CIT. Journal of Computing and Information Technology, Vol. 30, No. 1, March 2022, 51–65
doi: 10.20532/cit.2022.1005499

Behavior Analysis of User Interaction on Online Short Video Platform

Guang-Ming Sun[1, 2], Shuo Wang[1], Yun-Kai Zhang[1, 2], Yang Liu[1, 2], Jin Gao[1, 2] and Qin Xie[1, 2]

[1]Department of Electrical and Information Engineering, Hebei Jiaotong Vocational and Technical College, Shijiazhuang, China
[2]Road Traffic Perception and Intelligent Application Technology R&D Center of Universities in Hebei Province, Shijiazhuang, China

Online short video platform (OSVP) can disseminate information in an intuitive and three-dimensional (3D) way, and achieve commercial value in a mobile, socialized, life-oriented manner. To fully understand the information dissemination mode of short videos, it is of practical significance to explore user behaviors and their interactive relationship. Therefore, this paper carries out a behavior analysis on user interaction on OSVP. Firstly, an OSVP user interaction model was established based on three aspects: activity, attention, and interactivity. Next, user preference for short videos was examined through cluster analysis and evaluation. Finally, the authors summarized the behavior features of OSVP user interaction and investigated user interaction to decide which videos should be pushed to users. The average utility and average cost of user interaction behavior were compared, indicators of degree centrality were summarized, and the validity of the proposed algorithm was verified by experimental results.

ACM CCS (2012) Classification: Human-centered computing → Collaborative and social computing → Collaborative and social computing systems and tools → Social networking sites

Keywords: online short videos, user interaction, interactive behavior analysis

1. Introduction

Online short video platform (OSVP), an organic combination between videos and we-media, can disseminate information in an intuitive and three-dimensional (3D) way, and achieve commercial value in a mobile, socialized, life-oriented manner. At this stage, OSVPs exhibit a trend of rapid development in technology and scale [1–4]. Experts predict that OSVP users will reach 421 million, and the market value will surpass 25 billion yuan in 2025 [5, 6]. To fully understand the information dissemination mode of short videos, it is of practical significance to explore user behaviors and their interactive relationship. Therefore, this paper carries out an analysis on user interaction on OSVP.

So far, domestic and foreign scholars have achieved lots of results through behavior analysis of OSVP users [7–9]. Galdi *et al.* [10] defined the concept of short video, analyzed the dissemination paths and development features of OSVP information, and provided countermeasures for public opinion governance.

The human computer interaction (HCI) function of OSVP can effectively boost user participation and improve viewing experience [11–14]. After analyzing the text contents of online short videos, Yonezawa *et al.* [15] summarized the types of narration and the presentation modes of three interaction motives.

The entertainment property of interactive short videos is affected by multiple factors, such as length, professional level, and user psychology. Based on Randall Collins' interaction ritual chain, Wang [16] analyzed the performance and influence of the interaction rituals of popular science short videos on TikTok, and created the corresponding short video interaction ritual chain.

The interaction between academic journals and readers can also be completed with short videos

[17–19]. To improve the interaction efficiency of readers, Chi *et al.* [20] studied the operation mode and features of short videos of academic journals.

With the development of we-media and online video technology, more and more celebrities and official media have settled on relevant OSVP apps. McCord *et al.* [21] conducted a feature analysis of commercial interaction advantages of mobile Internet short videos plus advertising, and provided a reference to the popularization and promotion of short video commercialization.

After carefully sorting out the existing research results, it was found that field scholars generally pay more attention to analyzing the user behavior characteristics of OSVPs or building user interaction relationship network structures to extract the features of user relationship [22–26]. Few studies take user interest or preference into account.

This paper carries out a behavior analysis on user interaction on OSVP. The main contents are, as follows: Section 2 establishes an OSVP user interaction model based on three aspects: activity, attention, and interactivity; Section 3 examines user preference for short videos, and presents the approaches of cluster analysis and evaluation; Section 4 analyzes the behavior features of OSVP user interaction; Section 5 improves the decision-making of short video pushing through user interaction analysis. Experimental results demonstrate the effectiveness of the proposed method.

2. Model Construction

Users of OSVPs always follow the content, so all of the video products are facing a few common problems: bottle neck in the growth of new users; difficulties of increasing user activity and retention rate; and insufficient motives for users to participate in interaction and sharing. In fact, the essence of deep-layer user interaction lies in the users' personal experience, cognition, emotion, or sentiments that are similar to the interactive behavior, so we need to analyze them to improve the current application situations of OSVPs.

Figure 1 shows our OSVP user interaction model. Based on the model, this paper sets up an evaluation index system (EIS) for OSVP user interaction, which covers three aspects: activity, attention, and interactivity. The activity was measured by the number of posted videos, the number of forwards, and the time of posting; the attention was measured by the number of followed and the number of followers (which characterize the range of social relationship), view count (which characterizes the degree of

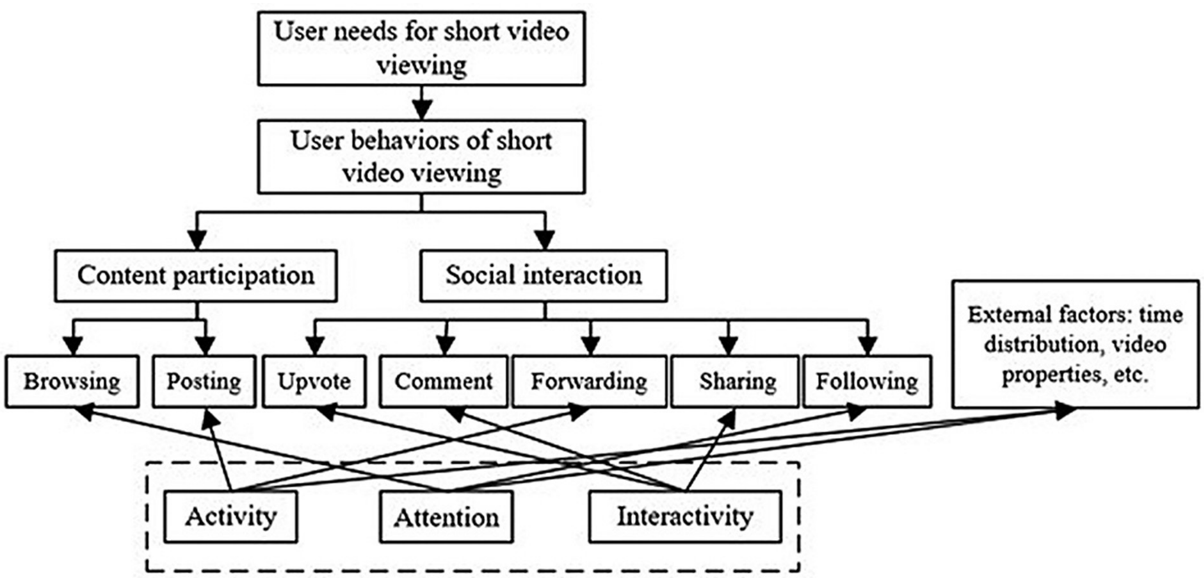

Figure 1. OSVP user interaction model.

attention), and authenticated identity (which characterizes the identity of users); the interactivity was measured by the number of likes, the number of comments, and the number of sharing (which characterize the interaction between users). When analyzing above factors, it is necessary to comprehensively consider the directly-related and indirectly-related factors.

Here, the sum of number of posted videos and number of forwards is defined as the number of posts. The scatterplot on the number of posts of OSVP users is shown in Figure 2, where the number of posted videos and the number of forwards represent the number of original short videos posted by users, and the number of their own or others' short videos being forwarded by users. The two parameters reflect the activity and contribution of users.

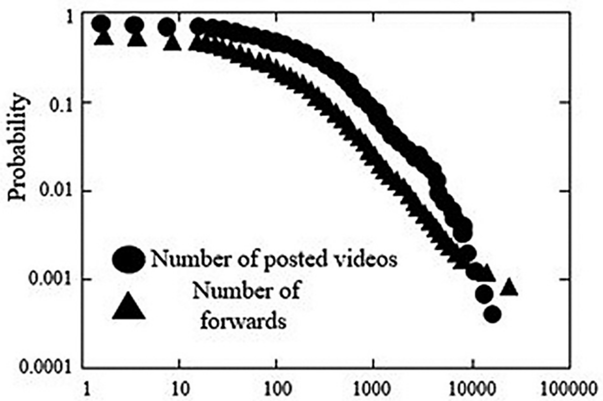

Figure 2. Scatterplot on the number of posts of OSVP users.

3. Preference Analysis

Unlike Weibo and other social platforms, OSVP has no open application programming interface (API). It is impossible to acquire data by calling an API. A possible way is to crawl the webpage of each short video with crawler software, or crawl information like the list of followers with a self-compiled R program. Due to the high crawling frequency, the same user could be sampled repeatedly in a time grid. The repeated sampling indicates that the user is watching the short video during that period. The viewing time was measured to evaluate the user preference for short videos with different attributes and features.

The dwell time of a short video was defined as the time for user i to remain in time grid w, watching the short video, *i.e.*, the difference between the start time and end time of viewing the short video. Let TI_{i-w}, TI_{i-wr}, and TI_{i-ws} be the dwell time, start time, and end time of user i in the time grid w, respectively; TI_{i-all} be the total time of user i watching short videos. The dwell time of a user varies with time grids. The proportion of the dwell time of user i in time grid w can be calculated as:

$$TI_{i-w} = \frac{TI_{i-wr} - TI_{i-ws}}{TI_{i-all}} \tag{1}$$

Formula (1) shows that the proportion of the dwell time can characterize the user preference for short videos. The proportion of the dwell time for each user was described as a row vector $TI_i = (TI_{i-1}, TI_{i-2}, ..., TI_{i-w})$.

To analyze the user preference for short videos, it is necessary to identify the preference range through a cluster analysis on the time distribution features and video properties in the historical data on short video viewing. Due to the sheer volume of historical data, this paper dynamically determines the number of clusters for user viewing of short videos. The difference between short video viewing sample i and its preferred class was measured by Euclidean distance $g(i)$, and the minimum distance between sample i and another preferred class was denoted as $h(i)$. Then, the Silhouette value measuring the cluster effect of sample i can be calculated as:

$$SI(i) = \frac{h(i) - g(i)}{\max\{g(i), h(i)\}} \tag{2}$$

Formula (2) shows that $SI(_i)$ falls between −1 and 1. If the $SI(i)$ value is close to 1, there is a difference between sample i and its preferred class, which facilitates the correct classification of sample i. If the $SI(i)$ value is close to 0, there is a small difference between sample i and two preferred classes, that is, sample i is very likely to fall between the two classes. If the $SI(i)$ value is smaller than 0, sample i is clustered unreasonably. If the $SI(i)$ value is close to −1, there is a large probability that sample i belongs to another preferred class.

Owing to the immense size of the historical data, it is impossible to determine the values of two important clustering parameters: cluster radius *eps* and the minimum number of points *min points*. Therefore, an effective method was developed to determine the values of the two parameters adaptively, according to the actual distribution and overall features of the historical data of different users viewing short videos. Let m be the total number of data samples. The distance between samples i and j in the sample set can be characterized as the elements in distance distribution matrix RAN_{m*m}:

$$RAN_{m*m} = \{r(i, j), 1 \le i \le m, 1 \le j \le m\} \quad (3)$$

Sorting the rows in RAN_{m*m} by size, the nearest l-th distance points to all the points in the matrix obeying Poisson's distribution. By maximum likelihood method, the parameter estimation for the distribution of distance points can be completed as:

$$\mu = \bar{a} = \frac{1}{m}\sum_{l=1}^{m} a_l \quad (4)$$

The expectation of μ in formula (4) was taken as the *eps* for the clustering of user preference for short videos. Formula (4) includes two parameters, but the influence of the total sample number μ on the expectation is merely kept within a certain range, so a clustering analysis is required.

Online short videos cover all sorts of information, ranging from news, sports, military to entertainment. This paper counted the user attention on different types of short videos on the target platform. Figure 3 shows the mean number of followers of short videos on the platform. It can be inferred that fun, gourmet, news, pets, and traveling videos attract many followers, while home design, digital technology, culture, and animation videos receive a low attention.

In this paper, the clustering effect of user preference for short videos is evaluated by an internal standard. The basic standard of cluster analysis is to minimize intra-class distance and maximize inter-class distance. This paper chooses two indices to evaluate the clustering

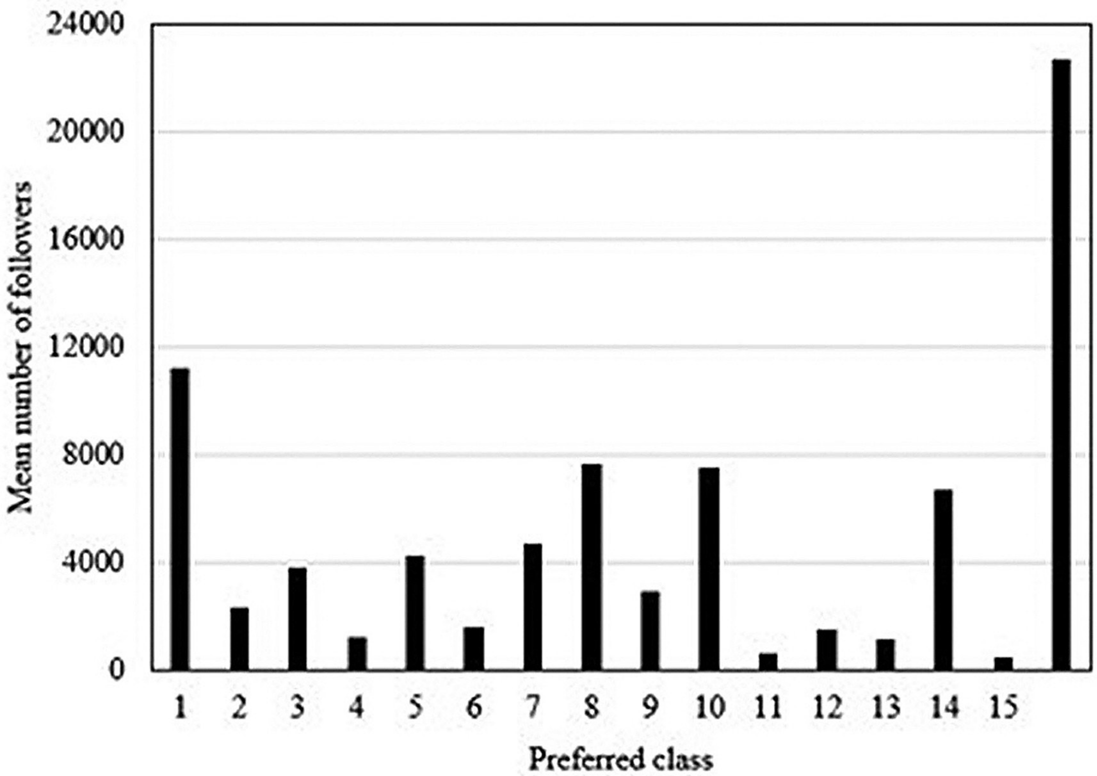

Figure 3. Mean number of followers of short videos on the platform.

effect: cohesion and separation. Let Γ_i be the set of all $|\Gamma_i|$ type i sample points; q_i be the cluster head of type i sample points; l be the number of clusters. Then, the mean distance AD_i from type i sample points to each cluster head, and can be calculated as:

$$AD_i = \frac{1}{|\Gamma_i|} \sum_{A_i \in \Gamma_i} \| a_i - q_i \| \tag{5}$$

The mean AD of the mean intra-class distances of all classes can be calculated as:

$$AD = \frac{1}{l} \sum_{i=1}^{l} AD_l \tag{6}$$

Formula (6) shows that AD is negatively correlated with the intra-class clustering distance.

Let q_i and q_j be the cluster heads of type i and type j sample points, respectively. Then, the inter-class separation can be characterized as the mean distance of all cluster heads:

$$CD = \frac{2}{l^2 - l} \sum_{i=1}^{l} \sum_{j=i+1}^{l} \| q_i - q_j \|_2 \tag{7}$$

Formula (7) shows that CD is positively correlated with intra-class clustering distance.

Through clustering, the centroid of user behaviors was derived for each preferred class. The similarity of user behaviors in different preferred classes could be measured by the distance between different behavior centroids. Cosine similarity means to evaluate the similarity between two vectors by calculating the cosine value of the included angle between them. This paper adopted cosine similarity to measure the similarity of user behavior preferences. Let ξ_{i-j} be the distance between the behavior preferences of user i and user j. The ξ_{i-j} value is negatively correlated with the similarity of short video preferences between users i and j. Let $\xi_{\max}$ and $\xi_{\min}$ be the maximum and minimum distances from user i to the centroid of the other users' short video viewing behaviors, respectively. Then, the mean distance between multiple behavior centroids can be normalized as:

$$\xi_{i,j} = \frac{\xi_{\max} - \xi_{i-j}}{\xi_{\max} - \xi_{\min}} \tag{8}$$

For the historical data on short video viewing by a few users, whose preferred class was preset as N, collected with a short time interval, the frequency of the preferred classes of all users was counted with 12h as the time window. That is, the historical data of each user could be viewed as a 12*N matrix. Then, the preferred class of each user was analyzed separately. Let $O_{i-k-\tau}$ and $FR_{i-k-\tau}$ be the preference and frequency of user i for the short video related to preferred class k in time window τ, respectively; K be the set of preferred classes of short videos of user i. Then, the proportion of the preference for class k short videos in time window τ in personal preference can be calculated as:

$$O_{i-k-\tau} = \frac{FR_{i-k-\tau}}{\sum_{k \in K} FR_{i-k-\tau}} \tag{9}$$

For the historical data on short video viewing by many users collected with a long time interval, the data collection spans across a long period. Unlike the hour-based frequency count for the historical data of a few users, the frequency of the preferred classes of each user was calculated separately. Let O_{jk} and FR_{i-k} be the preference and frequency of user i for the short video related to preferred class k, respectively; K be the set of preferred classes of short videos of user i. Then, the preferred class of the historical data on short video viewing by many users can be calculated as:

$$O_{i-k} = \frac{FR_{i-k}}{\sum_{k \in K} FR_{i-k}} \tag{10}$$

In formula (10), the preferred class is characterized by the proportion of the preference for class k short videos of each user in his/her personal preference. In this way, it is possible to obtain a complete set of user preferences for short videos: $O_i = (O_{i-1}, O_{i-2}, ..., O_{i-k})$.

4. Feature Analysis

To analyze the features of OSVP user interaction, each user was treated as an independent node U in OSVP social network, and each interactive relationship between users as an edge S connecting the corresponding nodes. Then, the nodes and edges could form an undirected graph $NE = (U, S)$ of the user interaction network. The OSVP social network mainly has three properties: degree centrality, betweenness centrality, and eigenvector centrality.

Let χ_{ij} be the binary function reflecting whether user node i is directly connected to user node j. If the two nodes are directly connected, $\chi_{ij} = 1$; otherwise; $\chi_{ij} = 0$. Let M_U be the total number of user nodes. In the feature analysis of OSVP user interaction, the centrality of user nodes can be measured by degree centrality:

$$EOC_i = \frac{\sum_{j-1}^{M_U} \chi_{ij}}{M_U - 1} \ (i \neq j) \tag{11}$$

where the numerator on the right side is the total number of nodes connected to user node i. Formula (11) shows that, the greater the value of $EOC_i \in (0, 1)$, the stronger the influence of user i in OSVP. Let ε^i_{po} be the number of shortest paths from user node p to user node o; ε_{po} be the number of the said shortest paths passing through user node i. Then, the intermediate nodes between two user nodes can be described by betweenness centrality δ_i:

$$\delta_i = \sum_{i=p=o \notin U} \frac{\varepsilon^i_{po}}{\varepsilon_{po}} \tag{12}$$

Formula (12) shows that, the greater the value of δ_i, the stronger the influence of user i in OSVP.

The importance of a user node depends on both the number of nearby user nodes and their importance. The eigenvector centrality CV_i of user node i and that CV_j of a nearby user node meet the following conditional relationship:

$$CV_i \propto \sum CV_j \tag{13}$$

Formula (13) shows that CV_i is positively correlated with the sum of CV_j.

For the historical data on short video viewing by a few users, the cosine similarity between any two users i and j in short video preference could be calculated from their preferences for short videos. On this basis, the similarity $SLS_{1(i,j)}$ between users in short video preference can be calculated as:

$$SLS_{1(i,j)} = \cos(TI_i, TI_j) \tag{14}$$

The higher the similarity in short video preference, the greater the similarity between the two users in the dwell time distribution for the same class of short videos, and the closer their preferences for short videos.

The cosine similarity between any two users i and j in short video preference in a time window τ could be derived from the preference of each user for short videos in that time window. On this basis, the similarity $SLS_{2(i,j)}$ between users in short video preference in time window τ can be calculated by:

$$SLS_{2(i,j)} = \cos(O_{i-k-\tau}, O_{j-k-\tau}) \tag{15}$$

For the historical data on short video viewing by many users, a user interaction network was also constructed to analyze the intensity of interactive relationship between any two friend users in the network. A weight was assigned to the edge between the two user nodes. The intensity of interactive relationship was measured by two factors: distance to behavior centroid and similarity in short video preference. The similarity in short video preference between users i and j can be calculated by cosine similarity:

$$COM_{i,j} = \cos(O_i, O_j) \tag{16}$$

$E_{ij} = \gamma_1 * COM_{ij} + \gamma_2 * \xi_{ij}$ and $E_{ij} = COM_{ij} * \xi_{ij}$ were defined as the formulas for the intensity of correlation between two friend users, and a threshold ω was defined. If $E_{ij} > \omega$, the edge between user nodes i and j should be retained; otherwise, the edge should be deleted.

Tables 1 to 4 compare the number of user nodes (points), the number of edges, and the edge-node (point) ratio under several different parameter combinations.

With the changes in parameter values, the user interaction network witnessed a decline in the number of edges and edge-node ratio. Figures 4 and 5 present the user interaction networks at the two lowest edge-node ratios (3.14 and 1.82). It can be inferred that the original user interaction network could be clustered based on the user preference for short videos and user friendship. The clustering effect depends on the parameter values. According to the requirements of subsequent experiments, different user interaction networks were constructed for later use.

Table 1. User interaction network at $\gamma_1 = 0.4$ and $\gamma_2 = 0.6$.

ω	Number of points	Number of edges	Edge-point ratio
$\omega = 0.5$	58	452	7.79
$\omega = 0.6$	56	379	6.76
$\omega = 0.7$	55	336	6.10
$\omega = 0.8$	51	313	6.13
$\omega = 0.9$	49	196	4

Table 2. User interaction network at $\gamma_1 = 0.5$ and $\gamma_2 = 0.5$.

ω	Number of points	Number of edges	Edge-point ratio
$\omega = 0.5$	57	450	7.89
$\omega = 0.6$	55	384	6.98
$\omega = 0.7$	54	336	6.22
$\omega = 0.8$	52	279	5.36
$\omega = 0.9$	45	145	3.22

Table 3. User interaction network at $\gamma_l = 0.7$ and $\gamma_2 = 0.3$.

ω	Number of points	Number of edges	Edge-point ratio
$\omega = 0.5$	57	439	7.70
$\omega = 0.6$	55	364	6.61
$\omega = 0.7$	54	332	6.14
$\omega = 0.8$	42	249	5.92
$\omega = 0.9$	35	110	3.14

Table 4. User interaction network at $E_{ij} = COM_{ij}{*}\xi_{ij}$.

ω	Number of points	Number of edges	Edge-point ratio
$\omega = 0.5$	55	326	5.92
$\omega = 0.6$	52	295	5.67
$\omega = 0.7$	50	234	4.68
$\omega = 0.8$	48	157	3.27
$\omega = 0.9$	39	71	1.82

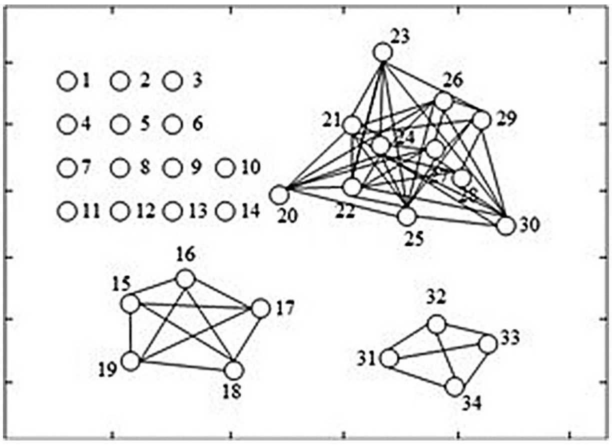

Figure 4. User interaction network at edge/node ratio of 3.14.

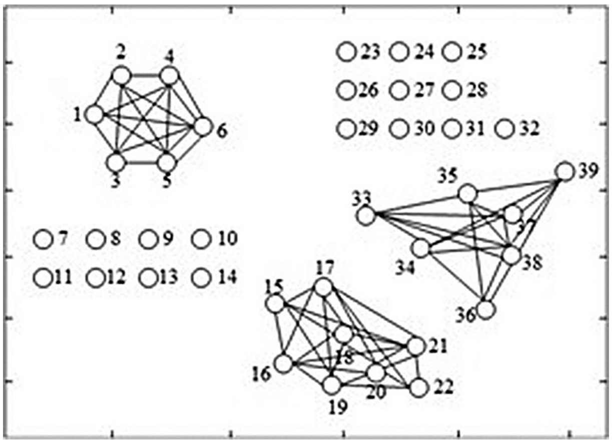

Figure 5. User interaction network at edge/node ratio of 1.82.

5. User Interaction Analysis

The user interaction network generally consists of two parts: historical data on short video viewing and user friendship data. After analyzing video preference, user preference, and user interaction features, the user interaction analysis can be performed to support the decisions on short video pushing (Figure 6). During the decision-making, the user selection process is essentially the matching between user preference and the properties of the video being pushed. To make a decision $\psi_l = (LA_1, LO_1, PO_1, C_1, N_1)$ on short video pushing, the first step is to locate the push time to the current time window w according to the properties of the short video. Then, the dwell time of user i in time window w determines the probability ψ_l of completing an interaction within that time window. The probability ψ_l of completing an interaction about a short video can be calculated as:

$$\xi_{i-l} = TI_{i-w} \tag{17}$$

Formula (17) shows that, the greater the value of $\xi_{i,\, l}$, the more likely for user i to complete an interaction about the short video; the inverse is also true.

Based on user behavior centroid, it is possible to calculate the distance ξ_{i-l} between the user and the short video pushing, which completes the interaction. Let ξ_{i-l} be the distance between user i and interaction ψ_l; ξ_{ran} be the distance between user i's behavior centroid and interaction ψ_l; $\xi_{\max}$ and $\xi_{\min}$ be the maximum and minimum distances between a friend user of user i and interaction ψ_l. Then, we have:

$$\xi_{i-l} = \frac{\xi_{max} - \xi_{ran}}{\xi_{max} - \xi_{min}} \tag{18}$$

Formula (18) shows that, the smaller the ξran, the greater the ξ_{i-l}, the more likely for user i to complete interaction ψ_l. The inverse is also true.

Then, the probability for a user to complete interaction T_k can be calculated based on the complete set of user preferences for short videos $O_i = (O_{i-1}, O_{i-2}, ..., O_{i-k})$. Let IT_l be the user preference for the preferred class of T_k. Then, the cosine similarity $\cos_{i-l}$ between the preferred class of T_k and user preference for short videos can be calculated by:

$$\cos_{i-l} = \cos(O_i, IT_l) \tag{19}$$

From $\cos_{i-l}$, it is possible to further compute the matching degree between user i and interaction ψ_l.

Related to interaction intensity and mutual friends, the intimacy INT_{ij} between users i and j can be calculated as:

$$INT_{ij} = \beta * FR_{ij} + (1-\beta)\frac{d_i \cap d_j}{d_i \cup d_j} \tag{20}$$

where FR_{ij} is an indicator of the friendship between users (if $FR_{ij} = E_{ij}$, then user i is a friend of user j; if $FR_{i-j} = 0$, then user i is not a friend of user j); d_i and d_j are the interaction networks of user i and user j, respectively; $d_i \cap d_j$ are the mutual friends of user i and user j; $d_i \cup d_j$ are the union set of friends of user i and user j. The greater the $INT_{ij} \in (0, 1)$, the higher the intimacy between users i and j.

The objective factors affecting whether a user completes an interaction about a short view can be characterized by the probability CH of user j, which is predicted to complete interaction, completing the interaction on that video:

$$CH = \beta_1 \xi_{j-l} + \beta_2 \cos_{j-l} \tag{21}$$

Parameters β_1 and β_2 can be adjusted according to the specific type of interaction, provided that $\beta_1 + \beta_2 = 1$.

The subjective factors can be characterized by the subjective influence SU0 of user i starting

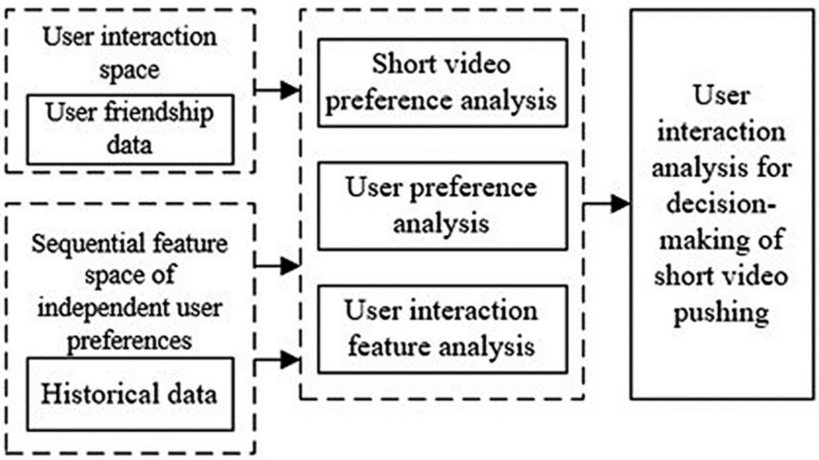

Figure 6. Framework of user interaction analysis for decision-making of short video pushing.

the interaction on user *j* responding to the interaction:

$$SU_0 = \alpha_1 * INT_{i,j} + \alpha_2 * EOC_i \tag{22}$$

Parameters α_1 and α_2 can be adjusted according to the specific type of interaction, provided that $\alpha_1 + \alpha_2 = 1$.

During the decision-making of short video pushing, the influence of the user starting the interaction on the user responding to the interaction accumulates with time, rather than diminish over time. Once the cumulative influence surpasses the interaction activation threshold for the responder, the user responding to the interaction will be activated to interact with the initiator. The threshold could be described by a linear model, where the number of neighbors interacting with user j is denoted as M_{NE-j}, *i.e.*, the total number of users capable of interacting with user *j*. Following the most basic mode of short video pushing, the probability CH' for user *i* to start the interaction with user *j* can be calculated as:

$$CH' = \frac{1}{M_{NE-j}} \tag{23}$$

During the interaction, a user prefers to interact with those sharing a highly similar preference for short videos with him/her. For the independent cascading model, the subjective influence of user *i* starting the interaction with user *j* responding to the interaction is denoted as SU_0. Then, the probability CH'' for user i to start the interaction with user *j* can be calculated as:

$$CH_2 = 1 - \frac{1}{e^{CH_0 + SU_0}} \tag{24}$$

The short video pushing decision is executed differently on different OSVPs. Let m_E be the number of interacting users in the interaction network of user *i*; m_i be the total number of that network; φ_1 and φ_2 be two adjustment parameters ($\varphi_1 + \varphi_2 = 1$). Then, the evaluation function can be defined as:

$$V_i = \varphi_1 \frac{m_E}{m_i} - \varphi_2 \frac{m_E}{M_U} \tag{25}$$

The greater the utility V_i of the short video pushing decision, the greater the proportion of users capable of interaction in the platform, and the better the short video pushing effect of the platform.

6. Experiments and Results Analysis

As mentioned before, the desired clustering results on user preference for short videos should minimize intra-class distance and maximize inter-class distance. In this section, comparative experiments are conducted by clustering the short video preferences of 4,100 OSVP users with different methods. Figures 7 and 8 show the variation of inter-class separation and intra-class cohesion of 120 users, respectively. It can be seen that our clustering method achieved a better clustering effect than traditional algorithms like KMC and FCM.

Under a small historical dataset, this paper compares the mean utility of user interactions about different types of short videos, using linear threshold model and independent cascading model. The results are shown in Figure 9, where the *x*-axis is the user number in user interaction network, and the *y*-axis is the mean utility over 100 short videos. Due to the small size of user interaction network, zero-interaction subnetwork might easily occur. It can be seen from Figure 9 that there was a difference between the mean interaction utility obtained by linear threshold model and that obtained by independent cascading model. The latter model achieved a much higher mean utility than the former. The reason is that the linear threshold model considers the probability of user interaction as irrelevant to the friendship of the responder, while the independent cascading model takes account of the preference and intimacy of the responder before the user starting the interaction, which makes the interaction more pertinent.

Under the same small historical dataset, this paper further compares the mean interaction cost about different types of short videos, using linear threshold model and independent cascading model. The results are shown in Figure 10, where the *x*-axis is the user number in user interaction network, and the *y*-axis is the mean cost over 100 short videos. More users completed interactions under the independent cascading model than those under the linear threshold model, which pushes up the cost of interaction under the former model. This is because linear threshold model targets short videos pushed aimlessly, while independent cascading model fully considers the execution rate of the responder before an interaction is even started, that is, ensures the pertinence of short video pushing. In case of different scales of history datasets, there will be differences in the execution effect of the algorithm. The average cost it takes for users to complete interactions was analyzed in the case of a small-scale history dataset, however, under normal conditions, the historical dataset has a large sample size, the proposed algorithm would exhibit more obvious advantages in terms of large-scale history datasets.

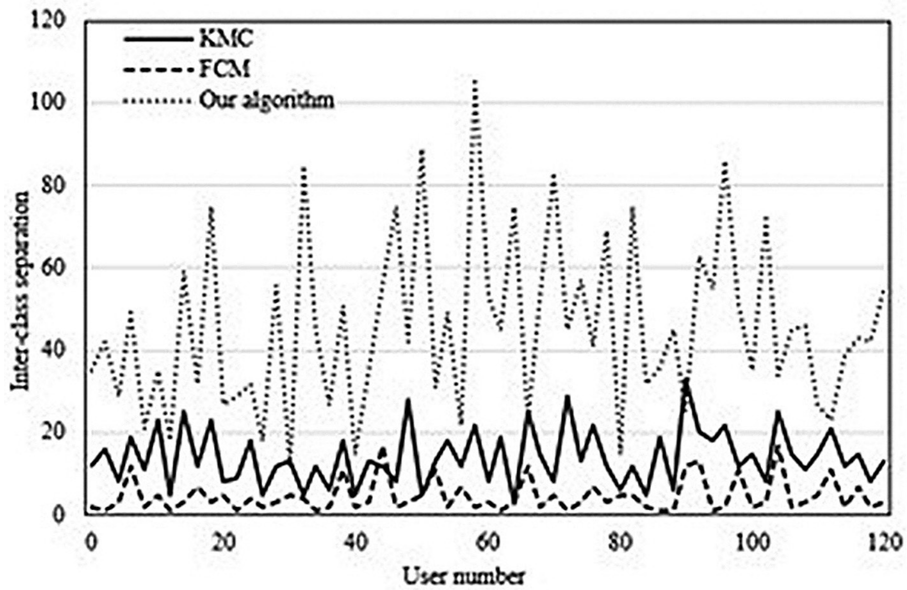

Figure 7. Inter-class separation of user preference.

Note: KMC and FCM are short for *k*-means clustering and fuzzy *c*-means clustering, respectively.

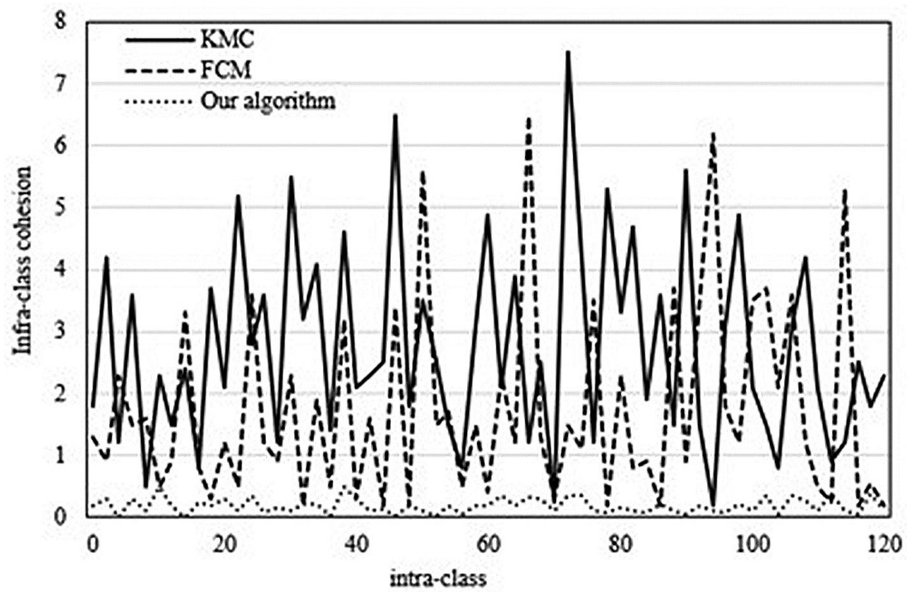

Figure 8. Intra-class cohesion of user preference.

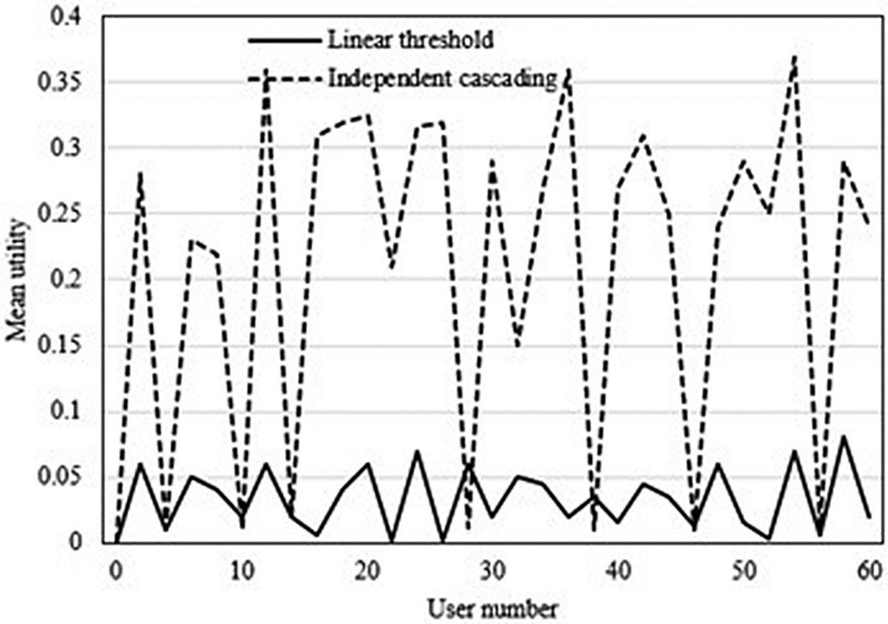

Figure 9. Mean interaction utility of users in a small historical dataset.

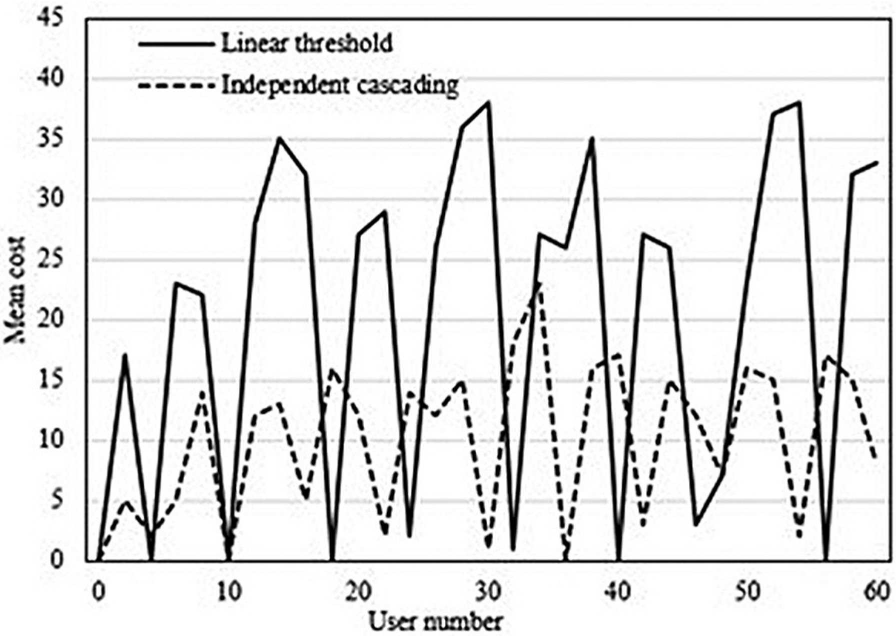

Figure 10. Mean interaction cost of users in a small historical dataset.

Under a large historical dataset, this paper compares the mean utility of user interactions about different types of short videos, using linear threshold model and independent cascading model. The results are shown in Figure 11, where the x-axis includes 350 users and their user interaction network, and the y-axis is the mean utility over 100 short videos. The experimental results were not very different from those on the small historical dataset. But the mean utility of users completing interaction in the independent cascading model was far higher than that in the linear threshold model.

Under the same historical dataset, the mean interaction cost about different types of short videos, using linear threshold model, is compared with that using independent cascading model in Figure 12, where the x-axis includes 350 users and their user interaction network, and the y-axis is the mean utility over 100 short videos. It can be seen that the mean cost of the independent cascading model was far smaller than that of the linear threshold model. This is basically in line with the results on the small historical dataset.

In this study, the out-degree in the undirected graph of user interactions represents the interaction from a user to another user, *e.g.*, following the latter, and viewing, liking, commenting on, and sharing the latter's short videos. The in-degree means a user receives the interaction from another user. As shown in Table 5, the user interaction network had an out-degree of 18.845%, and an in-degree of 21.357%. Therefore, the OSVP users being followed are concentrated, with a high centrality, while the users following others are dispersed, with a low centrality. The research data were collected from popular users with many followers. The above analysis result, *i.e.*, the followed are concentrated, agrees well with the actual statistics.

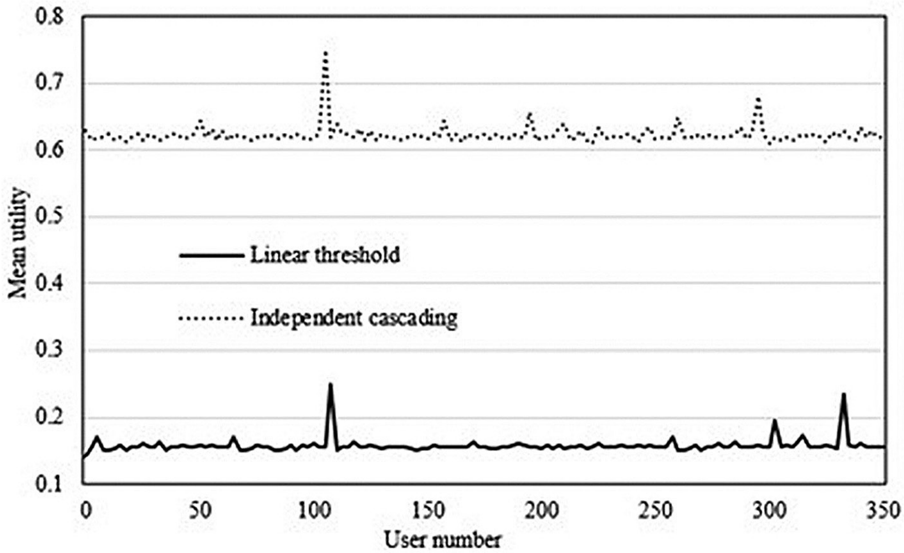

Figure 11. Mean interaction utility of users in large historical dataset.

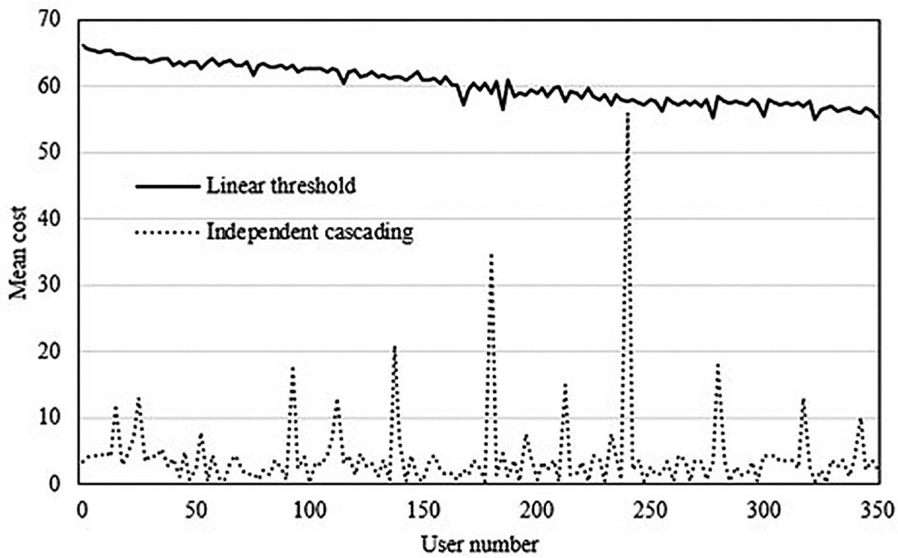

Figure 12. Mean interaction cost of users in a large historical dataset.

Table 5. Indices of degree centrality.

Index	In-degree	Out-degree	Normalized out-degree	Normalized in-degree
Minimum	0.001	0.001	0.001	0.001
Maximum	50.002	64.003	20.675	26.034
Mean	6.792	6.794	2.812	2.894
Standard deviation	7.819	11.264	3.234	4.574
Variance	61.085	123.923	10.439	20.852
Network out-degree = 18.845%; Network in-degree = 21.357%				

7. Conclusion

This paper explores the user interactions on OSVP. The authors firstly established an OSVP user interaction model, and then analyzed the user preference for short videos and the features of user interactions. After that, the user interaction was investigated to facilitate the decisions on short video pushing. Through experiments, the inter-class separation and intra-class cohesion of user preferences were obtained, which demonstrates that our method outperforms traditional KMC and FCM. In addition, the mean utility and mean cost of users completing interaction, using linear threshold model, were compared with those using independent cascading model, on both small and large historical datasets. Finally, the degree centrality indices were summarized to obtain the in- and out-degree centralities of the user interaction network for short videos. This research topic has a large scope, so we only selected two aspects: the influencing factors and the features to study the information interaction behavior, and some aspects hadn't been fully considered, such as the selection of subjects and the time variability of users' requirements for information. These aspects need to be studied further in the future.

Acknowledgement

This paper was funded by the High-level Talents Funding Project of Hebei Province (Grant No.: A202105006); and the Hebei Provincial Higher Education Science and Technology Research Key Project (Grant No.: ZD2021317).

References

[1] W. Qi and D. Li, "A User Experience Study on Short Video Social Apps Based on Content Recommendation Algorithm of Artificial Intelligence", *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 35, no. 2, p. 2159008, 2021. https://doi.org/10.1142/S0218001421590084

[2] M. M. Nezhad *et al.*, "Joint Peak Clipping and Load Scheduling Based on User Behavior Monitoring in an IoT Platform", *IEEE Systems Journal*, vol. 15, no. 1, pp. 1202–1213, 2020. https://doi.org/10.1109/JSYST.2020.3009699

[3] V. Lombardi *et al.*, "Behavior Control-Based Approach to Influencing User & Apos; S Cybersecurity Actions Using Mobile News App", in *Proceedings of the 36th Annual ACM Symposium on Applied Computing*, 2021, pp. 912–915. https://doi.org/10.1145/3412841.3442103

[4] S. Babaee *et al.*, "A New Approach for Index Construction: The Case of the Road User Behavior Index", *Computers & Industrial Engineering*, vol. 152, p. 106993, 2021. https://doi.org/10.1016/j.cie.2020.106993

[5] J. Gutzeit *et al.*, "Information Behavior on Video on Demand Services: User Motives and Their Selection Criteria for Content", *Information*, vol. 12, no. 4, pp. 173, 2021. https://doi.org/10.3390/info12040173

[6] N. Lubold *et al.*, "Effects of Adapting to User Pitch on Rapport Perception, Behavior, and State with a Social Robotic Learning Companion", *User Modeling and User-Adapted Interaction*, vol. 31, no. 1, pp. 35–73, 2021. https://doi.org/10.1007/s11257-020-09267-3

[7] S. S. Jadhav and P. C. Kalita, "The Future of Home Service: Integration of User Behavior and

Scenario Planning in the Domestic Plumbing Service Design", *In Design for Tomorrow*, vol. 2, pp. 3–15, 2021.
https://doi.org/10.1007/978-981-16-0119-4_1

[8] W. Cui and K. Liao, "Effect of Core Competence and Brand Personality of Short Video Websites on User Loyalty", *Tehnički vjesnik*, vol. 26, no. 6, pp. 1771–1776, 2019.
https://doi.org/10.17559/TV-20191007110828

[9] L. Ma *et al.*, "Research on User Loyalty of Short Video App Based on Perceived Value—Take Tik Tok as an Example", In *Proc. of the 2019 16th International Conference on Service Systems and Service Management (ICSSSM)*, 2019, pp. 1–6.
https://doi.org/10.1109/ICSSSM.2019.8887751

[10] C. Galdi *et al.*, "Secure User Authentication on Smartphones via Sensor and Face Recognition on Short Video Clips", in *Proc. of the International Conference on Green, Pervasive, and Cloud Computing*, 2017, pp. 15–22.
https://doi.org/10.1007/978-3-319-57186-7_2

[11] J. Lokoč *et al.*, "What are the Salient Keyframes in Short Casual Videos? An Extensive User Study Using a New Video Dataset", in *Proc. of the 2015 IEEE International Conference on Multimedia & Expo Workshops (ICMEW)*, 2015, pp. 1–6.
https://doi.org/10.1109/ICMEW.2015.7169765

[12] M. Shoaib, and N. Sayed, "A Deep Learning Based System for the Detection of Human Violence in Video Data", *Traitement du Signal*, vol. 38, no. 6, pp. 1623–1635, 2021.
https://doi.org/10.18280/ts.380606

[13] M. Shahbaz *et al.*, "Environmental Air Pollution Management System: Predicting User Adoption Behavior of Big Data Analytics", *Technology in Society*, vol. 64, p. 101473, 2021.
https://doi.org/10.1016/j.techsoc.2020.101473

[14] H. S. M. Bilal *et al.*, "Towards User-Centric Intervention Adaptiveness: Influencing Behavior-Context Based Healthy Lifestyle Interventions", *IEEE Access*, vol. 8, pp. 177156–177179, 2020.

[15] T. Yonezawa *et al.*, "Dynamic Video Tag Cloud: A Cooking Support System for Recipe Short Videos", in *Proceedings of the 25th International Conference on Intelligent User Interfaces Companion*, pp. 122–123, 2020.
https://doi.org/10.1145/3379336.3381476

[16] Y. Wang, "Humor and Camera View on Mobile Short-Form Video Apps Influence User Experience and Technology-Adoption Intent, an Example of TikTok (DouYin)", *Computers in Human Behavior*, vol. 110, p. 106373, 2020.
https://doi.org/10.1016/j.chb.2020.10637

[17] N. Yadav and D. Naik, "Generating Short Video Description using Deep-LSTM and Attention Mechanism", in *Proc. of the 2021 6th International Conference for Convergence in Technology (I2CT)*, pp. 1–6, 2021.
https://doi.org/10.1109/I2CT51068.2021.9417907

[18] P. Agrafioti *et al.*, "Scaling Recovery of Susceptible and Resistant Stored Product Insects after Short Exposures to Phosphine by Using Automated Video-Tracking Software", *Pest Management Science*, vol. 77, no. 3, pp. 1245–1255, 2021.
https://doi.org/10.1002/ps.6135

[19] D. Cores *et al.*, "Short-Term Anchor Linking and Long-Term Self-Guided Attention for Video Object Detection", *Image and Vision Computing*, vol. 110, p. 104179, 2021.
https://doi.org/10.1016/j.imavis.2021.104179

[20] X. Chi *et al.*, "Pricing Mode Selection for the Online Short Video Platform", *Soft Computing*, vol. 25, no. 7, pp. 5105–5120, 2021.
https://doi.org/10.1007/s00500-020-05513-3

[21] A. McCord *et al.*, "Short Video Game Play Improves Executive Function in the Oldest Old Living in Residential Care", *Computers in Human Behavior*, vol. 108, p. 106337, 2020.
https://doi.org/10.1016/j.chb.2020.106337

[22] F. Baumgarte *et al.*, "You'll Never Share Alone: Analyzing Carsharing User Group Behavior", *Transportation Research Part D: Transport and Environment*, vol. 93, p. 102754, 2021.
https://doi.org/10.1016/j.trd.2021.102754

[23] M. Nabati and A. Behrad, "Video captioning using boosted and parallel Long Short-Term Memory networks", *Computer Vision and Image Understanding*, vol. 190, p. 102840, 2020.
https://doi.org/10.1016/j.cviu.2019.102840

[24] S. Kaur *et al.*, "Deepfakes: Temporal Sequential Analysis to Detect Face-Swapped Video Clips Using Convolutional Long Short-Term Memory", *Journal of Electronic Imaging*, vol. 29, no. 3, p. 033013, 2020.
https://doi.org/10.1117/1.JEI.29.3.033013

[25] N. Eswara *et al.*, "Streaming Video QoE Modeling and Prediction: A Long Short-Term Memory Approach", *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 30, no. 3, pp. 661–673, 2019.
https://doi.org/10.1109/TCSVT.2019.2895223

[26] R. Anuranji and H. Srimathi, "A Supervised Deep Convolutional Based Bidirectional Long Short Term Memory Video Hashing for Large Scale Video Retrieval Applications", *Digital Signal Processing*, vol. 102, p. 102729, 2020.
https://doi.org/10.1016/j.dsp.2020.102729

Received: December 2022
Revised: January 2023
Accepted: February 2023

Contact addresses:
Guang-Ming Sun
Department of Electrical and Information Engineering
Hebei Jiaotong Vocational and Technical College
Shijiazhuang
China
Road Traffic Perception and Intelligent Application
Technology R&D Center of Universities in Hebei Province
Shijiazhuang
China
e-mail: gmsun@hejtxy.edu.cn

Shuo Wang*
Department of Electrical and Information Engineering
Hebei Jiaotong Vocational and Technical College
Shijiazhuang
China
e-mail: sgmez@sina.com
*Corresponding author

Yun-Kai Zhang
Department of Electrical and Information Engineering
Hebei Jiaotong Vocational and Technical College
Shijiazhuang
China
Road Traffic Perception and Intelligent Application
Technology R&D Center of Universities in Hebei Province
Shijiazhuang
China
e-mail: zyk@hejtxy.edu.cn

Yang Liu
Department of Electrical and Information Engineering
Hebei Jiaotong Vocational and Technical College
Shijiazhuang
China
Road Traffic Perception and Intelligent Application
Technology R&D Center of Universities in Hebei Province
Shijiazhuang
China
e-mail: 202101002@hejtxy.edu.cn

Jin Gao
Department of Electrical and Information Engineering
Hebei Jiaotong Vocational and Technical College
Shijiazhuang
China
Road Traffic Perception and Intelligent Application
Technology R&D Center of Universities in Hebei Province
Shijiazhuang
China
e-mail: gaoj1219@163.com

Qin Xie
Department of Electrical and Information Engineering
Hebei Jiaotong Vocational and Technical College
Shijiazhuang
China
Road Traffic Perception and Intelligent Application
Technology R&D Center of Universities in Hebei Province
Shijiazhuang
China
e-mail: xieqin@hejtxy.edu.cn

Guang-Ming Sun received the BSc degree in computer science and technology from Wuhan University of Science and Technology, Wuhan, China, in 2003 and MSc degree in computer science and technology from Beijing Jiaotong University, Beijing, China, in 2009. Since 2017, he has been an associate professor with the Department of Electrical and Information Engineering, Hebei Jiaotong Vocational and Technical College. His research interests include complex network analysis and personalized recommendation algorithms.

Shuo Wang received the BSc degree in computer science and technology from Shijiazhuang Tiedao University, Shijiazhuang, China, in 2003 and M.Sc. degree in computer application technology from Hebei University of Science & Technology, Shijiazhuang, China, in 2016. Since 2011, she has been an assistant professor at Hebei Jiaotong Vocational and Technical College. Her research interests include machine learning and personal recommendation systems.

Yun-Kai Zhang received the BSc degree in radio technology from Hebei University, Baoding, China, in 1986, the MSc degree in computer application from Beijing University of Posts and Telecommunications, Beijing, China in 1997, and the PhD degree in computer application from Xidian University, Xi'an, China in 2006. Since 2020, he has been a professor at Hebei Jiaotong Vocational and Technical College. His research interests include computer networks and application technologies.

Yang Liu received the BSc degree in physics from Hebei Normal University, Shijiazhuang, China, in 2007 and the MSc degree in educational technology from Hebei Normal University, Shijiazhuang, China, in 2011. From 2021 to 2022, he was a research engineer at Hebei Jiaotong Vocational and Technical College. His research interests include data mining and data analysis.

Jin Gao received the BSc degree from the School of Data and Computer Science, Sun Yat-sen University, Guangzhou, China, in 2018 and the MSc degree from the Gansu Provincial Key Laboratory of Wearable Computing, School of Information Science and Engineering, Lanzhou University, Lanzhou, China. Her research interests include machine learning and affective computing.

Qin Xie received the MSc degree in Circuits and Systems from Hunan Normal University, Changsha, China in 2015. Since 2017, she has been an assistant professor at the Department of Electrical and Information Engineering, Hebei Jiaotong Vocational and Technical College. Her research interest includes data acquisition and processing.