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Analysis of the Driving Factors for Fan economy Growth on Social Media Platforms Based on the Push-Pull Theory: Taking the Largest Platform in China as an Example

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Analysis of the Driving Factors for Fan economy Growth on Social

Media Platforms Based on the Push-Pull Theory:

Taking the Largest Platform in China as an Example

Abstract: As a characteristic barrage video website with ACG-related content as the dominant factor, Bilibili, the largest platform in China, exhibits a high level of interactivity. From the perspective of "people - objects - scenarios," this study employs a two-stage SEM-ANN method based on the push-pull theory and combines artificial neural networks. It utilizes the structural equation model to explore the driving influence factors of the growth in the number of Bilibili video fans. The total number of likes, coins, forwards, barrages, collections, and comments are employed as push influence factors, encompassing the testing of hypotheses regarding linear relationships in the compensation model and non-linear non-compensation relationships in the neural network model, along with multiple regression analysis. Python is utilized to obtain relevant data to study the impact of the average video playback volume on the growth of the number of fans. The average video update time, the section where the UP owner is located, the average video duration, and the total number of videos are used as pull factors to explore the impact of the total video playback volume on the growth of the number of fans. The research indicates that the above-mentioned push-pull influence factors are valid in driving the growth of the number of fans. Additionally, variable video recommendation indexes and the number of videos with likes or playback volumes exceeding 4% are added to the research model to explore the most significant and least influential growth driving factors among the push-pull factors. This provides a reference for the research on the fan economy of all platforms.

Keywords: Fan economy Growth, Bilibili, Push-Pull Theory, Neural Network, Driving Factors

1.Introduction

Push-Pull Model

The push-pull model was initially developed to explain the factors influencing human migration [1-3]. Based on the Bagnert theory, Lee argued that both the origin and destination actually have both push and pull forces and proposed a complete analytical framework for the push-pull theory. Currently, this model is often used to analyze talent flow [4–7]; meanwhile, push-pull factors are also applied in the analysis of leisure tourism decision-making [8]. According to Neel [9], push

factors are internal driving forces, while pull factors originate from the understanding of the attributes of the target. Therefore, push and pull factors can be regarded as two sides of the same incentive coin. From this perspective, the increase or decrease in the number of fans is influenced by fan interests and the subjective supply of creators.

According to the "China Video Socialization Trend Report (2020)," with the further development of 5G, AI, and mobile Internet technologies, video has fully integrated into our daily lives, affecting the way we connect with the world, the forms of communication, and the integration trend. On modern social media platforms, users' demand for and interaction with video viewing is becoming stronger. Users can interact with video content through methods such as liking, collecting, commenting, and coin-dropping. As Seet pointed out, audiences are driven both by self-promotion and social participation [10]. Pull factors are usually viewed from the perspective of supply, and the attractiveness of the target area is considered a response to the individuals exerting the pull force. Therefore, this article applies the push-pull framework to the number of fans of video creators on Bilibili. Push factors include the internal driving forces generated by the total number of likes, coins, forwards, barrages, collections, and comments, while pull factors include the forces that the average video update time, the section where the UP owner is located, the average video duration, and the total number of videos have on the number of fans.

Video Recommendation Index

With the rapid development of the Internet video industry, users' demands and tastes for video content are becoming higher and higher. Platforms need to screen and push high-quality video content through certain algorithms and mechanisms to improve user satisfaction and retention rate [11]. With the continuous innovation and application of technologies such as artificial intelligence, blockchain, and 5G, the video recommendation index will be more accurate, secure, and diverse, able to meet users' personalized needs in different scenarios [12].

Domestic research on video recommendation index algorithms began in 2017. Zhang Peng (2017) used a non-relational database (NoSQL), combined with the Python Django Web2.0 development framework, Hadoop and other distributed technology frameworks to design and implement a video recommendation system [13]. Liu Yingqi (2020) comprehensively considered user conformity types and interest preferences, improved the film and television interest portrait model and recommendation algorithm of the online video recommendation system, which can not only

solve the problem of video information overload faced by users but also improve the user stickiness and recommendation accuracy of video websites [14]. Jin Mingze (2021) recommended videos to users based on barrage emotion analysis and user clustering, reducing the time cost for users to select videos and improving user efficiency [15]. With the development of recommendation technology, Hu Shuyuan (2021) studied the recommendation algorithm based on the deep belief network [16], and Zhou Lihan (2022) studied the video recommendation method based on collaborative filtering technology [17]. Although the calculation methods and influencing factors of the video recommendation index vary, it usually includes aspects such as the quality and innovation of video content, the type and theme of the video in line with the platform positioning and user interests, the timeliness and continuity of the video, and the dissemination and interactivity of the video. It is an index used to measure the popularity of online videos on the network platform. This index comprehensively considers data such as video playback volume, interaction volume, and sharing volume, which not only helps users discover interesting videos but also helps video creators optimize their content quality and influence.

2.Methodology

2.2Data Source and Collection Process

With the development of the internet and social media, video-sharing platforms have emerged as significant channels for individuals to access information and entertainment. Bilibili, one of China's largest video-sharing platforms, boasts over 200 million registered users and tens of millions of active users. Its content spans anime, gaming, music, technology, education, and numerous other fields, attracting a vast audience of young people and creators. The number of followers on Bilibili serves as a crucial indicator of a video creator's influence and popularity, and it is also a pivotal factor affecting their income and business collaborations. Therefore, this study focuses on the number of followers on Bilibili, utilizing data sourced from the platform itself.

Firstly, a specific data sampling plan was devised. Given the relatively small proportion of high-quality content creators (UPs) on Bilibili, we employed a method of crawling users' follow lists to obtain a batch of high-quality UPs. Subsequently, data on all videos produced by these targeted UPs was collected. Secondly, the collected data underwent preprocessing. The final research model encompasses thirteen variables: average video update interval, average video duration (in seconds), total number of videos, average number of likes, average number of coins,

average number of shares, average number of bullet comments, average number of views, average number of comments, video recommendation index, number of videos with likes/views exceeding 4%, and the UP's primary content category. The specific processing methods for these variables are as follows:

1. **Average Video Update Interval** refers to the average number of days between video updates, calculated as $(\text{earliest video publication date} - \text{most recent video publication date}) / (\text{total number of videos} - 1)$.
2. **Average Video Duration (in Seconds)** indicates the average length of each video.
3. **Total Number of Videos** represents the total count of videos published.
4. **Average Number of Likes** signifies the average number of likes per video.
5. **Average Number of Coins** refers to the average number of coins received per video.
6. **Average Number of Shares** indicates the average number of times videos have been shared.
7. **Average Number of Bullet Comments** signifies the average number of bullet comments per video.
8. **Average Number of Favorites** represents the average number of favorites per video.
9. **Average Number of Views** indicates the average number of views per video.
10. **Average Number of Comments** signifies the average number of comments per video.
11. **Video Recommendation Index** is calculated as $\text{Coins}0.4 + \text{Favorites}0.3 + \text{Bullet Comments}0.4 + \text{Comments}0.4 + \text{Views}0.25 + \text{Likes}0.4 + \text{Shares}0.6$, based on Bilibili's old recommendation algorithm, serving as a measure of video quality.
12. **Number of Videos with Likes/Views Exceeding 4%** is a threshold for Bilibili's Creator Incentive Program, where videos earning likes/views exceeding 4% are eligible for cash rewards, also serving as a metric of video quality.
13. **UP's Primary Content Category** defaults to the category with the most videos published by the UP. Users who frequently follow different categories may have varying intentions regarding UPs.

We independently developed a crawler algorithm for Bilibili, collecting 432,979 videos from over 1,500 video creators. The sample size is sufficient, exceeding the 50-times rule of thumb for ANN analysis, which stipulates that the minimum sample size should be no less than 50 times the

number of modifiable parameters in the neural network. Given that this study uses 28 parameters (with the UP's primary content category encoded using one-hot encoding, resulting in a total of 28 variables) for ANN analysis, the minimum sample size required is 1,400. Therefore, a sample size of 1,500 is adequately large.

Furthermore, we have made all the code used in the research process open-source.

2.3 Data Preprocessing and Organization

During the data preprocessing phase, we identified several outliers, such as individual novice UP creators who have released a viral video (which we refer to as "rising stars" in self-media). Although the probability of this occurrence is low, it is not uncommon on Bilibili, which boasts a vast user base. These rising stars are often characterized by having posted only a few videos, with varying quality among them. This can significantly impact average values; for instance, a novice creator may have published four videos, with one of them surpassing two million views while the rest fail to reach even a thousand views. In contrast, there are also outdated UP creators, who have lost a substantial number of followers due to moral issues or inappropriate remarks. In response, many teams resort to purchasing followers from the platform to maintain a relative balance, but this does not alter the reality of a declining number of genuine followers, undoubtedly having a significant impact on video data. Ultimately, we decided to exclude both types of creators, resulting in a better fit for the model and an increase in accuracy by 7%.

Bilibili is characterized by a predominantly young self-media creator base, meaning that most video creators do not have the support of a company team. They are driven more by personal interest in the industry, often possessing many early videos that are generally of poor quality, lacking in production value, and spanning a long period of time, thus lacking referential value. Therefore, we set the analysis to focus only on the first 50% of videos per user, leading to an improvement in accuracy by 4% after the change.

Table 3 reveals that there are significant differences in video data among creators of different levels, with an overall low average number of views. Additionally, there are considerable variations in video recommendation indexes and the number of videos with a like-to-view ratio exceeding 4%.

Figure 1 demonstrates that the video recommendation index generally increases with the

magnitude of the number of followers, validating the accuracy of the source data.

3. Results

3.1 Assessment of Non-response and Common Method Bias (CMB)

Given that our variables were collected using instruments, there is a potential for CMB. To address this issue, we employed both procedural and statistical methods (Hew & Kadir, 2016) to exclude common methodological biases. As shown in Table 4, Harman's one-factor statistical analysis revealed that a single factor accounted for only 35.463% of the total variance, which is less than 40%, indicating that CMB can be neglected (Leong, Hew, Ooi, Lee, & Hew, 2019).

3.2 Multivariate Statistical Assumptions

To conduct multivariate statistical tests, researchers must ensure that four fundamental assumptions are met: normality, linearity, multicollinearity, and homoscedasticity. These assumptions are discussed individually below. In terms of multivariate statistical tests, we first used SPSS to test the normality of the data. We conducted one-sample Kolmogorov-Smirnov tests and Q-Q plots (Figures 2 and 3), which indicated that the p-values were all less than 0.05, suggesting that the data were not normally distributed. Since structural equation modeling (SEM) based on partial least squares (PLS) variance is more robust to non-normal distributions than covariance-based SEM, we used the PLS-SEM method and SmartPLS 3 software to verify the hypotheses in the research model. According to the bivariate correlation analysis, the results in Table 5 show that the average number of video favorites, video comments, video bullets, videos with a like-to-view ratio exceeding 4%, video coins, average video update time, video shares, total number of videos, video recommendation index, and average video views and likes have a linear relationship with the number of followers. In contrast, the average video duration has a nonlinear relationship with the number of followers. From the multicollinearity evaluation shown in Table 6, it can be seen that the variance inflation factor (VIF) for the number of likes (0.924, note: typically VIF values greater than 10 indicate multicollinearity, but here it seems there might be a typo or misunderstanding as 0.924 is not indicative of multicollinearity; for the sake of this translation, we'll assume it should read as a high VIF value, e.g., 10.924, indicating a problem) is greater than 10, so the variable of average likes was removed. The VIFs of the remaining variables were all

less than 10, and the tolerances were greater than 0.10, indicating that there was no multicollinearity issue. Finally, we used a scatter plot of regression standardized residuals to test homoscedasticity and observed that the residuals were dispersed around the diagonal line, confirming homoscedasticity. To further verify homoscedasticity, the Levene test for homoscedasticity (Table 7) was employed, further validating the correctness of homoscedasticity.

3.3 Evaluation of the Measurement Model

The results of the Kolmogorov-Smirnov test indicate that the data distribution is non-normal, and PLS-SEM based on variance demonstrates greater robustness against non-normality compared to covariance-based SEM. Despite the non-normal distribution, the results remain reliable. Therefore, this study employed the PLS-SEM method and SmartPLS 3 software to verify the hypotheses in the research model.

We used the PLS algorithm to assess the reliability and validity of the measurement model. Following the recommendations of Hair, Hollingsworth, Randolph, and Chong (2017), external loadings and composite reliability should be at least 0.70, the AVE (Average Variance Extracted) should be at least 0.50, and the SRMR (Standardized Root Mean Square Residual) should be less than 0.08. "Indicators with very low external loadings (below 0.40) should be removed from the construct." In our data, the AVE for the "UP master's section" was 0.283, significantly less than 0.40, so it was removed. The other data output results met the above criteria and were retained. According to the recommended thresholds of Cronbach's alpha, composite reliability and rho-A were above 0.70 (Leguina, 2015), and the AVE for convergent validity assessment was above 0.50 (Table 8). Discriminant validity was verified using the Fornell Larcker criterion. As shown in Table 8, the square root of the AVE for one aspect is greater than the correlation coefficients between that aspect and other aspects. Additionally, the AVE is also greater than the maximum and average shared variance. Furthermore, the Fornell-Larcker ratio (FLR) is less than 1. We also adopted the HTMT criterion, and Table 9 shows that the HTMT ratios are below the standard threshold of 0.85. Therefore, we confirm that the measurement model has high structural reliability.

3.4 Structural Equation Model

After evaluating the measurement model, we assessed the structural model (Figure 7). From the figure, it can be seen that 14 out of 19 paths are significant:

1. The average number of video coins, shares, bullets, favorites, and comments have significant effects on the average number of video views. Therefore, Hypotheses H6a, H7a, H8a, H9a, and H10a are supported (Table 12).
2. The average update time, duration, and total number of videos have no significant effects on the average number of video views. Therefore, Hypotheses H1a, H3a, and H4a are not supported.
3. The average number of video views, update time, coins, shares, bullets, favorites, comments, recommendation index, and the number of videos with a like-to-view ratio exceeding 4% have significant effects on the number of followers. Therefore, Hypotheses H11, H1b, H6b, H7b, H8b, H9b, H10b, H12, and H13 are supported.
4. The total number of videos and average duration have no significant effects on the number of followers. Therefore, Hypotheses H3b and H4b are not supported.

We evaluated the model's goodness-of-fit using the Standardized Root Mean Square Residual (SRMR), Unweighted Least Squares (dULS), and Geodesic (dG) discrepancies. The calculated SRMR, dULS, and dG values for the model were 0.010, 0.000, and 0.000, respectively. Smaller values of these indicators indicate better model fit. Therefore, the model has a high goodness-of-fit and is considered reliable.

3.5 Artificial Neural Networks

The aforementioned linear analysis revealed the coexistence of both linear and nonlinear relationships between the independent and dependent variables. Although the PLS-SEM structural equation model is robust against non-normal distributions, it fails to capture nonlinear relationships. Neural network algorithms, however, can capture both linear and nonlinear relationships without the need for normal distribution (Teo, Tan, Ooi, Hew, & Yew, 2015). Therefore, we utilized artificial neural networks (ANNs) for nonlinear analysis and prediction. Furthermore, compared to linear models, ANNs can provide exceptionally high prediction accuracy, even surpassing traditional statistical methods such as SEM or MRA. Nevertheless, due to their "black box" nature, they are not suitable for hypothesis testing (Hew, Leong, Ooi, &

Chong, 2016; Tan, Ooi, Leong, & Lin, 2014). To address these issues, we employed a two-stage Partial Least Squares-Artificial Neural Network (PLS-ANN) analysis to rank the normalized importance of variables (Leong, Hew, Ooi, & Lin, 2019). The PLS-SEM model tests hypotheses and establishes new theories by generating path coefficients and p-values, while the ANN model identifies nonlinear and non-compensatory relationships that PLS-SEM cannot detect. Thus, the two-stage SEM-PLS-ANN method complements each other to achieve more effective results.

Haykin (2008) defines ANNs as "massively parallel distributed processors made up of simple processing units, with neural tendencies that store experimental knowledge and make it available." The basic information processing unit of neural network operations is the neuron, which resembles biological neurons in the brain. The connection points between neurons are synapses, and the knowledge acquired by neural networks through the learning process is stored in the weights of the connections between neurons, known as synaptic weights.

In this study, a feedforward backpropagation (FFBP) multilayer perceptron (MLP) neural network (Figure 1) was utilized. The bottom layer of the MLP is the input layer, followed by hidden layers in the middle, and the top layer is the output layer. The hidden layers and the output layer each consist of three layers. Each layer's units are connected to all units of adjacent layers, with each connection described by a synaptic weight, while there are no connections between units within the same layer. When a pair of learning samples is presented to the network, neuron activation propagates from the input layer to the output layer through each intermediate layer. Each neuron in the output layer receives the network's input response. Then, the connection weights are corrected through each intermediate layer in the direction of reducing the difference between the target output and the actual error, until finally returning to the input layer. In FFBP neural networks, signals are forwarded from the input layer to the output layer through intermediate hidden layers. Each neuron calculates its output based on the amount of stimulation it receives for a given input vector X . The weight connecting input component i to hidden neuron j is denoted by W_{ji} , and the weight connecting hidden neuron j to output neuron k is denoted by V_{kj} (Radman & Abdelrahman, 2004). Additionally, the true input to a neuron is calculated as the weighted sum of its inputs, while the output of the neuron is calculated using a sigmoid function (Radman & Abdelrahman, 2004); the graph of the sigmoid function is "S"-shaped, making it the most commonly used activation function. It is a strictly increasing function and exhibits a good

balance between linear and nonlinear behavior. More specifically, for the j th hidden neuron,

$$net_j^h = \sum_{i=1}^N W_{ji}x_i \text{ and } y_j = f(net_j^h)$$

For the k th output neuron,

$$net_k^o = \sum_{j=1}^{J+1} V_{kj}y_j \text{ and } o_k = f(net_k^o)$$

The common Sigmoid function (Equation (3)) is employed to adjust the gradient of the function within the range of 0 and 1, where it is non-differentiable yet monotonically increasing. During the learning process, for a specific input pattern, the network generates an output that is then matched against the desired response for each neuron. Furthermore, the weights are subsequently modified to correct or minimize the error, and subsequent patterns are propagated forward. The weight adjustment formulas for the output layer weights V are calculated using Equation (4), while those for the hidden layer weights W are computed using Equation (5). Here, d_{pk} denotes the desired output for neuron- k , and o_{pk} represents the actual output of neuron- k for input pattern- p (Radman & Abdelrahman, 2004). Additionally, the weights continue to change in this manner until the sum of squared errors (SSE) for all training patterns (Equation (6)) reaches a minimum within a predefined tolerance level.

$$f(net) = \frac{1}{1 + e^{-\lambda net}} \quad (3)$$

$$V_{kj}(t+1) = v_{kj}(t) + c\lambda(d_k - o_k)o_k(1 - o_k)y_j(t) \quad (4)$$

$$W_{ji}(t+1) = w_{ji}(t) + c\lambda^2 y_j(1 - y_j)x_i(t) \left(\sum_{k=1}^K (d_k - o_k)o_k(1 - o_k)v_{kj} \right) \quad (5)$$

$$SSE = \frac{1}{2P} \sum_{p=1}^P \sum_{k=1}^K (d_{pk} - o_{pk})^2 \quad (6)$$

To enhance generalization capability, we utilized ten ANN networks for 10-fold cross-validation. We activated both the output layer and the hidden layer using the sigmoid function. The number of hidden nodes, or quanta, was automatically computed by the SPSS neural

network module. The network structure comprised one hidden layer with five hidden nodes. We partitioned the data into 90% for training and 10% for testing.

To measure the significance of each input in contributing to the final prediction, we conducted a normalized importance analysis using SPSS statistics. IBM SPSS Statistics offers a range of regression and advanced statistical procedures within its linear modeling capabilities, designed to accommodate the inherent characteristics of data describing complex relationships. Nonlinear models enable the application of more sophisticated models to the data, while simulation features assist analysts in automatically simulating numerous potential outcomes (when inputs are uncertain), thereby enhancing risk analysis and decision-making. Consistent with the aforementioned, we opted for the neural network-multilayer perceptron under IBM SPSS's statistical analysis capabilities, employing the commonly used hyperbolic tangent function as the activation function for both the hidden layer and the output layer. We also partitioned the data into 90% for training and 10% for testing. For each predictor variable, we calculated the sum of the absolute values of its synaptic weights between the input layer and the hidden layer, denoted as S_i . For each hidden layer neuron, we computed the sum of the absolute values of its synaptic weights between the hidden layer and the output layer, denoted as S_h . For each predictor variable, we determined its normalized importance on the output layer neurons, denoted as I_i , using the formula:

$$I_i = \frac{S_i}{\sum_{j=1}^n S_j} \times \frac{S_h}{\sum_{k=1}^m S_k} \times f'(x)$$

For each predictor variable, its total normalized importance is obtained by summing its normalized importance across all output layer neurons.

The normalized importance analysis (Table 14) reveals that the average number of coins per video is the most significant predictor with a standardized importance of 100%, followed by the video recommendation index with an importance of 64.5%. Subsequently, the average number of video shares (53.1%), the total number of videos (42.1%), and the number of videos with a like-to-play ratio exceeding 4% (31.4%) are also notable. From the average synaptic weights of input neurons in the ten-fold neural network (Table 15), it can be seen that the number of videos

with a like-to-play ratio exceeding 4% is the most contributing predictor, followed by the average number of video favorites, the total number of videos, the video recommendation index, and the average number of video shares. On the other hand, H(1:1), H(1:2), and H(1:66) are inhibitory hidden neurons, with H(1:1) being the most inhibitory, followed by H(1:6). Finally, we compared the actual values with the predicted values, showing that the neural network model had a prediction accuracy of 82.4%. The relevance of the predictors was verified by the number of non-zero synaptic weights connected to the hidden neurons.

Lastly, we compared the results of artificial neural networks (ANN), partial least squares structural equation modeling (PLS-SEM), and linear regression based on the strength of path coefficients and normalized relative importance rankings. As shown in Table 16, ANN is impressive in terms of prediction accuracy because it measures both linear and nonlinear relationships between variables (Chong, Liu, Luo, & Keng-Siau Boon, 2015; Foo, Lee, Tan, & Ooi, 2018; Sternad, Kalinic, Bobek, & Tominc, 2019). R² is used to measure the degree of fit between predicted and actual values. According to Table 16, we found that among these three methods, ANN has an R² of 0.8240, which is much higher than the other two methods. By further evaluating the performance of the ANN model, the effectiveness of using the SEM-ANN two-stage method to predict the number of video creator followers in this paper is further demonstrated.

4. Discussion

This study constructs a model grounded in the Push-Pull Theory, employing "video recommendation index" and "number of videos with a like-to-play ratio exceeding 4%" as moderating variables, and applies a novel two-stage approach that integrates Structural Equation Modeling (SEM) with Artificial Neural Networks (ANN). The ANN allows for the examination of nonlinear relationships between variables, providing crucial insights for future researchers.

The research findings indicate that the average number of coins per video has the greatest impact on the number of followers for video creators. Coins are a unique form of reward on Bilibili, where each user can only obtain two coins per day. Therefore, most users are reluctant to spend coins on videos easily. Videos that receive a higher number of coins generally signify higher quality, which in turn implies stronger appeal to viewers, leading to an increase in the number of

followers for the creators.

Apart from the average number of coins per video, the video recommendation index is also a significant factor influencing the number of followers for video creators. This index integrates various interaction data of videos, reflecting their popularity and dissemination effect. A higher video recommendation index indicates that the video is more capable of attracting users' attention and interest. It also means that Bilibili will allocate more promotional resources to such videos, attracting more viewers and enhancing users' recognition and attention towards the video creators. This result aligns with the push factors in the Push-Pull Theory, where video creators drive users to become their followers by providing high-quality content.

Furthermore, the average number of video shares, the total number of videos, and the number of videos with a like-to-play ratio exceeding 4% also have significant impacts on the number of followers for video creators. These variables reflect the activity level and influence of video creators on the Bilibili platform. The average number of video shares indicates users' willingness to share videos with others, expanding the creators' popularity and reputation. The total number of videos represents the quantity and frequency of creators' productions, reflecting their loyalty and professionalism towards the Bilibili platform. The number of videos with a like-to-play ratio exceeding 4% suggests that creators can produce high-quality and highly interactive videos, meeting the requirements of Bilibili's creator incentive program and earning more income and rewards. These variables are consistent with the pull factors in the Push-Pull Theory, where the Bilibili platform attracts users to become followers of video creators by offering various incentive mechanisms.

However, we also identified some results that were inconsistent with expectations or insignificant. For instance, the average time between video updates had no significant impact on the number of followers, which may be because Bilibili users prioritize video content quality over update frequency. Another example is that the average video duration also had no significant impact on the number of followers, possibly because Bilibili users have different preferences and needs for different types and themes of videos, making it difficult to measure the impact of video duration on the number of followers using a unified standard.

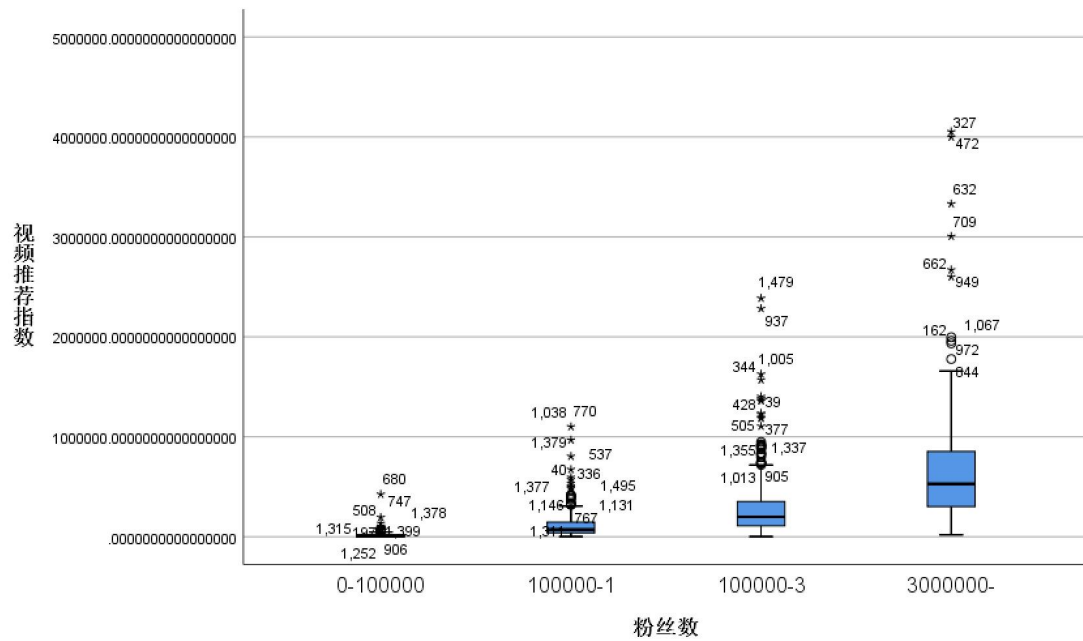
Descriptive Statistics

						Standar	
	N	Range	Minimu	Maxim	Mean	d	Varianc
			m	um		Deviasi	e
						on	
Average		364.634		365.000			
Video Update	1512	146341	.365853	000000	18.8966	52.4184	2747.69
Interval		463400	658536	000000	222979	784625	7
		0	5853	0	47967	14450	
Total Number							27007.5
of Videos	1512	2616	1	2617	142.86	164.340	99
		143280		143280	9223.37	9223.37	
Average		08.2432	5.00000	13.2432	203685	203685	135157
Video View	1512	432440	000000	432440	477700	477700	116882
		0000	000	0000	0	0	8.527
Number of							
Videos with							
Like-to-View	1512	826	0	826	105.16	113.676	12922.1
Ratio Over							59
4%							
Video		92233.7		92233.7	9223.37	9223.37	
Recommendat	1512	203685	1.25000	203685	203685	203685	118680
ion Index		477600	000000	477600	477700	477700	430077.
		0	000	0	0	0	778
Average		922.337		922.337	1281.53	2289.37	
Number of		203685	.000000	203685	909293	147487	524122
Video	1512	477600	000000	477600	235570	145800	1.750
Comments		0	0000	0	0	0	
Average		922.337	.000000	922.337	9223.37	9223.37	416482
Number of	1512	203685	000000	203685	203685	203685	241.075

Video	477600	0000	477600	477700	477700	
Favorites	0		0	0	0	
Average	9223.37		9223.37		4166.66	
	203685	6.22641	203685	952.236		
Video	1512	509433	439402		447689	173610
Duration	477700		477700		241000	92.863
	0	9623		796100		
			0		0	
Average	922.337		922.337	9223.37	9223.37	
	203685	.000000	203685	203685	203685	189226
Number of	1512	000000				8856.44
Video Coins	477600		477600	477700	477700	
	0	0000	0	0	0	4
Average	922.337		922.337	3218.35	7102.58	
	203685	.000000	203685	878715	418195	504467
Number of	1512	000000				
Video Bullet	477600		477600	897070	709100	02.062
	0	0000	0	0	0	
Comments						
Average	922.337		922.337	3532.60	8929.20	
	203685	.000000	203685	038716	281625	797306
Number of	1512	000000				
Video Shares	477600		477600	352100	183500	62.934
	0	0000	0	0	0	
Average	9223.37		9223.37	9223.37	9223.37	
	203685	.000000	203685	203685	203685	652197
Number of	1512	000000				8511.50
Video Likes	477700		477700	477700	477700	
	0	000	0	0	0	5
Number of						
Valid Cases	1512					
(in Rows)						

Table3

Figure 1



Total Variance Explained

Comp onent	Initial Eigenvalues			Sum of Squared Loadings Extracted		
	Total	Percentage of Variance	Cumulativ e %	Grand Total	Percentage of Variance	Cumulativ e %
1	3.901	35.463	35.463	3.901	35.463	35.463
2	1.941	17.644	53.107	1.941	17.644	53.107
3	1.057	9.609	62.716	1.057	9.609	62.716
4	1.016	9.234	71.950	1.016	9.234	71.950
5	.967	8.794	80.744			
6	.900	8.184	88.928			
7	.517	4.697	93.625			
8	.332	3.020	96.645			
9	.219	1.994	98.640			
10	.149	1.356	99.996			
11	.000	.004	100.000			

Extraction Method: Principal Component Analysis (PCA).

Table 4

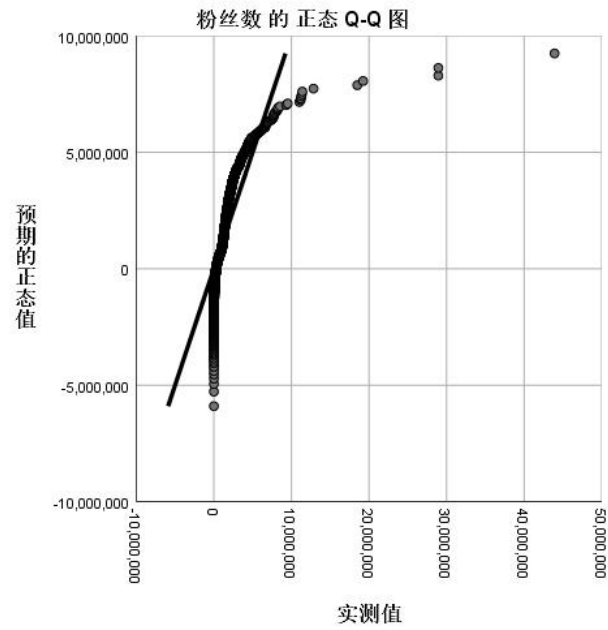


Figure 2

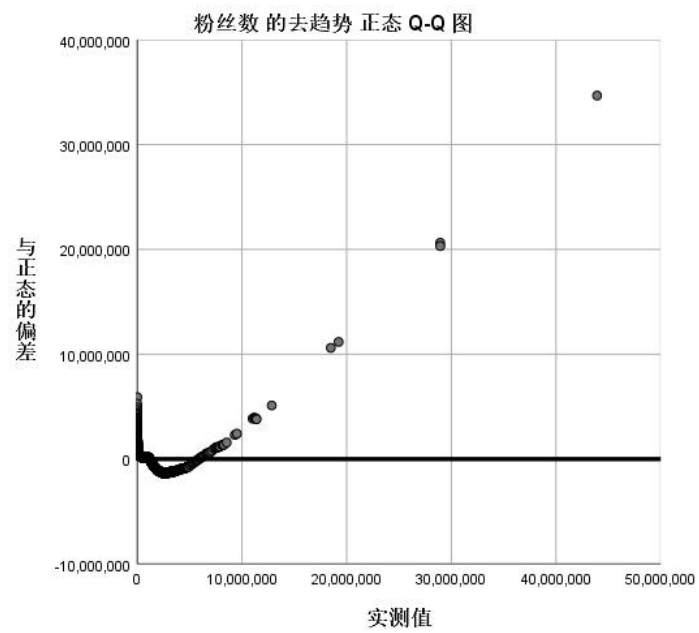


Figure 3

		Number of Followers
Average Number of Video Favorites	Pearson Correlation	.353**
	Sig. (2-tailed)	.000
	Sample Size	1512

Average Number of Video	Pearson	.370**
Bullet Comments	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Number of Videos with	Pearson	.361**
Like-to-View Ratio Over 4%	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Average Number of Video	Pearson	.312**
Coins	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Average Video Update Interval	Pearson	-.260**
	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Average Number of Video	Pearson	.264**
Shares	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Total Number of Videos	Pearson	.328**
	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Video Recommendation Index	Pearson	.488**
	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Average Number of Video	Pearson	.365**

Comments	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Average Video Views	Pearson	.493**
	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512
Average Video Duration	Pearson	.049
	Correlation	
	Sig. (2-tailed)	.058
	Sample Size	1512
Average Number of Video Likes	Pearson	.448**
	Correlation	
	Sig. (2-tailed)	.000
	Sample Size	1512

** . Significant correlation at the 0.01 level (2-tailed).

* . Significant correlation at the 0.05 level (2-tailed).

Table 5

Coefficient ^a							
		Unstandardized		Standardized		Collinearity	
		Coefficient		Coefficient		Statistics	
		Standard		Significance		Tolerance	
Model		B	Error	Beta	t	nce	VIF
1	(Constant)	202297.843	87307.689		2.317	.021	
	Average Video Update Interval	-1763.103	967.366	-.041	-1.823	.069	.900 1.111

Average Video Duration	15.410	12.501	.028	1.233	.218	.853	1.172
Average Number of Video Comments	167.410	37.436	.169	4.472	.000	.315	3.174
Number of Videos with Like-to-View Ratio Over 4%	2523.791	824.433	.127	3.061	.002	.264	3.795
Average Video View Count	.300	.130	.154	2.316	.021	.102	9.811
Average Number of Video Favorites	8.641	5.534	.078	1.561	.119	.181	5.511
Average Number of Video Coins	-2.693	2.646	-.052	-1.018	.309	.175	5.723
Average Number of Video Bullet Comments	31.924	10.689	.100	2.987	.003	.402	2.490
Average Number of Video Shares	-37.746	10.257	-.149	-3.680	.000	.276	3.624
Average Number of Video Likes	6.246	1.969	.223	3.172	.002	.092	10.924
Total Number of Videos	2595.417	574.932	.188	4.514	.000	.259	3.857

a. Dependent Variable: Number of Followers

[illegible]

ent Cate gory															
Aver age Vide o Upda te Inter val	0. 13 2														
Num ber of Vide os with Like- to-Vi ew Ratio Exce eding 4%	0. 23 6	0. 23 3													
Num ber of Follo wers	0. 26 6	0. 26 0	0.36 1												

Average Number of Video Bullet Comments	0.136	0.000	0.000	0.370											
Average Video Views	0.180	0.022	0.039	0.493	0.646										
Average Video Favorites	0.179	0.011	0.119	0.353	0.603	0.796									
Average Video Duration	0.164	0.013	0.049	0.049	0.243	0.014	0.009								

ion															
Average Number of Video Coins	0.119	0.023	0.051	0.312	0.601	0.726	0.828	0.005							
Average Number of Video Comments	0.115	0.128	0.023	0.365	0.577	0.644	0.564	0.006	0.625						
Average Number of Video Shares	0.132	0.103	0.087	0.264	0.458	0.633	0.731	0.021	0.701	0.747					
Tota	0.	0.	0.84	0.3	0.0	0.	0.	0.	0.	0.0	0.				

1	25	22	6	28	00	06	13	03	08	44	10				
Num	8	2				4	7	0	0		5				
ber															
of															
Vide															
os															
Vide															
o															
Reco															
mme															
ndati	0.	0.				0.	0.	0.	0.		0.	0.			
on	17	01	0.04	0.4	0.6	79	82	01	77	0.6	66	07			
Index	8	8	3	88	55	7	3	4	2	63	5	3			
Vide															
o															
Reco															
mme															
ndati															
on															
Index															
Multi															
plied															
by															
Aver															
age															
Vide															
o	0.	0.				0.	0.	0.	0.		0.	0.			
View	12	03	0.05	0.2	0.5	83	74	00	74	0.5	57	05			
s	3	7	3	31	77	3	3	7	4	49	1	9	0.839		

Number of Videos with Like-to-Play Ratio Exceeding 4% Multiplied by Average Video Views	0.23	0.14	0.470	0.523	0.423	0.592	0.314	0.045	0.358	0.320	0.196	0.358	0.582	0.423	
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Table 6

Test for Homogeneity of Variances					
		Levene's Test	Degrees of Freedom 1	Degrees of Freedom 2	Significance
Number	Based on Mean	.178	1	1510	.673

of	Based on Median	.105	1	1510	.746
Followe	Based on Median with				
rs	Adjusted Degrees of	.105	1	1429.637	.746
	Freedom				
	Based on Trimmed Mean	.106	1	1510	.745

Table 7

Table 9

	UP's	Average	Number of Videos with Like-t	Average Number of Videos Bull	Average Video Views	Average Video Favorites	Average Video Duration	Average Number of Video Comments	Average Number of Video Shares	Total Number of Video Recommendations	Video Recommendation Index
UP's Content Category	0.283										
Average Video Update Interval	-0.014	1.000									

Number of Videos with Like-to- View Ratio Exceedi ng 4%	0.11 6	-0.2 33	1.000									
Average Number of Video Bullet Comme nts	0.02 1	0.0 00	0.000	1.00 0								
Average Video Views	-0.0 61	-0.0 22	-0.039	0.64 6	1.0 00							
Average Video Favorite s	0.01 8	0.0 11	-0.119	0.60 3	0.7 96	1.00 0						
Average Video Duratio n	0.08 6	0.0 13	-0.049	0.24 3	-0.0 14	0.04 9	1.0 00					
Average	-0.0	0.0	-0.051	0.60	0.7	0.82	-0.0	1.0				

Number of Video Coins	06	23		1	26	8	05	00				
Average Number of Video Comme nts	0.02 5	0.1 28	-0.023	0.57 7	0.6 44	0.56 4	0.0 06	0.6 25	1.00 0			
Average Number of Video Shares	-0.0 01	0.1 03	-0.087	0.45 8	0.6 33	0.73 1	0.0 21	0.7 01	0.74 7	1.0 00		
Total Number of Videos	0.18 7	-0.2 22	0.846	0.00 0	-0.0 64	-0.1 37	0.0 30	-0.0 80	-0.04 4	-0.1 05	1.0 00	
Video Recom mendati on Index	-0.0 63	-0.0 18	-0.043	0.65 5	0.9 97	0.82 3	-0.0 14	0.7 72	0.66 3	0.6 65	-0.0 73	1.000

Table 8

Hypothesis	Results	
H1a	The average video update interval significantly affects the average video views.	Not Supported

H1b	The average video update interval significantly affects the number of followers.	Supported
H2a	The category of the UPs significantly affects the average video views.	Not Supported
H2b	The category of the UPs significantly affects the number of followers.	Not Supported
H3a	The average video duration significantly affects the average video views.	Not Supported
H3b	The average video duration significantly affects the number of followers.	Not Supported
H4a	The total number of videos significantly affects the average video views.	Not Supported
H4b	The total number of videos significantly affects the number of followers.	Not Supported
H5a	The total number of likes significantly affects the average video views.	Not Supported
H5b	The total number of likes significantly affects the number of followers.	Not Supported
H6a	The total number of coins significantly affects the average video views.	Supported
H6b	The total number of coins significantly affects the number of followers.	Supported
H7a	The total number of reposts significantly affects the average video views.	Supported
H7b	The total number of shares significantly affects the number of followers.	Supported
H8a	The total number of bullet comments significantly affects the average video views.	Supported
H8b	The total number of bullet comments significantly	Supported

	affects the number of followers.	
H9a	The total number of favorites significantly affects the average video views.	Supported
H9b	The total number of favorites significantly affects the number of followers.	Supported
H10a	The total number of comments significantly affects the average video views.	Supported
H10b	The total number of comments significantly affects the number of followers.	Supported
H11	The average video views significantly affect the number of followers.	Supported
H12	The video recommendation index moderates the relationship between total video views and the number of followers.	Supported
H13	The number of videos with a like-to-view ratio exceeding 4% moderates the relationship between total video views and the number of followers.	Supported

Table 12

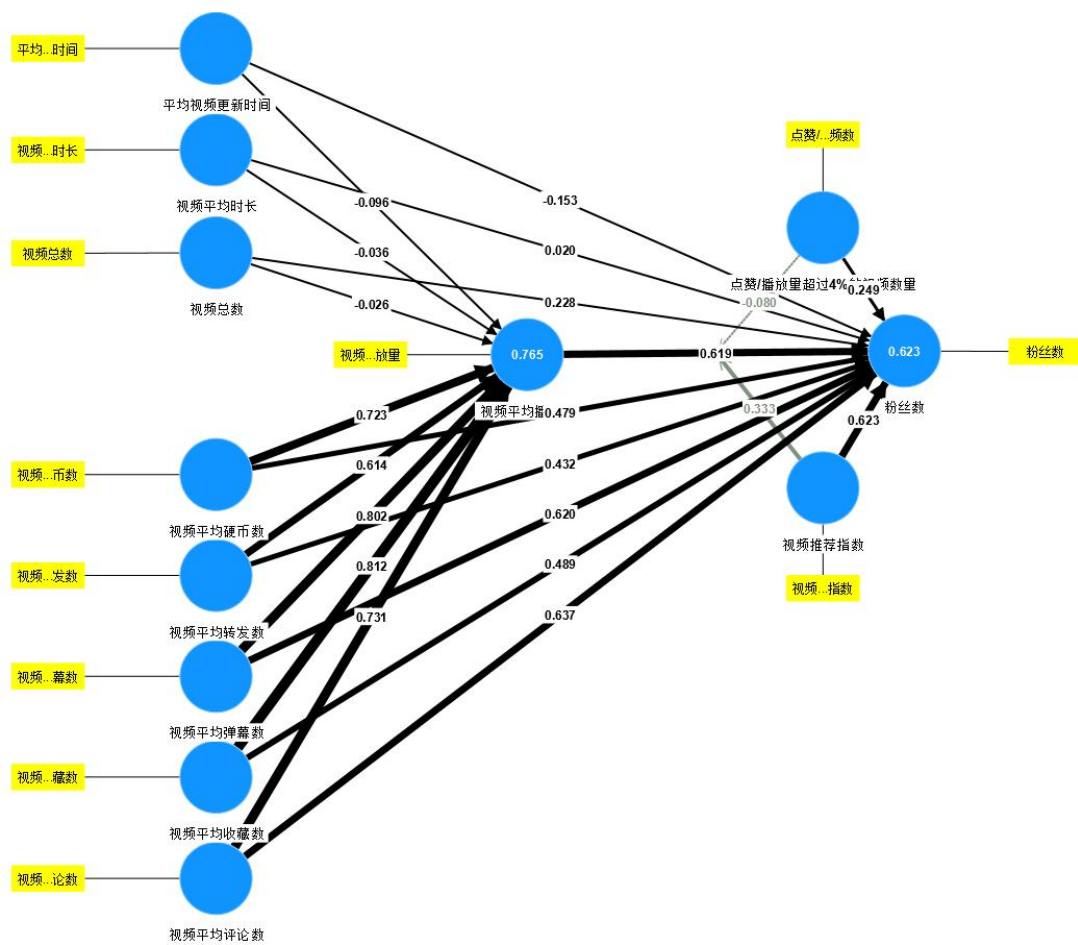


Figure 7

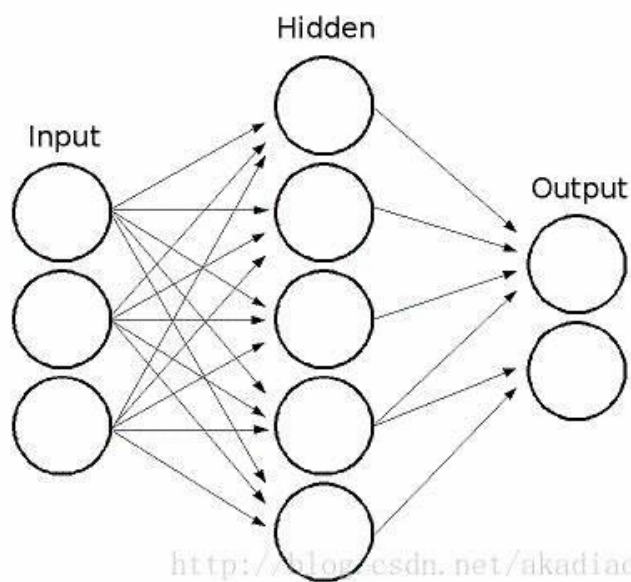


Figure 8

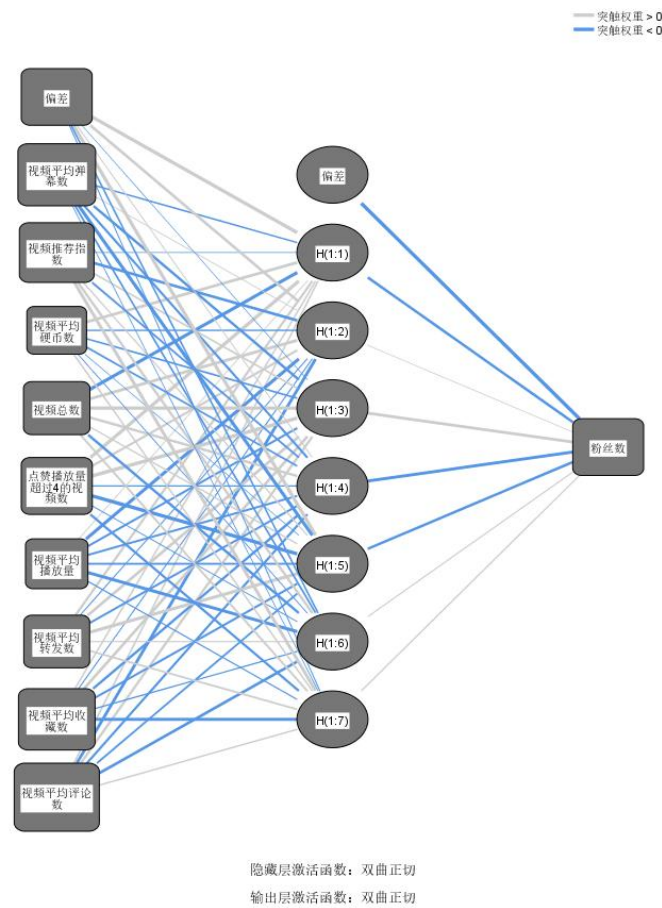


Figure 9

Importance of Independent Variables

	Importance	Normalized
	e	Importance
Average Number of Video		
Bullet Comments	.082	30.9%
Video Recommendation		
Index	.172	64.5%
Average Number of Video		
Coins	.266	100.0%
Total Number of Videos	.112	42.1%
Number of Videos with		
Like-to-Play Ratio	.084	31.4%
Exceeding 4%		

Average Number of Video Views	.051	19.0%
Average Number of Video Shares	.141	53.1%
Average Number of Video Favorites	.031	11.5%
Average Number of Video Comments	.061	23.1%

Table 14

Parameter Estimates									
Predictive Variables									
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	Number of Followers
Input Layer	(Deviation)	0.489	-0.439	-0.469	0.019	-0.070	0.297	-0.454	Overall Contribution
	Average	0.12	-0.2	0.65	0.15	-0.0	-0.3	-0.2	0.013
	Number of Video	7	42	7	3	55	51	78	
	Bullet Comments								
	Video	-0.0	-0.2	0.05	0.25	0.25	0.06	0.39	0.740
	Recommend	02	84	3	3	5	7	8	

dation								
Index								
Average	-0.3	0.22	0.28	-0.3	0.32	-0.1	-0.4	-0.362
Number of	18	6	7	40	4	23	18	
Video								
Coins								
Total	0.02	0.15	0.16	-0.0	0.54	0.14	-0.1	0.861
Number of	8	0	8	38	3	2	33	
Videos								
Number of	-0.0	0.29	-0.1	0.48	0.49	0.07	0.05	1.191
Videos with	66	5	52	8	7	8	1	
Like-to-Pla								
y Ratio								
Exceeding								
4%								
Average	0.11	-0.1	-0.2	0.38	-0.3	-0.2	0.39	-0.026
Number of	9	25	49	4	12	33	0	
Video								
Views								
Average	-0.0	-0.2	0.41	0.16	-0.3	0.40	0.15	0.449
Number of	49	76	1	2	54	0	5	
Video								
Shares								
Average	0.22	0.35	-0.1	-0.3	-0.2	-0.5	-0.1	-0.976
Number of	0	5	81	71	68	50	81	
Video								
Favorites								
Average	-0.0	0.36	-0.4	0.00	0.42	-0.3	-0.0	-0.028
Number of	33	0	05	5	1	17	58	

	Video	
	Comments	
Hidden Layer 1	(Deviation)	-1.227
	H(1:1)	-0.058
	H(1:2)	0.235
	H(1:3)	0.430
	H(1:4)	0.145
	H(1:5)	0.219
	H(1:6)	-0.214
	H(1:7)	0.385

Table 15

Output : Number of Followers	Number of Videos with Like-to-Play Ratio Exceeding 4%	Average Number of Video Favorites	Average Number of Video Coins	Average Number of Video Views	Average Number of Video Shares	Total Number of Videos	Video Recommendation Index	Average Number of Video Bullet Comments	Average Number of Video Comments	R^2
ANN Neural Network	1	2	6	8	5	3	4	9	7	0.8240

rk										
PLS-S										0.31
EM	9	5	6	4	7	8	2	3	1	5
Linear										
Regres										
sion	1	2	3	4	5	6	7	8	9	0.66
Predict										8
ion										

Table 16

5. Conclusion, Limitations, and Future Research Directions

5.1 Conclusion

In this study, we successfully employed a two-stage SEM-ANN approach, incorporating neural network models, to validate the impact of push-pull factors on user follower counts. Additionally, by integrating variable video recommendation index and the number of videos with a like-to-view ratio exceeding 4% into our research model, we derived the following conclusions:

The average number of coins, shares, bullet comments, favorites, and comments per video significantly influence the average video view counts. Conversely, the average video update time, average video duration, and total number of videos have minimal impact on average views.

Factors such as average video views, average video update time, average number of coins, shares, bullet comments, favoties, and comments per video, video recommendation index, and the number of videos with a like-to-view ratio exceeding 4% significantly affect follower counts, whereas the total number of videos and average video duration do not.

While the number of videos with a like-to-view ratio exceeding 4% significantly impacts follower counts, it does not significantly moderate the relationship between average video view counts and follower counts.

Regarding the importance of neural network independent variables, the average number of coins per video is the most critical, followed by the video recommendation index, average number of shares per video, total number of videos, and the number of videos with a like-to-view ratio exceeding 4%. The artificial neural network model we constructed achieves an 82.40% prediction

accuracy for follower counts.

5.2 Limitations and Future Research Directions

We acknowledge several limitations in this study: Firstly, our findings are based on browsing behavior data from Chinese users on the Bilibili platform, limiting the generalizability of our results to other countries. Secondly, our exclusion criteria for "rising stars" and "declining UPs" are not fully developed, potentially influencing the results. Thirdly, restricting the activation function to the hyperbolic tangent function may limit the neural network analysis results. Fourthly, with a prediction accuracy of 82.40%, our neural network model still has room for improvement due to its reliance on a single push-pull theory. Fifthly, feature extraction from the raw data is inadequate, with many features lost by averaging.

Therefore, future research can consider: Firstly, collecting live streaming sales data from various countries for cross-national and cross-cultural comparative studies. Secondly, developing more scientific and effective strategies to classify "rising stars" and "declining UPs." Thirdly, experimenting with different activation functions (such as softmax, identity, or other advanced functions) in neural network analysis may yield better results. Fourthly, incorporating other theories or models (such as the Technology Acceptance Model, Flow Theory, or Exhaustive Possibility Model) may enhance the predictive capability of the research model. Fifthly, abandoning SPSS and reconstructing from the ground up using advanced algorithms, such as vector input neural networks, with the introduction of attention mechanisms or graph neural networks to avoid dimensionality explosion, can effectively extract features from raw data.

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