Animated short video viewing rough behavior with stochastic rough decision modeling

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Abstract

China's short video platform has shown rapid development in terms of user scale and its industry since 2015. As of June 2021, the number of short video users has reached 888 million(China Internet Network Information Center, 2021), an increase of 14.4 million compared with December 2020, accounting for 87.8% of the overall. Animated short videos have a subtle effect and influence on the healthy growth of young minds. As some animated short videos containing harmful information such as violence, pornography and vulgarity are spreading across social media through mobile Internet, they induce some adolescents to watch them obsessively and form addictive behaviors, which seriously endanger the physical and mental health of adolescents. Therefore, this study aims to reduce the unsafe behaviors of adolescents watching short animation videos based on the theory of planned behavior and S-Rough set theory. From the perspective of the Theory of Planned Behavior, the paper investigates the main factors and decision-making mechanisms that influence viewing behavior. To address the limitations of the Theory of Planned Behavior, S-Rough set theory is used to explore users' uncertain subjective crude behaviors due to individualized needs and random emotions, identify the key attributes that influence users' decisions, and construct a crude behavior model $w = \bigcup_i [w(x)]$ *of animated short video viewing. The Rough behavior model is constructed by using the equivalence classes of SC (Subjective Choice) set X and CI (Choice Intention) set Y* $\alpha_R(X) = \frac{|\underline{R}(X)|}{|\overline{R}(X)|}$ *and* $\beta_R(X) = \frac{|\underline{R}(Y)|}{|\overline{R}(Y)|}$ *, establishing a Rough law analysis method to study the interrelationship between SC and CI, propose a random decision method for user animation viewing behavior. The results of this study show that Rough set theory can be applied to the study of random and individualized behavior. The research results show that the theory in analyzing the decision of animated short video viewing behavior is a way, which can provide new ideas for in-depth analysis of animated short video viewing behavior and provide targeted suggestions and strategies for animated short video development, recommendation, and users' safe viewing.*

Keywords

theory of planned behavior; S-Rough set theory; animated short videos; crude behavior; decision rules; crude decision model

1 Introduction

The rapid development of short video on mobile platforms, the huge population base of users, and multiple types of live streaming platforms have made China and the world start at the same starting line, and "ByteDance" has become a leading company in the world.

According to the "2020 China Internet Audio-Visual Development Research Report (China Association of Network Audiovisual Program Services, 2020), the size of short video users in China has reached 818 million, accounting for 87.0% of all Internet users, and it has become the audiovisual product with the highest single-day usage time of 110 minutes per capita. From the viewpoint of market share, domestic short video software TikTok and Kuai are at the top of the industry with a 56.7% share. There are 61.237 million users following the industry brand "Yi Chan Xiaoheshang", 43.017 million users following "Zhu Pideng" and 3966.39 users following "Tang Tang" respectively. The number of animated short video accounts has reached more than 30 million.

Animated short videos, represented by two-dimensional animation, have been increasingly active in recent years. Its sub-categories in TikTok have more than 20 subdivided content categories including virtual idols, anime episodes, cosplay, hanbok, blind boxes, handbooks, and so on. And Kuai, according to the "2020 Kuai Two-dimensional Content Inventory, it is also divided into three segments: anime, daimyo, and tide play.

According to QuestMobile data (QuestMobile, 2021), in December 2020 the post-90s accounted for 35% and 32.9% of TikTok and Kuai users respectively, ranking first among all age circles with their high coverage; the post-00s accounted for 13.7% and 15.7%, respectively. Two-dimensional users have become the growth point of the new platform. AI Media Consulting (Emmy, 2021) thinks that as a fast-growing type of mobile product in the 4G era, short videos can aggregate social and e-commerce attributes, and the two-dimensional industry is in the process of moving from niche to mass and from community culture to mainstream culture.

As an important branch of the short video industry, the animated short video industry is developing rapidly, and some contents filled with violence, pornography, vulgarity and other undesirable information are spreading across regions through the Internet, which makes some teenagers form bad habits and addictive behaviors of surfing the Internet for a long time. How to guide the industry to a healthy development path to avoid negative guidance to the youth mind. The Chinese government has introduced a short video content audit and youth consumption behavior safety management system in recent years and set up a youth model to prevent their addictive behavior of watching short videos. To build an entertainment life that promotes positive energy, theoretical research becomes an indispensable part of the industry towards maturity and is an important concern for society and related departments.

Most of the studies are limited to subjective discussion of the problem and lack of standardized theoretical research and quantitative analysis. This study is an in-depth theoretical discussion on subjective selectivity and random viewing from the perspective of user viewing, with a view to exploring a new path and sharing it with peers.

2 Related Work

2.1 Relevant Foreign Research Work

2.1.1 Theory of planned behavior

Theory of planned behavior is a new theory proposed by Ajzen in 1985 based on the theory of rational behavior (Ajzen, 1985).

The theory (Wittenberg et al., 2018) argues that the best predictors of behavior are determined by behavioral attitudes, subjective norms, and perceived behavioral control. Armitage and Conner (Armitage & Conner, 2001)argue that the theory has good predictive and explanatory power for behavior. Stern(Stern et al., 1999) put behavioral attitudes first and thought that individual pro-environmental behavior is in fact primarily influenced by factors such as knowledge and habits, which are not taken into account by the theory of planned behavior.

Gopi et al. (Gopi & Ramayah, 2007) applied the theory of planned behavior to a study in the area of online stock trading and concluded that there is a direct positive relationship between attitudes, subjective norms, and perceived behavioral control for behavioral intentions in the area of trading.

In the field of education, TPB is mainly used to predict teacher and student behavior, such as teacher professional development activities (Dunn et al., 2018), etc.
Planned behavior has been used as a method to explain and predict various human behaviors and has gained more use in psychology, management, sociology, and political participation, environmental protection, etc.

In terms of short video user behavior, domestic and foreign scholars mainly study short video user behavioral intention and usage behavior from the perspective of rooting theory, fit theory, and planned behavior theory.

2.1.2 Research work related to short video viewing behavior

With the gradual formation of different groups of short video APP users, each group has its representative characteristics. In recent years, some scholars have devoted themselves to doing in-depth analysis of the characteristics of each group of short video APP users, and to discovering the connection between users and smart information devices by mastering their social behaviors and personality characteristics in order to solve some social problems. Yang (Yang, H., 2019) used focus groups and in-depth interviews to understand how young people's Snapchat behaviors affect their relationships. Snapchat is a double-edged sword that can lead to relationship breakdowns. Balachandran et al (Balachandran et al., 2012) argued that specific online video viewing endpoints affect the user's experience and thus the user's engagement behavior in exploring the experiential criteria of online video quality.

In summary, no relevant quantitative research has been seen in terms of the theory of planned behavior and the theoretical research about short video viewing behavior, and no literature discussing the characteristics and change patterns of user viewing behavior has been found. In this paper, we use the theory of planned behavior to study the determinism of teenagers' viewing behavior and establish an RB (Rough Behavior) model of animated short video users' viewing behavior with S-rough set theory to explore in depth the randomness affecting users' viewing behavior.

2.2 Domestic Related Work

2.2.1 Aspects of the Theory of Planned Behavior

Liu,Y.W. (Liu,Y.W., 2008) argues that attitudes depend on relative personal interests, relative social interests, and complexity, subjective norms depend on internal and external norms, and perceived behavioral control depends on self-efficacy and facilitation.

Du, X. (Du, X.,2012) The three factors of consumers' behavioral attitudes, subjective norms, and perceived behavioral control all have significant effects on consumer behavior intentions, with behavioral attitudes having the most significant effect on apparel consumption intentions, followed by perceived behavioral factors, and subjective norms having the least effect.

Huang, F., et al. (Huang, F., & Wang, J., 2013) proposed a model of consumer acceptance behavior based on perceived value and conducted an empirical study on the acceptance intention of online games by students in a university in Macau, concluding that perceived value is the most important influencing factor reflecting the basic characteristics of consumers for the acceptance intention of information technology applications.

2.2.2 Research Results of Short Video Viewing Behavior

Yang, S. (Yang, S, 2020) proposed that the content of short video APPs should be interactive and interesting to strengthen users' stickiness to use the software.

Wang, X. (Wang, X., 2021) thought that as an important group of people in the online communication ecology, college students' use of short videos has greatly influenced the media landscape. We should address the phenomenon of college students' screen addiction and guide their mainstream values so that they can use short video software as a tool for their life and study.

Hao, R.X. (Hao, R.X., 2020) conducted a study of rural "local" short videos and found that the content of food, funny, and skill-based videos are consistent with the inherent perceptions of rural audiences, dwarfing the image of rural areas to a certain extent, and affecting the online ecological environment with overly vulgar content.

Cheng, X., et al. (Cheng, X., & Shao,Y.H., 2020) found in the study that users' behavioral attitudes and perceptual behavioral control were significant factors that could positively influence the production of short-form video content, reflecting that short-form video content producers have a strong desire to explore and master the emerging medium, and pursue the uniqueness of self-presentation with distinctive independent self-construction attributes.

2.2.3 Relevant Achievements In Computing

In terms of quantitative analysis, domestic and foreign quantitative analysis based on "random forest", "deep forest", "decision tree" and "rough set ". The quantitative analysis of users' behavior motivation and behavior intention has achieved good results.

Tatsuya Iwasaki (Iwasaki, 2021) studied by quantitative survey analysis method people's behavioral motives

for making multiple visits to anime shrines. Factor analysis was used to derive behavioral motivations, and the desire scores of "sense of belonging and oneness" and "wanting to get in touch with the nature of the tour site" were high for low participation in a specific anime mecca; moderate participants were " The desire to gain self-confidence" and "to gain a new outlook on life" scored high; the desire to "lead others" and "to communicate with local people" scored high for high participants. High participants scored high on "want to lead others" and "want to communicate with local people.

Ge, S.L. (Ge, S.L.2019) studied by user purchase behavior prediction model based on "deep forest", by constructing user behavior feature engineering to establish the overall user behavior feature model; propose the user purchase behavior prediction method based on deep forest and achieve efficient behavior prediction training effect.

Chen, J.Q. (Chen,J.Q., 2019) studied the decision tree prediction user purchase behavior model, set the Cart decision tree algorithm as an example, by judging the attribute information of product users, in order to achieve the prediction of purchase behavior, service merchants, and bring convenience to users.

Yang, B.Z. (Yang, B.Z., 2010) studied rough set can deal with uncertain data, which means S-rough set theory is used to obtain the association rules between personal online behavior information and users' purchasing tendency, and the detailed steps and methods of obtaining rules are described. The main steps include data preprocessing, attribute simplification, value simplification, rule acquisition, and weight calculation, etc.

2.3 Research On The Development of China's Animated Short Video Industry

2.3.1 Development Stages of Animated Short Video Platform

The short video platform rises from 2012 to 2015. As a form of content consumption in line with user fragmentation, short videos gradually be concerned about and loved. The emergence of platforms such as Kuai, Miao Pai, and Weishi, opened the curtain of the short video era user creation enthusiasm ignited, and short video content types gradually rich.

Information short video platform "Pear Video" was born from 2016 to 2017, Pear Video and related bosses United, Weila Video and other information short video column with Zoomin.tv, Ele.me and other platforms to build a global patron network more traditional media began to explore the field of short video. CCTV in 2016 Launched Amazing, our 2016, V view and other series of short videos of current affairs People's Daily, Xinhua News Agency and other mainstream media have opened TikTok accounts.

According to the 48th Statistical Report on the Development of China's Internet, as of June 2021, the number of China's cell phone users reached 1.007 billion, an increase of 20.92 million over December 2020, and the proportion of Internet users using cell phones to access the Internet was 99.6%. In the same period, the number of China's Internet video (including short video) users reached 944 million, an increase of 17.07 million over December 2020, accounting for 93.4% of Internet users 93.4% of overall. Among them, the scale of short video users reached 888 million, up 14.4 million from December 2020, accounting for 87.8% of Internet users as a whole (as shown in Figure 1).



Figure 1 Trend of short video user usage

2.3.2 Related Work On Video Viewing Behavior

Wang, H.H. (Wang, H.H., 2021) believed that students' needs, motivation to watch videos, gender, grade, and major have an impact on video viewing behavior, and college students with strong achievement and entitlement needs are predominantly planned viewers in video viewing. Female, affinity-needy college students are predominantly impulsive in their video viewing.

Fu, F.D. (Fu, F.D., 2020) built a model of pre-screening ad viewing behavior based on the theory of planned behavior, the results showed that the main factors influencing viewers' willingness to watch pre-screening commercials are viewing attitude, subjective behavioral norms and perceived behavioral control, and viewing attitude is mainly influenced by attitudinal beliefs and subjective norms.

Deng, Y.C. (Deng, Y.C., 2021) investigated the relationship between Chinese drama viewing and Chinese cultural identity among international students, a questionnaire survey of Chinese students in the UK and semi-structured interviews with six of them were used to collect data on their Chinese drama viewing habits, Chinese cultural identity level, identity needs and needs satisfaction.

Gu, J. (Gu. J., 2020) took the outstanding domestic animation films from 2010 to the present as examples to explore the aesthetic psychology of all-age audiences watching domestic animation films and concluded that audiences invoke aesthetic perception mechanism, emotional mechanism, and understanding mechanism when watching domestic animation films. They watched the films for entertainment motivation, interpersonal motivation, and aesthetic motivation, which has implications for the success of domestic animation films.

Yi. X.R., et al. (Yi, X.R., 2019 #375) took user values and preference habits as the entry point to form a TV user viewing behavior analysis method by extracting implicit information from user history. A matrix of user preference habit characteristics based on activity and stability is constructed, and user preference habits are divided into four cluster categories to quantify and analyze user preferences.

To sum up, the act of watching short videos is not only a form of entertainment, its content is closely related to the social life of the general public and will have an important impact on the ideology of all levels of society. At present, the research on users' motivation and behavioral decision of watching movies and related influencing factors is not deep enough, and there is a lack of quantitative research data, so it becomes a very important and urgent proposition to deeply study the motivation of users' watching behavior.

3 Factors Influencing Users' Viewing Behavior and Decision-Making Mechanism

3.1. Animated Short Video Users Features

With the development of social media technology, user viewing behavior has become a new way of entertainment for the public with smart terminals as the carrier. According to the 2019-2020 China Secondary Video Industry Special Research Report (Ai Media Large Cultural Entertainment Industry Research Center, 2020), the number of two-dimensional video users on short video platforms such as TikTok and Kuai will exceed 332 million, and is expected to exceed 400 million in 2021. QuestMobile data shows that in December 2020, the proportion of post-90s among TikTok and Kuai users is 35% and 32.9% respectively, and the proportion of post-00s is 13.7% and 15.7% respectively. In terms of market share, TikTok and Kuai are in the first echelon of the industry with a 56.7% share of the two. The first is "Yichan Xiao Heshang" with 61,237,000 total fans, the second is "Zhu Pideng" with 43,017,000 total fans, and the third is "Tang Tang" with 3,966.39 total fans. "listed third, the above three is also the only three short video animation accounts that have fans of the number of 30 million +.

By June 2021, users show the following characteristics: the age group below 25 years old is the main group of online video users, with a high proportion of 72.1%. Most of their education level is high school, college or bachelor's degree, and they access the Internet for more than 5 hours per week. In terms of gender differences, the ratio of male to female Internet video users is 54.3:45.7, and the proportion of monthly income below RMB 3,000 is 71.3%.

3.2 Factors Influencing User Viewing Behavior

In the mobile terminal environment, behavioral science research shows that the applied interactive behavior is caused by the purpose of motivation and demand, which drives the short video creation and viewers to reach specific goals and drives the wide dissemination of short video information content.

Users watching short videos is a complex process, influenced by their own cultural needs, interests and time, etc. Cultural needs mainly include educational content, religious beliefs and entertainment culture, through the interactive communication between the short video content information and the viewer. Regardless of the number of factors that determine the occurrence of viewer behavior, it can usually be roughly divided into two processes:

1. Planned behavior process: It refers to the process of selecting content classification and categorizing content when users watch short videos. This process studies people's behavioral decision-making by first considering the goals as the way of action as well as the expected results, and second, taking actions to achieve these goals. As far as the behavioral process of watching animated short films is concerned, the intention and actual behavior that affects an individual's viewing of animated short films is determined by the individual's positive or negative attitude toward watching the film and its level of interest and depends on his or her personal behavioral intention and attitude, and the decision power of subjective and perceived behavior.

2. Random selection behavior process: refers to the randomness of the user in choosing to watch or give up watching. Whether a user wants to watch an animated short video is directly related to his psychological state

at that time. From the aspect of the user's psychological reflection of watching, if he frequently participates in the social behavior of retrieving, watching, commenting, sharing, and forwarding the short video content, his social cognitive ability and emotional control ability will be enhanced, and vice versa will affect his emotional regulation ability.

Users' initial viewing behavior is usually dominated by generating internal pleasure and relaxation, and the higher the emotional intensity and emotional pleasure of the moment obtained, the greater the positive fluctuation and the stronger the tendency of random selection behavior. Similarly the stronger the user's depression and anxiety, the more time he or she is likely to spend on watching and using it to alleviate the social pressure of the moment, and the more uncertain the random choice behavior of watching. Therefore, the psychological factors that affect the random choice of users watching are: 1) Random emotions needed for watching: passion, immersion, trolling, entertainment and other emotions that appear in the process of reprinting, reviewing and sharing when watching short animated videos; 2) Random emotional factors: users watching love or dislike, dissatisfaction, disappointment and other random emotions reflected in the animation content, such as watching the film on the emotion of dissatisfaction expressed by the crude production; the emotion of anger expressed by the negative energy content; the emotion of hate expressed by the malicious criticism or personal attack by other users when a user publishes a review after watching; 3) The random selection factor of watching animation content, the emotion of choosing to watch or giving up watching shown by whether the current short video content matches their own psychological state in the process of user watching.

3.3 Decision-Making Mechanism of User Viewing Behavior

User viewing behavior decision mechanism refers to the process of a series of decisions and behaviors that users make when watching animated short video content. This process includes which type of media content the user chooses to watch, how to browse and filter the available media content, and how to interact with the media content. The different factors of this decision process include users' personal preferences, current context, social influences, and many other factors. By deeply understanding and analyzing the decision-making mechanism of users' viewing behavior, we can provide content recommendation and personalization services for media platforms and content providers to improve user experience and content appeal.

The decision mechanism of users watching animated short videos is divided into: 1) Video topic selection: users usually choose the topics they are interested in to watch. The choice of video themes is the key point of the decision mechanism. Common themes include funny, music, food, travel, etc. Video platforms recommend videos with corresponding themes based on users' viewing history and search keywords to help users quickly find content of interest; 2) Video titles and headlines: the titles and headlines of short videos can attract users to click and watch. According to user preferences and search history, video platform improve the click rate of the video through AI intelligent algorithms can generate titles and headlines ; 3) Video length and content quality: the length of the video and content quality is a factor in the decision of user viewing behavior. Users usually prefer short and concise videos, but some users will prefer long videos with rich content. The video platform can combine the user's viewing history and behavior to recommend suitable videos; 4) Related video recommendation: the video platform can also attract users to watch by recommending related videos. The recommended video is related to the video topic the user is watching, and can also be related to the user's viewing history; 5) Social factors: social factors also affect the user's viewing behavior decisions. Users may be recommended by friends or family members to watch a particular video. Video platforms can

expand the reach of videos through social media sharing features, thus attracting more viewers to watch them.

Animated short video user viewing behavior decision mechanism is a comprehensive process involving user interests, topic selection, video length and content quality, related video recommendations and social factors. Video platforms can match users' precise experience through intelligent algorithms and data analysis to meet their different viewing needs.

4 A Study On Modeling The Rough Behavior of Short Video Viewing

4.1 Rough knowledge of subjective behavior

4.1.1 Rough Collection of Subjective Behaviors Viewed by Users

In daily life, human behavior is often determined by subjective consciousness, which mainly includes the planning of behavior (see 2.2.1 and 3.2 for details) and the randomness of behavior, and its composition is complex and comprehensive analysis is composed of life experience, common sense, education, social environment, emotions, and other content.

The subjectivity of behavior (such as online shopping, watching movies, etc.), is influenced by the CW (Choice Willingness), with strong randomness. The CB (Choice Behavior) is influenced by product style, style, color, preference, and other psychological characteristics.

Analyzed from the perspective of watching short animation videos, users' subjectivity is mainly expressed in the degree of acceptance of the content aspect of the work, such as the entertainment of the content, picture style, color, fun and other aspects.

CW is an important judgment of choice behavior, and its decisiveness is related to the reputation of the online platform, user evaluation, current emotional needs, previous viewing experience and other factors. Therefore, the SB (Subjective Behavior) (referred to as RB (Rough Behavior) of users' short video viewing can be seen as a combination of CM(Choice Motivation) and CW, which are influenced and contained by each other.

Think of a user's viewing RB (Watch, W) as a theoretical domain U, where: $W = \{w_1(x), w_2(x)..., w_i(x)\}$. The RB can be seen as a crude collection of CM and CW:

Denoted as: $W = \bigcup_i [w(x)]_I$, and has the set of attributesα , andβ .

Among them $\{x_1, x_2, ..., x_n\}$, the concept of CM, family X, represents a limited number of factors in subjective consciousness, such as story content, artistic style, knowledge transmission, entertainment, and viewing experience.

Let Y $\{y_1, y_2, ..., y_m\}$ is a limited subset of CW factors such as reputation, retweets, likes, comments, tweets and current sentiment.

Let a relationship system K be formed by CM and CW, and CW to CM forms an interference set, then.

$$K = (W(X^Y), R) \quad (1)$$

where R is the set of families of equivalence relations on W.

4.1.2 Rough Knowledge Expression of Subjective Behavior

Definition 1 A division on W is a system of relations with respect to Eq. (1)K , then K is called the BRKB (Behavioral Rough Knowledge Base) . where $U \neq \varnothing$, R is the set of families of equivalence relations on W .

W /R is the set consisting of all equivalence classes of R.

Definition 2 Define the accuracy of the approximation on the set X as

$$\alpha_R(X) = \frac{|\underline{\boldsymbol{R}}(X)|}{|\overline{\boldsymbol{R}}(X)|} \qquad (2)$$

where $X \neq \varnothing$, approximate accuracyα_R (X) , 0≤α_R (X)≤1 .

The subset of CM X set is determined by [0,1], and when CW is close to or equal to 0, the user abstains from watching, and when intention is close to or equal to 1, the user decides to watch.

CW that varies between 0 and 1 is called HV(Hesitation Value), which indicates the randomness of RB. The HV indicates the randomness of the RB. Therefore, 0.5 is the inflection point of HV, and 0 and 1 are the decision poles of HV.

For the convenience of exploration, we remove the decision pole value and replace it with a decision range, then the user's state of whether to watch an animated short video work usually starts from the inflection point value, (0.1, 0.5] is the hesitant lower approximation_R and [0.5, 0.9) is the upper approximation¯R . Then, 0.1≤β_R (Y)≤0.9 , this change does not affect the outcome of the user's decision to watch.

Definition 3 Let "choice intention" be the interference set of subset Y under W to X.

$$\beta_R(X) = \frac{|\underline{\boldsymbol{R}}(Y)|}{|\overline{\boldsymbol{R}}(Y)|} \qquad (3)$$

where $X \neq \varnothing$, $Y \neq \varnothing$ approximate accuracy $\beta_R(Y)$, as β_R is an approximation ofα_R the interference set of β_R The definition domain of is set to $0.1 \leq \beta_R(Y) \leq 0.9$.

By approximating the accuracy $\beta_R(Y)$, it is convenient to explore the law of the interaction between each equivalence relation R and $X \subseteq W$ for the set of CW | X |, and the randomness of CM Y .

4.2 Subjective Behavior Rough Decision Making

4.2.1 Rough Decision Tree For Animation Viewing

Whether a user watches an animated video or not depends on his comprehensive judgment and analysis of the CM, CW" and TV(Time Variables) of the work he is about to choose. Randomness plays an important role in the outcome of the judgment. We depict this process as a decision tree, (shown in Figure 3). In which:

represents the decision objective;	represents the attribute;
Represents leaf nodes	Represents randomness of behavior

The behavioral decision of a viewer when deciding whether to watch a work can be roughly represented as an "animation viewing decision tree".

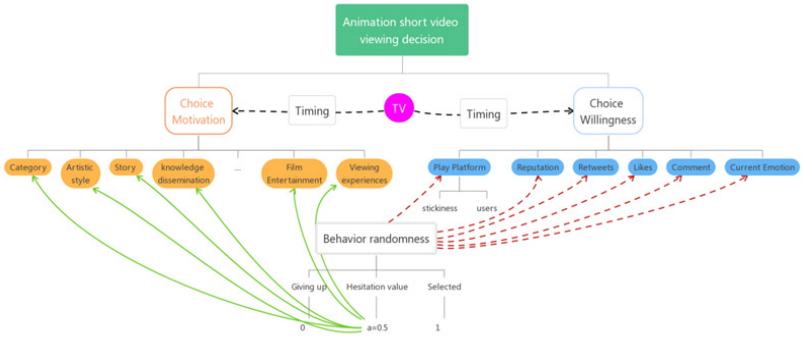


Figure 2 Animated view of the decision tree

The solid arrow line represents the initial hesitation value of 0.5 at the inflection point when deciding to watch the work, and the red dashed line represents the initial hesitation value of 0.0 for "choice intention" (see Table 3 for details).

Table 3 Initial state of the CM for viewing

Category	Artistic Style	Story	Knowledge Dissemination	Film Entertainment	Viewing Experience	....
0.5	0.5	0.5	0.5	0.5	0.5	

Table 3 shows that the variables are mainly subjective in nature, with "Category" representing the viewer's choice of category; "Artistic Style" representing the viewer's personal aesthetic ability; "Story" representing the content information of the short video; "Knowledge Dissemination" representing the knowledge of the short video; "Film Entertainment" representing the viewer's liking of the story content of the animation; and "Viewing Experience" representing the viewer's liking of the animation. represents the content information of the short video. The initial state of each variable in Table 3 is set to 0.5,. represents the other contents are ignored for the time being.

Table 4 The initial state of "willingness to choose" for viewing

Play Platform	Reputation	Retweets	Likes	Comments	Roast	Current Emotion	....
0.0	0.0	0.0	0.0	0.0	0.0	0.0	

Table 4 is designed with objective factors, "Play Platform" represents many platforms on the Internet at present; "Reputation" represents the word-of-mouth evaluation of the work by others; "Retweets " refers to the number of retweets of the animation by others; "Likes" refers to the number of likes of the animation by others; "Comments" represents the evaluation of the viewers on the platform (good and bad reviews); "Roast" refers to the comments of the viewers to vent their emotions, "Current Emotion" refers to the viewers' current emotional state, and the initial state of each variable in Table 4 is set to 0.0.

4.2.2 CM (Choice Motivation) ($\overline{R}$, $\underline{R}$) Rough law

In life, human subjective behavior is influenced by CM and TV. It is common for subjective impressions of the same event to change over time.

Definition 4 Let $X \subset W$ be the set of selection-motivated laws and R be the regular equivalence relation over time on X:

$$\alpha_R(X_t) = \frac{|\underline{R}(X)|}{|\overline{R}(X)|}, 0 \leq \alpha_R(X_t) \leq 1 \quad (4)$$

$$[\alpha]_j = \{ \alpha_1, \alpha_2, \ldots \alpha_m \}, \text{the} \alpha_j \in X \quad (5)$$

is the equivalence class of CM over time on X .

As shown in Figure 3, starting from the initial value of 0.5 for CM, the hesitation value of viewers' animated short video viewing fluctuates randomly over time within the green dashed line at $\overline{R}$ and in $\underline{R}$.

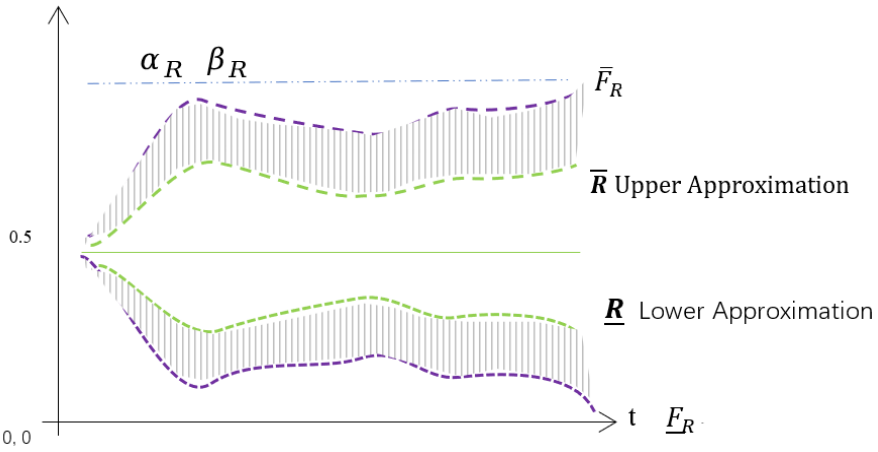


Figure 3 Rough pattern of animated short video users' viewing motivation

3.2.3 CW (Choice Willingness), ($\bar{F}$, the$\underline{F}$) Rough Law

A Rough decision tree is a knowledge-based open system whose node content at each level randomly moves in and out with the immediate state of the viewer, e.g., a animated short video that increases the willingness to watch due to hearing about the great visual effects of the production, or an animation work that was intended to be watched but was abandoned because it did not like the story.

It can be seen that the random movement in and out of node content is directly or indirectly influencing the viewers' decision of whether to watch or not.

Let $Y \subseteq W$ be the set of CW laws, and R be the equivalence of laws on Y. From equation (3), it follows that

$$\beta_R(Y) = \frac{|\underline{R}(Y)|}{|\overline{R}(Y)|}, 0 \leq \beta_R(Y) \leq 0.9 \quad (6)$$

$$[\beta]_m = \{ \beta_1, \beta_2, \ldots \beta_m \}, \text{the} \beta_j \in Y \quad (7)$$

It is the equivalence class of the CW stochastic behavior law on theY.

As shown in Figure 4, starting from the initial value of 0.5 for CW, the hesitation value of viewers' animated short video viewing fluctuates randomly over time between the purple and green dashed vertical lines.

Set the randomness function can be selected to have a positive or negative value option in the online platform; for example:the difference between the number of likes and bad comments, theδ=δ^+ - δ^- , where: the random fluctuation function isδ ,δ^+ is the positive evaluation, andδ^- is the inverse evaluation. To simplify

the calculation, it is chosen that

When$\delta>0$ is taken as$\delta= 0.1$; (8)

When$\delta<0$ take$\delta = -0.1$; (9)

Definition 5 $X \subseteq W$ is the set of subjective behavioral laws:

$\underline{F} = \{\underline{f}_1, \underline{f}_2, \ldots \underline{f}_n\}$, , and$\overline{F} = \{\overline{f_1}, \overline{f_2}, \ldots \overline{f_n}\}$, (10)

$X^{(\underline{F},\overline{F})}$is the S-bidirectional set of X, then the random decision to watch can be expressed as

$W = \{w_1(x), w_2(x) \ldots, w_i(x)\}$ Disturbed set

$\beta_R^{(\underline{F},\ \overline{F})}$Impact generation:

$\alpha_R^{\beta_R} = \alpha_R^{(\underline{F},\ \overline{F})} = \alpha_R \cup \alpha_R^{\underline{F}} - \alpha_R^{\overline{F}}$ (11)

The Rough boundaries for animated short video viewing are (as shaded in Figure 4):

$W(X^Y) = W(X^{(\underline{F},\ \overline{F})}) = \overline{W_R}^{(\underline{F},\overline{F})}(X^{(\underline{F},\ \overline{F})}) - \underline{W_R}^{(\underline{F},\overline{F})}(X^{(\underline{F},\ \overline{F})})$ (12)

Among them:

$\overline{W_R}^{(\underline{F},\overline{F})}(X^{(\underline{F},\ \overline{F})}) = \cup_j [w]_j$

$= \left\{w \middle| w \in X^{(\underline{F},\ \overline{F})}, [w] \subseteq X^{(\underline{F},\ \overline{F})}\right\}$ (13)

are the upper approximation laws for animated short video viewing;

$\underline{W_R}^{(\underline{F},\overline{F})}(X^{(\underline{F},\ \overline{F})}) = \cup_j [w]_j$

$= \left\{w \middle| w \in X^{(\underline{F},\ \overline{F})}, [w] \cap X^{(\underline{F},\ \overline{F})}\right\}$ (14)

for the lower approximation law.

5 Design of Stochastic Decision Systems For Rough Behavior

5.1 Animated Short Video User Viewing Behavior Metadata Abstraction

Analyzed from the dimension of information content, the animated short video is roughly in the content search, content viewing and other information needs for information publication, reprint, evaluation, likes and other interaction and interaction. From the analysis of information behavior, the information behavior of animated short video can be defined as the following levels: 1) loading behavior: the use of mobile short video App, the formation of animated short video viewing consumption needs; 2) search behavior: the viewer's search and selection behavior of animated short video content; 3) information interaction behavior: the user for animated short video about short video retrieval, play, comment, like and other behavior; 4) random behavior of short video watching: mainly shows the randomness of users' motivation and choice intention when watching animation; 5) information interaction behavior: shows the behavior of sharing, commenting, liking and publishing information among users.

The obtained web data material is labeled with descriptive words such as viewing behavior, willingness to watch, and engagement, and the fragmented concepts are symbolically extracted, semantically reorganized and labeled, and the metadata abstraction of viewing behavior is shown in Table 5.

Table 5 Watching Behavior Metadata Abstraction

Metadata	Metadata abstraction
data1 Viewing behavior	Animated short videos are rich in content, with a mix of text, images, voice, video and other data, choose the type set to (d1 animation classification); user viewing behavior through voice, pictures, text, video within the character action expression, judgment choose to watch the information (d2 choose content information); use fragment time to get more valuable information in time (d3 play length).
data2Willingness to watch	Animated short videos are rich in knowledge, bringing users a lot of common sense in life and innovating the form of knowledge dissemination (d4 innovation of the story); where the character is exaggeratedly fun, knowledgeable and beautiful, which is the basic willingness of users to watch (d5 willingness to watch).
data3 Participatory	The number of times the short video was forwarded determines the video content evaluation and heat (d6 video heat); users share with each other in a timely manner and share the joy (d7 timely sharing)! User participation in short video comments is to expand the influence and social capabilities, user social demandability is also very important (d8 social demand).
data4 Comment richness	Statistics on comments saying yes, bad, etc., based on the positivity and negativity of the video comments (d9 comments are abundant).
data5 Video artistry	The artistry and artistic value of the video images are the motivation for viewers to share and comment on the review (d10 artistic value).
data6 Video Infectious	The story protagonist, exaggerated language, rich action, can move the user to watch the demand, strong infection, there will be more people willing to watch, thus determining the number of willing to share comments (dl1 strong infection).
data7 Safety	For underage users, the reaction to animated short video content determines the basic connotation of its safety, and the high level of positive content is a parameter for judging the safety of short videos (d12 safety)
data8 Subjective randomness	Animated short videos are more subjective and random, depending on the user's mood and preference at the time (dl3 subjective randomness).
data9 Usefulness	The indicator parameter of the usefulness of watching animated short video products, the student population is mainly learning knowledge, they provide knowledge in animated short videos richly explained, is an important way to obtain knowledge outside of class (dl4 learning knowledge).
data10 Ease of use	App short video platform gives everyone a knowledge innovation platform, whether it is the artistry of video production, or regular content playback, can be passed to others through the short video production process, ease of use has become an important indicator of App platform stickiness (dl5 platform ease of use)

There are many excellent works of animated short videos. They all have the commonality of beautiful images that drive the interactive behavior of information that users are willing to share and comment on to stimulate their engagement. The complexity of the online environment makes it imperative for national regulation to regulate the safety of short videos as necessary. Therefore, the setting of research variables becomes a key as-

pect of this study.

Table 6 Metadata Labeling Design

Number	Metadata Design	Label Design	Meaning
1	Viewing Behavior	data1d123	Animation classification, selection of content information, playback length
2	Willingness to watch	data2d45	Willingness to watch on the innovation of the story,willingness to watch
3	Participatory	data3d678	Participatory with video hotness, sharing, social demand indicator sex
4	Comment Richness	data4d9	The richness of the work review
5	Video Artistry	data5d10	Artistic value of the work
6	Video Influence	data6d11	Platform Infectious
7	Safety	data7d12	Safety of the work
8	Subjective randomness	data8d13	Subjective randomness of animated short video selection
9	Usefulness	data9d14	Learning intellectuality
10	Ease of use	data10d15	Platform Ease of Use
...	....	....	....

5.2 Rough Behavior Empirical Algorithm Design

5.2.1 Ecosystem Design of Technical Systems

The ecosystem selection and framing of the technical architecture is the current mainstream trend of cross-platform development of web systems, and this project mainly uses:

1) Vue and Vuex: as front-end technology environment; 2) node.js: as back-end technology environment; 3) mysql and eggjs: as cloud database technology environment; 4) uniapp as front-end technology compilation environment; 5) vscode as back-end database compilation environment.

5.2.2 Rough Behavior Knowledge Base Construction

Set $K = (U, R)$ be a knowledge base for $X \subseteq U$, with

$$\underline{R_a}X \to \underline{R_{0.5}}X = \cup\{E \in U/R : c(E, X) < 0.5\} \quad (15)$$

$$\overline{R_a}X \to \overline{R_{0.5}}X = \cup\{E \in U/R : c(E, X) > 0.5\} \quad (16)$$

$$\mathrm{BND}_{\alpha}(X) \to \mathrm{BND}_{0.5}(X) = \cup\{E \in U/R : c(E, X) = 0.5\} \quad (17)$$

$$\mathrm{BNG}_{\alpha}(X) \to \mathrm{BNG}_{0.5}(X) = \cup\{E \in U/R : c(E, X) > 0.9\} \quad (18)$$

$$\mathrm{BNG}_{\alpha}(X) \to \mathrm{BNG}_{0.5}(X) = \cup\{E \in U/R : c(E, X) < 0.1\} \quad (19)$$

The set $\mathrm{BND}_{0.5}(X)$ is the absolute bound of X, where α denotes the misclassification rate.

Table 7 Rough Behavior Knowledge Base

U	a (Comments)	b (likes)	c (forwarding)	d (expression)	e (roasting)	f (favorite)
1	0.6	0.3	0.7	0.5	0.3	0.8
2	0.1	0.3	0.5	0.4	0.3	0.8
3	0.5	0.2	0.6	0.3	0.1	0.8
...	...	...	...	...	...	...

Where: U represents the animated short video tag, and the numbers in the table represent the behavioral values of short video content information.

expression (15) representing the lower approximation of the user's viewing choice;

expression (16) represents the upper approximation of the user's viewing choice;
expression (17) represents a state of hesitation in which the user has not yet begun to view the selection;

expression (18) represents the decision state in which the user chooses to watch;
expression (19) represents the decision status of the user to abandon viewing;

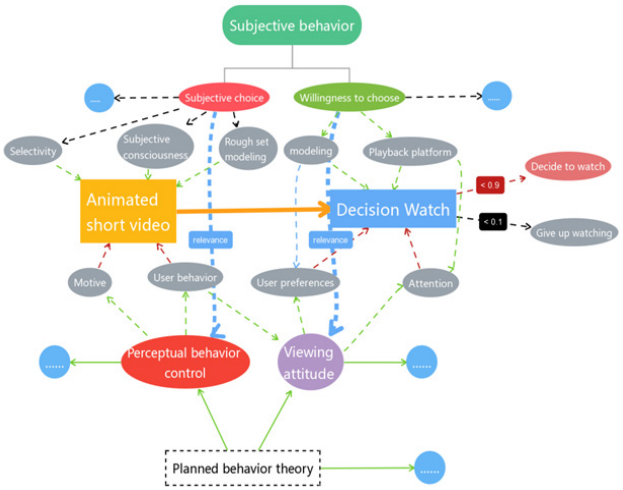


Figure 4 Consistency diagram between the findings of this study and behavioral planning theory

From the perspective of action plan theory, whether viewers decide to watch short animated videos is influenced by many factors such as perceptual control behavior, viewing attitudes, user preferences and attention span.

From the perspective of action plan theory, whether viewers decide to watch short animated videos is influenced by many factors such as perceptual control behavior, viewing attitudes, user preferences and attention span.

This study extracts variables related to users' subjective behaviors to study, and the Rough rule of "subjective behavior" is to incorporate the theory of behavioral attitudes and behavioral intentions into the subjective behavior and stochastic Rough decision model, which proves that this study is consistent with the findings that

perceptual behavioral control, viewers' viewing attitudes, subjective norms, and perceptual behavioral control positively affect viewers. conclusions are consistent.

The process of watching short videos by users consists of two main parts: the process of selecting short videos by users and the process of watching short videos by users:

1)The user selection process for short videos depends on the user's subjective behavioral judgments, usually based on the user activity impact of the short video to determine:

$$\text{User activity influence } \bar{x} = \frac{\alpha_R^{\beta 1_R} + \alpha_R^{\beta 2_R} + \ldots + \alpha_R^{\beta k_R}}{\sum_1^k f_i} \quad (20)$$

As shown in Figure 3, the Rough rule of subjective random behavior, short video users choose to watch or give up watching is determined by the randomness of users' subjective willingness.$\alpha_R^{\beta_R}$(See Equation 11.) When the value is greater than 0.5, the user's willingness moves in the direction of choosing to watch, and when the $\alpha_R^{\beta_R}$ value is less than 0.5, the user's willingness is in the direction of giving up watching.

2)User watching short video process:Depending on the user watching short video status than:

state = user(t)-movieT/movieT (21)

Where: user(t) represents the time to watch the movie; movieT total time to play the movie

When the user starts to play, state >0, the user's "choice intention" to watch increases with the increase of playing time; when state <0.5, stop playing, it means the user gives up watching; when state>0.5, the short video continues to play; it means the user chooses to watch.

5.2.3 Rough behavior decision algorithm

step1:Create a decision tree: assign null value to the decision tree, initialize the classification α_R initialize to 0.5, classify β_R initialize to 0.0;

step2:Input the dataset and extract the knowledge base in the order of the decision tree from the root node to the leaf nodesK=(U,R) Classification rules;

step3:User selection process analysis of short video: input user activity influence set

User activity influence $\bar{x} = \frac{\alpha_R^{\beta 1_R} + \alpha_R^{\beta 2_R} + \ldots + \alpha_R^{\beta k_R}}{\sum_1^k f_i}$ (See Equation 20 for details)

When $\bar{x}$<0.1, the user usually chooses to give up the choice, when $\bar{x}$>0.1 the user enters a state of choice hesitation;

Calculate the decision value when:

$\alpha_R^{\beta_R} = \alpha_R^{(\underline{F},\ F)} = \alpha_R \cup \alpha_R{}^{\underline{F}} - \alpha_R{}^{\overline{F}} \geq 0.9$; indicating the decision to watch;

$\alpha_R^{\beta_R} \leq 0.1$; indicates that viewing is abandoned.

$0.1< \alpha_R^{\beta_R} < 0.9$ is when viewers are hesitant to watch short animation videos.

step4:Extract the data of the test dataset with classification labels to obtain the approximate upper and lower values of "subjective choice";

step5:Continue with step4 to obtain the approximate upper and lower values of "choice intention";

step6:The state analysis of the user watching the short video process, when the user triggers to watch the "state function".

User viewing state ratio state = user(t)-movieT/movieT, (21)
user(t) represents the time to watch the movie; movieT is the total time to play the movie

When the user starts to play, state >0, the user's "choice intention" to watch increases with the increase of playing time; when state <0.5, stop playing, it means the user gives up watching; when state>0.5, the short video continues to play; it means the user chooses to watch.

6 Conclusion

This paper analyzes the Rough rules of viewers' "Subjective Choice" and "Choice Willingness" in watching short animation videos by using the dynamic features of S-rough set theory, and reveals the random change characteristics of animation viewing decision by comparing and analyzing the actual questionnaires.

The results of this study have positive reference value for studying the subjective selectivity and stochastic decision making of animated short video viewing, especially for the related industries in the design and operation of animated content.

This study constructs a conceptual model of animated short video users' viewing Rough behavior and the compiled technical ecological environment, and empirically studies and carefully analyzes the overall characteristics of animated short video users' viewing Rough behavior, and the behavioral characteristics of user content information retrieval, publishing and sharing on the empirical system.

(1) Conceptual model of animated short video user viewing behavior: user viewing behavior is influenced by the role of user information needs, which is expressed as information retrieval, acquisition, release and information sharing behavior, forming the whole process of content selection, production, sharing, commenting and fan accumulation throughout the short video App platform.

(2) Animated short video user viewing behavior process analysis: user viewing under the behavior process is mainly composed of two parts: the planning behavior process and random selection behavior process, and the user viewing process can be decomposed into user selection short video process and user viewing short video process. Provide the above process analysis is more objective and reasonable to verify the reasonableness and practicability of animated short video watching Rough behavior and random Rough decision modeling.

The deficiency of this study is that because the current test samples are small, many further changes in the description of decision-making need to be further studied.

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References

Acfun. https://www.acfun.cn/a/ac24237003

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. in Action Control (pp. 11-39). https://doi.org/10.1007/978-3-642-69746-3_2

Armitage, C. J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: a meta-analytic review. Br J Soc Psychol, 40(Pt 4), 471-499. https://doi.org/10.1348/014466601164939

Aimedia Research Center for Cultural and Entertainment Industries. (2020). 2019-2020 China secondary video industry special research report. Aimedia Report. https://www.iimedia.cn/c400/69592.html

Balachandran, A., Sekar, V., Akella, A., Seshan, S., Stoica, I., & Zhang, H. (2012). A quest for an Internet video quality-of-experience metric Proceedings of the 11th ACM Workshop on Hot Topics in Networks, Redmond, Washington. https:/ /doi.org/10.1145/2390231.2390248

China Internet Network Information Center. (2021). The 48th Statistical Report on the Development of the Internet in China. http://www.ccncc.org/ccncc/m/8/2022/0105/239.html

China Association of Network Audiovisual Program Services. (2020). 2021 China Internet Audio-Visual Development Research Report. http://www.cnsa.cn

Chen, J.Q. (2019). Predicting users' purchase behavior based on decision tree model implementation. Communication World, 04.

Cheng, X.A., & Shao, Y.H. (2020). Exploring the factors influencing mobile short video users' participation in content production - Based on the theoretical model of planned behavior. Journalism Research Guide, 11(24), 1-3.

Deng, Y.C. (2021). Exploring the relationship between domestic drama viewing behavior and Chinese cultural identity. Shanghai Foreign Studies University. https://doi.org/10.27316/d.

Du,X. (2012). A study on the influencing factors of green clothing consumption based on the theory of planned behavior [Master, Beijing Institute of Fashion].

Dunn, R., Hattie, J., & Bowles, T. (2018). Using the Theory of Planned Behavior to explore teachers' intentions to engage in ongoing teacher professional learning. studies in Educational Evaluation, 59, 288-294. https://doi.org/https://doi.org/10.1016/j.stueduc.2018.10.001

Emmy.com. (2021). Analysis of the current development of China's short video market in 2020-2021 - The head platform has obvious advantages in terms of user scale. https://www.iimedia.cn/c460/76691.html

Fu, F.D. (2020). A study of pre-screening advertisement viewing behavior intention based on the theory of planned behavior. Journal of Culture, 11, 135-145.

Ge, S.L., Ye., He, M.C.. (2019). A deep forest-based model for predicting user purchase behavior. Computer Science, 46(9), 190-194. https://doi.org/10.11896/j.issn.1002-137X.2019.09.027

Gu, J., (2020). A study of audience's aesthetic psychology and viewing behavior motivation in domestic ani-

mation films. Drama House (27), 155-157.

Gopi, M., & Ramayah, T. (2007). Applicability of theory of planned behavior in predicting intention to trade online. International Journal of Emerging Markets, 2(4), 348-360. https. //doi.org/10.1108/17468800710824509

Hao, R.X. (2020). Research on the development of "earthy" short videos under use and satisfaction theory. Media (08), 94-96.

Huang, F., & Wang, J. (2013). A model and empirical study of consumer acceptance behavior based on perceived value. Business Research(6), 19-27.

Iwasaki, Tatsu. (2021). An analysis of the actions of the visitors to the sacred sites of the Japanese media : -relevance and motivation‖. Annual Report of the Institute of Economics and Business Administration, Kanto Gakuin University, 43, 15-27. https://cir.nii.ac.jp/crid/1050569236106545664

Liu, Y.W. (2008). Theory of planned behavior and Chinese consumers' green consumption behavior. China Circulation Economy (08), 66-69.

QuestMobile. (2021). 2021 China Mobile Internet User Trends Insights Report.

Stern, P. C., Dietz, T., Abel, T. D., Guagnano, G. A., & Kalof, L. (1999). A Value-Belief-Norm Theory of Support for Social Movements: The Case of Environmentalism. Human Ecology Review, 6, 81-97.

Wang, H.H. (2021). A study on the influence of individual factors on video viewing behavior of college students. Media Forum, 4(24), 78-80.

Wang, X. (2021). Analysis of the causes, potential risks and coping strategies of the short video fever phenomenon among college students. Thought Theory Education (01), 93-97. https://doi.org/10.16075/j.cnki.cn31-1220/g4.2021.01.016

Wittenberg, I., Blöbaum, A., & Matthies, E. (2018). Environmental motivations for energy use in PV households: Proposal of a modified norm activation model for the specific context of PV households. Journal of Environmental Psychology, 55, 110-120. https://doi.org/https://doi.org/10.1016/j.jenvp.2018.01.002

Yang, B.Z. (2010). Research and Implementation of E-commerce Recommendation and Visualization System Based on Rough Sets.vol3. M.S., Beijing University of Posts and Telecommunications.

Yang, H. (2019). Research on the Motivation and Usage Behavior of Short Video Users of "ShakeYin". China Business Journal (13), 233-235. https://doi.org/10.19699/j.cnki.issn2096-0298.2019.13.233

Yang, S. (2020). Research on the factors influencing users' willingness to continue using mobile short video app after 90 years.vol08 .Hebei University.