) introduced the concept of subjective norms, closely linked to informational social influence. They found that peer and colleague influence significantly affects users' decisions to continue using technology, especially when individuals rely on expertise and social validation.

Recent findings (Nguyen & Habók, 2021; Zhang et al., 2022) confirm that peer recommendations are key motivators in digital learning communities. However, their influence may vary based on perceived source credibility and platform type. Short video platforms, which blend entertainment and learning, provide a unique setting where social cues may play a stronger role. This interaction remains underexamined in educational contexts. Based on the literature review, this study proposes the following research hypothesis:

H6: Informational social influence has a significant influence on continuous intention when using short video platforms for learning.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this study integrates Information System Success Theory (ISST), Flow Theory, and the Technology Acceptance Model (TAM), along with insights from previous research. Mou et al. (2021) identified key factors, including Product Novelty (PN), Satisfaction (SA), Continuous Intention (CI), and Privacy Protection Behavior (PPB). Additionally, Al Natour and Woo (2021) established relationships between Perceived Usefulness (PU), Perceived Enjoyment (PE), and Satisfaction (SA), while Jia et al. (2023) demonstrated the connection between Informational Social Influence (ISI) and Continuous Intention (CI). Building on these foundations, this study develops a conceptual framework, as illustrated in Figure 1.

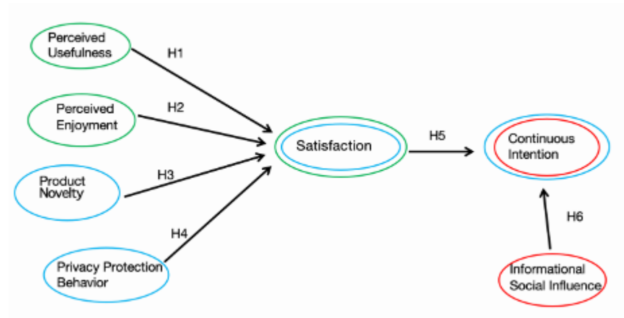

Figure 1: Conceptual Framework

The purpose of this study is to explore the factors influencing satisfaction and continuous use intention of short video platforms as a learning tool among liberal arts students at Chengdu Geely University. The key variables examined include Perceived Usefulness (PU), Perceived Enjoyment (PE), Product Novelty (PN), Privacy Protection Behavior (PPB), Satisfaction (SA), Informational Social Influence (ISI), and Continuous Intention (CI). To understand students' attitudes and behavioral intentions toward using short video platforms for learning, this study analyzes the causal relationships between these variables.

3.2 Research Methodology

This study employed a quantitative research design using non-probability sampling to collect data through an online questionnaire. The primary goal was to explore factors influencing students' satisfaction and continuance intention in using short video platforms for learning. The target population comprised liberal arts students from Geely University of China. Although non-probability sampling methods such as judgmental, quota, and convenience sampling enabled efficient participant recruitment, this approach may limit the generalizability of the results to broader student populations. Sampling bias may arise due to the lack of randomization.

The questionnaire consisted of three sections: (1) screening questions, (2) demographic questions (gender, age, academic level), and (3) 26 items across six constructs, measured on a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. The items were adapted from established instruments in prior studies and modified to suit the short video learning context.

To ensure content validity, three academic experts in education and information systems reviewed the items. The Item-Objective Congruence (IOC) Index was calculated, and all items scored between 0.80 and 1.00, exceeding the minimum threshold of 0.67, indicating acceptable content validity (Turner & Carlson, 2003).

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A pilot test was conducted with 50 liberal arts students who were not included in the final sample. The pilot results showed that all six constructs met the acceptable reliability threshold of 0.70 (Nunnally & Bernstein, 1994), with Cronbach's Alpha values ranging from 0.75 to 0.83. These results demonstrated that the questionnaire items were internally consistent and suitable for large-scale distribution.

3.3 Population and Sample Size

Using non-probability sampling, including judgmental and quota sampling, the researchers selected liberal arts students from two colleges at Geely University of China—the College of Education and the College of Art Design—as the survey population. Judgmental sampling was first used to select these two colleges based on their curricular relevance to media and educational technologies. Quota sampling was then employed to ensure proportional representation based on student enrollment numbers in each college. Questionnaires were distributed via an online platform. Table 1 presents the specific sampling details for this study.

In determining the sample size, the researchers referred to prior SEM studies recommending a minimum of 200–400 responses for reliable structural model estimation (Hair et al., 2019). Additionally, a commonly used rule of thumb in SEM suggests at least 10–15 respondents per observed variable (Kline, 2016). Given the 24 measurement items in the model, a sample size of 500 exceeds the required threshold, ensuring sufficient statistical power and robustness for model validation.

Table 1: Population and Sample Size of Liberal Art Colleges in Geely University of China

Liberal Art Colleges	Population Size	Proportional Sample Size
Education	2,765	389
Art Design	792	111
Total	**3,557**	**500**

Source: Constructed by Author

From February to July 2024, the researcher conducted a questionnaire survey. A data screening process ensured that the target population was appropriate. Only participants who reported being active short video platform users with at least one year of learning experience were included in the final dataset. A total of 500 valid questionnaires were collected from liberal arts students across both colleges.

4. Results and Discussion

4.1 Demographic Profile

Interviewee data provides insights into participants' demographic characteristics and short video usage patterns. This study collected information on gender, usage frequency, weekly viewing time, video preferences, and learning-related usage.

A total of 500 students from two liberal art colleges at Geely University of China participated. Among them, 325 were female (65%) and 175 were male (35%). Regarding weekly usage frequency, 68% used short videos more than 10 times per week. For weekly viewing time, 25% watched for less than 5 hours, 35% for 5–20 hours, 22% for 20–30 hours, and 18% for over 30 hours. In terms of video preferences, funny videos were the most popular (83.8%), followed by learning videos (75.2%). Lifestyle videos (63.4%) and current affairs videos (56%) were also frequently watched, while advertising videos had the lowest viewership (29.2%). Table 2 presents the detailed demographic information for this study.

Table 2: Demographic Information

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	175	35.0
	Female	325	65.0
Weekly Usage Frequency	0-5 times	59	11.8
	5-10 times	101	20.2
	More than 10 times	340	68.0
Weekly Usage Time	Less than 5 hours	125	25.0
	5-20 hours	175	35.0
	20-30 hours	110	22.0
	More than 30 hours	90	18.0
Types of Short Videos Frequently Watch (Multiple Selection)	Lifestyle Videos	317	63.4
	Current Affairs News Video	280	56.0
	Learning-type Video	376	75.2
	Advertising video	146	29.2
	Funny Videos	419	83.8
	Others	24	4.8
Weekly Usage Frequency for Learning	0-2 times	65	13.0
	2-5 times	219	43.8
	5-10 times	118	23.6
	More than 10 times	98	19.6

4.2 Confirmatory Factor Analysis (CFA)

This study employed Confirmatory Factor Analysis (CFA) to assess each variable within the conceptual framework. The results indicated that all scale items were statistically significant. Additionally, the factor loading values for each item were within an acceptable range, confirming that the conceptual framework demonstrated a good model fit. All factor loadings exceeded 0.30, p-values

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were less than 0.05, construct reliability (CR) values were above 0.70, and average variance extracted (AVE) values exceeded 0.50, establishing statistical significance. Table 3 presents these values.

Table 4 displays the square roots of the extracted variances, demonstrating that the correlations among all variables in this study were appropriate. The model fit was evaluated using Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normed Fit Index (NFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

The results as shown in Table 5 confirmed that the model met acceptable fit criteria. The results of convergent and discriminant validity were both deemed acceptable, confirming the validity and reliability of the structural model used in this study.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Perceived Usefulness (PU)	Chen et al. (2007)	5	0.906	0.801-0.831	0.906	0.659
Perceived Enjoyment (PE)	Al Natour and Woo (2021)	3	0.845	0.790-0.823	0.846	0.648
Product Novelty (PN)	Mou et al. (2021)	3	0.835	0.784-0.799	0.835	0.628
Privacy Protection Behavior (PPB)	Mou et al. (2021)	3	0.859	0.793-0.849	0.859	0.671
Satisfaction (SA)	Jia et al. (2023)	4	0.872	0.772-0.814	0.873	0.632
Informational Social Influence (ISI)	Dhoha et al. (2018)	5	0.905	0.774-0.835	0.905	0.656
Continuous Intention (CI)	Mou et al. (2021)	3	0.843	0.783-0.830	0.844	0.643

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 4: Discriminant Validity

Variable	Factor Correlations						
	PU	PE	PN	PPB	SA	ISI	CI
PU	**0.812**						
PE	0.295	**0.805**					
PN	0.244	0.312	**0.792**				
PPB	0.295	0.274	0.25	**0.819**			
SA	0.364	0.296	0.268	0.321	**0.810**		
ISI	0.3	0.255	0.21	0.26	0.366	**0.795**	
CI	0.305	0.307	0.311	0.314	0.362	0.303	**0.802**

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

Table 5: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	1.420
GFI	≥ 0.90 (Arbuckle, 1995)	0.944
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.929
NFI	≥ 0.90 (Hair et al., 2006)	0.947
CFI	≥ 0.90 (Hair et al., 2006)	0.981
TLI	≥ 0.90 (Hair et al., 2006)	0.984
RMSEA	< 0.08 (Pedroso et al., 2016)	0.029

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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.3 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is a statistical technique used to examine relationships among multiple variables within a validated research model. Hair et al. (2006) recommended that the Chi-square/degrees-of-freedom (CMIN/DF) ratio for model fit should be less than 3.00. Additionally, they suggested that the Tucker-Lewis Index (TLI) should be greater than 0.90. Greenspoon and Saklofske (1998) proposed that the Goodness-of-Fit Index (GFI) should exceed 0.85, while Sica and Ghisi (2007) recommended that the Adjusted Goodness-of-Fit Index (AGFI) should be greater than 0.80. Hair et al. (2006) also advised that the Comparative Fit Index (CFI) and Normed Fit Index (NFI) should both be above 0.90. Additionally, Pedroso et al. (2016) suggested that the Root Mean Square Error of Approximation (RMSEA) should be less than 0.08.

For this study, SPSS AMOS version 26 was used to perform SEM calculations and model adjustments. The fit index results indicated a good model fit, with CMIN/DF = 2.509, GFI = 0.885, AGFI = 0.862, NFI = 0.901, CFI = 0.938, TLI = 0.931, and RMSEA = 0.055. These values are presented in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	2.509
GFI	≥ 0.85 (Greenspoon & Saklofske, 1998)	0.885
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.862
NFI	≥ 0.90 (Hair et al., 2006)	0.901
CFI	≥ 0.90 (Hair et al., 2006)	0.938
TLI	≥ 0.90 (Hair et al., 2006)	0.931
RMSEA	< 0.08 (Pedroso et al., 2016)	0.055

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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Based on the regression weights and R^2 variances for each variable, the researcher assessed the significance of the study model. Table 7 presents the calculated results, which support all the hypotheses proposed in this study.

The standardized path coefficient (β) reflects the strength and direction of the relationship between variables, while t-values indicate whether these relationships are

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statistically significant. In this study, all t-values exceeded the threshold for $p < 0.05$, meaning each relationship is unlikely to be due to chance. Coefficients above 0.20, such as those in H1, H4, and H5, suggest moderate to strong influence in behavioral research (Hair et al., 2019

The findings indicate that Perceived Usefulness significantly influenced Satisfaction (β = 0.284), while Perceived Enjoyment (β = 0.168), Product Novelty (β = 0.155), and Privacy Protection Behavior (β = 0.224) also had significant positive effects on Satisfaction. Furthermore, Satisfaction strongly influenced Continuous Intention (β = 0.348), and Informational Social Influence had a notable impact on Continuous Intention (β = 0.223).

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: PU → SA	0.284	5.95*	Supported
H2: PE → SA	0.168	3.488*	Supported
H3: PN → SA	0.155	3.209*	Supported
H4: PPB → SA	0.224	4.656*	Supported
H5: SA → CI	0.348	6.857*	Supported
H6: ISI → CI	0.223	4.459*	Supported

Note: *=p-value<0.05

According to the results presented in Table 7, the researcher concluded the following:

H1: Perceived usefulness (β = 0.284) emerged as a key driver of satisfaction, indicating that students who perceive short video platforms as enhancing their learning efficiency are more likely to feel satisfied. This aligns with Al-Fraihat et al. (2020) and Kim et al. (2021), who emphasized the value of perceived usefulness in digital learning environments. In practical terms, this implies that to improve satisfaction, educational content must be perceived as clearly relevant and beneficial to learners' academic goals.

H2: Perceived enjoyment (β = 0.168) significantly influences satisfaction, albeit with a weaker effect than usefulness. This supports findings by Tamborini et al. (2011), who noted that enjoyment promotes engagement and emotional connection with learning platforms. However, the lower coefficient suggests that while enjoyment matters, it is not the primary driver of satisfaction in academic contexts, highlighting a partial contrast with studies on entertainment-oriented platforms. This implies that educators should blend engaging features with academic relevance.

H3: Product novelty (β = 0.155) positively affects satisfaction, confirming that students appreciate innovative and fresh content features. This supports Jin and Xu (2021) and Kang et al. (2023), who found that novelty boosts user satisfaction. However, the modest coefficient suggests novelty alone may not sustain satisfaction long term. Thus, platform designers should continuously introduce engaging formats while maintaining content quality.

H4: Privacy protection behavior (β = 0.224) has a substantial impact on satisfaction, suggesting that students value platforms that prioritize data security. This aligns with Cheng and Jiang (2020) and Ketema and Selassie (2020). This finding is especially relevant in education, where trust is essential for sustained engagement. Developers and institutions must implement transparent privacy policies and offer users control over personal data to enhance trust and satisfaction.

H5: Satisfaction (β = 0.348) strongly influences continuous intention, indicating that when students are satisfied with their learning experience, they are significantly more likely to continue using the platform. This is consistent with Expectation-Confirmation Theory (Bhattacherjee, 2001) and findings from Zhou (2013). The strength of this relationship suggests that improving satisfaction is critical for long-term adoption of short video learning tools in educational settings.

H6: Informational social influence (β = 0.223) plays a notable role in shaping continuous intention, reinforcing that students' decisions to keep using a learning tool are influenced by peers, instructors, or digital communities. This aligns with Wei et al. (2023) and Zhou (2013). In real-world contexts, this indicates that promoting platform use through social learning, peer recommendations, or group assignments may enhance long-term engagement.

The results validate the study's theoretical framework and provide actionable insights for educators and platform designers. Prioritizing usefulness, security, and peer influence can meaningfully improve learners' satisfaction and long-term use of short video platforms in education.

5. Conclusions and Recommendation

5.1 Conclusions

This study investigated the factors influencing student satisfaction and continuance intention in using short video platforms as educational tools. Given the rapid growth of the short video industry, these platforms have become increasingly relevant in both social and academic contexts. The aim was to evaluate their effectiveness in learning environments through a validated structural model.

A total of 500 liberal arts students from Geely University of China participated in the study. The sample was predominantly female (65%) and heavily engaged with short video content, with 68% using such platforms more than 10 times per week. Additionally, a large proportion of students (75.2%) regularly consumed learning-related short videos, while 83.8% favored humorous content, indicating a blend of entertainment and academic utility in platform usage.

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Data analysis using SPSS, JAMOVI, and AMOS confirmed the conceptual framework's validity. Confirmatory Factor Analysis (CFA) demonstrated a good model fit, and Structural Equation Modeling (SEM) validated all six hypotheses. The findings revealed that perceived usefulness had the strongest influence on satisfaction, followed by perceived enjoyment, product novelty, and privacy protection behavior. In turn, satisfaction and informational social influence significantly impacted students' continuous intention to use the platform.

These results highlight the combined importance of functional value, engaging content, novelty, and data security in driving learner satisfaction. Moreover, peer influence and emotional connection play critical roles in sustaining usage behavior, especially among younger, digitally native learners.

For educators, the study suggests that integrating short videos with pedagogically relevant content can enhance engagement and supplement traditional instruction. Designing content that is not only informative but also enjoyable and innovative can lead to greater learner satisfaction and retention. For policymakers, the findings emphasize the need to support digital learning strategies that reflect current media consumption behaviors. This includes investment in infrastructure, privacy regulation, and professional development for teachers in content creation and platform curation. Ensuring equitable access to engaging and secure digital learning environments is crucial in promoting inclusive and effective education.

Ultimately, this study offers a validated framework for understanding technology adoption in education and lays the groundwork for future research on the evolving role of short video platforms in e-learning, mobile learning, and broader digital education strategies.

5.2 Recommendations

Based on the findings, several actionable recommendations are proposed to enhance the effectiveness of short video platforms as learning tools. As student satisfaction and continued use are shaped by perceived usefulness, enjoyment, innovation, privacy, and social interaction, improving these aspects is essential for meaningful engagement.

To support learning outcomes, platforms should prioritize high-quality, credible educational content through partnerships with educators and institutions. Incorporating structured learning paths and AI-driven recommendations can guide users toward relevant and personalized content, enhancing both usefulness and efficiency. To maintain engagement, learning experiences should be enjoyable and interactive. Features such as gamification, visual storytelling, and AR-based explanations can make content more appealing, while social tools like comments, sharing, and peer collaboration foster a sense of community.

Innovation should be continuous, with regular updates and integration of emerging technologies such as adaptive learning systems and real-time feedback. These not only keep the platform dynamic but also address diverse learner needs. Privacy remains essential to user trust. Platforms should implement transparent data policies, encryption, and customizable settings to ensure security and compliance. Educators can amplify the platform's impact by integrating short video content into instruction and promoting digital literacy. Feedback systems, achievement tracking, and progress visualization can further motivate learners and support long-term engagement.

5.3 Limitation and Further Study

This study was conducted using a cross-sectional design, which limits the ability to infer causal relationships between variables. Future research could benefit from longitudinal or experimental approaches to capture behavioral patterns over time and strengthen causal interpretation.

The sample focused exclusively on liberal arts students from a single university, which may constrain the generalizability of the findings to other academic disciplines or institutional contexts. Expanding the sample across diverse educational settings could provide a more comprehensive view of learner behavior.

Cultural and institutional factors may also have influenced students' attitudes toward privacy, peer influence, and technology use. Conducting comparative studies across regions or countries would help explore the role of cultural variation in shaping learning behaviors.

Additionally, reliance on self-reported data introduces the risk of response bias. Integrating system log data or observational methods could enhance the accuracy and validity of future research outcomes.

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