Analysis of Supportive Communication Based on TVDM Social Network Information Propagation Dynamics Model: A Case Study of HIV Online Support Groups

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Utilizing digital health technologies for mental health and medical knowledge during HIV/ADS prevention becomes an emphasis proposed by the Joint United Nations Programme on HIV/AIDS (UNAIDS), and supportive communication within HIV online support groups can be its cutting point. Although previous research has delved into the social network structure of HIV online support groups and the content effects on support information, there remains a dearth of exploration about support information propagation within HIV online support groups. This research collects posts (n=1401), comments (n=2402), and reposts (n=1415) from December 2nd, 2016 to August 11th, 2023 within HIV online support groups on Sina Weibo and classes them into emotional and informational support information by SVM model, aiming at quantifying support information propagation probability based on the Time-Varying Damping Motion (TVDM) social network information propagation dynamics model, clustering each type of support information's propagation patterns based on T-SC time series clustering algorithm, and exploring factors of propagation probability with principal component regression. It is found that emotional support information tends to hold a higher propagation probability than informational one, while informational support information likely propagates multiple times. Furthermore, besides network-structural positive effects, the time interval between user posting and user encountering information is negatively associated with information propagation probability. This research provides insight into HIV digital prevention and caring for HIV patients' mental well-being.

Keywords: Supportive communication, HIV, Information propagation

Introduction

The Joint United Nations Programme on HIV/AIDS (UNAIDS) issued the Political Declaration on HIV/AIDS in 2021, highlighting the alarming prevalence of HIV/AIDS infections, underscoring the crucial role of social support and mental health in HIV/AIDS prevention once more, and advocating for the advancement of digital health technologies to empower every individual in attaining the utmost standard of mental well-being. As a representation of digital health technology, HIV online support groups, a primary space for supportive communication proven to buffer negative mental effects contributing to a high level of mental health by previous empirical studies, can be a cutting point for this declaration practice. Furthermore, due to increasingly advanced insight into data analysis methods tailored for big data, a wider array of data types, including behavioral data from online support groups, can now be comprehensively captured and meticulously analyzed. This rich dataset landscape and enhanced analytical tools empower research dedicated to exploring supportive communication within online support groups from multiple dimensions for better HIV prevention efforts.

As digitalization intertwines diverse data types, interdisciplinary collaboration is becoming increasingly prominent. More and more researchers introduce knowledge and methods for Statistics, Psychology, Medicine, and Computer Science to health communication to facilitate in-depth and specialized analysis. Notably, the application of social network information propagation dynamics is gaining traction. This approach leverages mathematical and physical models to scrutinize and predict the propagation patterns of health-related information. It is particularly effective in addressing the propagation of health-related misinformation and rumors. By modeling propagation modes and probabilities and simulating propagation pathways, dynamic models offer a theoretical framework for effectively managing health-related public sentiment and dispelling erroneous health-related notions.

Building upon this context, the present research introduces the Time-Varying Damping Motion (TVDM) social network information propagation dynamics model to explore supportive communication within HIV online support groups. This investigation aims to comprehensively depict the distribution of various types of social support, cluster their propagation patterns, and ascertain factors associated with propagation probability to lay the groundwork for advancing HIV digital prevention and comfort efforts.

Literature Review

Supportive Communication in HIV Online Support Groups

Supportive communication, a concept based on social support in the context of Communication Studies, is defined as proffering aid to individuals in need through verbal and nonverbal behaviors. There are 5 main research clues for supportive communication: (1) the health effect of participating in online support groups; (2) types of social support in online support groups; (3) topics of online support groups discussed; (4) factors that promote or inhibit people to seek for support in online support groups; (5) strategies about seeking for support in online support groups (Pan

& Hu, 2020). Among these clues, significant attention has historically been devoted to exploring supportive communication within HIV online support groups. Drawing on the definition of online support social groups and the research mapping the demographics and structure of HIV support online groups (Liu & Lu, 2018), it is proposed that HIV online support groups refer to a virtual space where HIV-positive patients, people suspecting initial HIV infection, individuals seeking information on behalf of others and people equipped with professional medical knowledge to gather, obtain and provide information and support, learn knowledge and find peers. Due to online support groups' affordance for less time-space constraints and more perceived anonymity, HIV patients tend to seek social support in online support groups rather than face-to-face (Maestre et al., 2018). Meanwhile, the usage level of online support groups, one of this tendency's outcomes, is positively associated with social support receiving, in turn, positively associated with higher levels of self-care self-efficacy to obtain better mental health (Mo & Coulson, 2012). Throughout the process of supportive communication in HIV online support groups, individuals are more likely to provide and seek emotional support than informational support (Guo & Goh, 2014). Also, indirect support-seeking strategies most likely evoke more empathetic emotional responses compared to direct counterparts (Maestre et al., 2018). Additionally, the provision of emotional and informational support within HIV online support groups can facilitate the mitigation of stigma and the attenuation of stigmatizing perceptions among participants (Bauermeister et al., 2019). Nevertheless, the dynamics of supportive communication within HIV online groups are not invariably beneficial. The research proposes that there are 4 types of disempowering processes in HIV online support groups including lack of physical connection, inappropriate online behaviors, real-life relationship decline, and misinformation, posing potential hazards (Mo & Coulson, 2014). While previous research has substantially outlined the theoretical framework and methodologies pertaining to supportive communication in HIV online support groups, there remains a dearth of studies that explore the expansion of this topic, particularly in light of the drivers of support information propagation and updated analysis methods for big data. Some scholars have applied methods for social network analysis and natural language processing (NLP) to dissect network structure and types of messages in HIV online support groups systematically (Liu & Lu, 2018), but lack insight into the temporal sequences and propagation patterns characterizing different types of social support information. And it falls short of elucidating why support information propagates within the current network structure. Summing up to the above, while methods for social network analysis are applied to research online support groups increasingly widely, the tendency to focus on the structure of networks and content features is dominant, sidelining the exploration of information propagation from a temporal dimension. Thus, this research attempts to assess two research questions:

RQ1: What factors affect propagation probability in supportive communication?

RQ2: What differences in information propagation do two types of social support information feature?

Information Propagation Dynamics in Health Communication

Social network information propagation dynamics, a central focus within the realm of social network studies, aims to analyze the influencing factors that govern the propagation of information throughout a network. By employing mathematical and physical models, it seeks to establish correlations and predictions for the evolving state of information propagation (Zhang, 2017). According to different focuses on model building, methods for social network information propagation dynamics can be categorized into 3 types: epidemic models, game models, and physical system models, of which epidemic models and game models are primarily utilized in health communication research.

The epidemic model postulates the information propagation process is the same as the infection. In this model, individuals are classified into three distinct compartments: susceptible (S), infectious (I), and recovered (R), which builds a basic epidemic model, the Susceptible-Infectious-Recovered (SIR) model. Drawing from the SIR model, extended models are built and applied to various research on health communication. Some scholars utilize the Susceptible-Exposed-Infectious-Recovered (SEIR) model to conduct a case study of the “2019-nCoV Explosion”, revealing the information propagation under public crisis is greatly influenced by propagation probability, the network structure, the initial spreader, and social effects (Zhang et al., 2021). To detect mechanisms of rumor reversal, another group of scholars constructs G-SCNDR online rumor reversal model by adopting scientific knowledge level theory and an external online rumor control strategy based on the SIR model, finding improving the popularization rate of the level of users' scientific knowledge and enhancing transformation efficiency of official nodes can positively control online rumors (Wang et al., 2021). Furthermore, in consideration of the repetition of behaviors, some scholars utilize the Susceptible-Infectious-Susceptible (SIS) model to explore the correlation between individual health behavior change and collective health behavior emergence by stimulating the propagation of information about exercise effect perception (Wang et al., 2022). Based on the Ignorant-Spreading-Removal (ISR) model derived from the SIR model (Daley & Kendall, 1964), scholars extend this model by considering persistent rumor spreaders, time delay mechanism and user mobility factors, showing the key to controlling rumors is to reduce the rate of rumor exposure, rumor concern and follower infection and to increase user mobility rate (Wang & Ye, 2023).

Game models provide a formal framework for analyzing how individuals or entities make decisions in situations where their opinions are influenced by the information propagated by others. From this perspective, interaction between each node can be detected to predict the evolution of social networks. Building upon evolutionary game theory, certain scholars delve into the privacy risk perception of users during information sharing, as well as the efficiency of COVID-19 prevention and control efforts, deducing the underlying reason for the inefficiency of COVID-19 prevention and control is the inconsistency between individual and collective rationality (Xiao et al., 2021). Additionally, starting with the network structure, another group of scholars uses evolutionary game theory and considers the vaccination dynamics of structured populations whose members simultaneously belong to disease transmission and information propagation networks, finding different structures of disease transmission networks can induce differences in propagation efficiencies in information propagation networks (Tanimoto, 2015). To ascertain the influences of behaviors of the network media, government, and netizens on misinformation propagation, scholars propose a tripartite evolutionary game model and provide different expected payoffs of three participants using different strategies (Li et al., 2022). Besides, some scholars combine evolutionary game theory and the SIR/V model to introduce the concept of relative information cost. Based on two-strategy and two-under-two strategy games and the effect of information buzz, they calculate the effect of information cost, mapping the final epidemic size, vaccination coverage, and average social payoff (Kabir & Tanimoto, 2019).

While diverse information propagation dynamics models are utilized in health communication, what they principally gear toward is health-related misinformation and prevention control efforts for public health issues like COVID-19 and vaccination. And their applications are rarely considered in supportive communication and online support groups. Meanwhile, current research on supportive communication and online support groups lacks theoretical and methodological insights into support information propagation dynamics. Therefore, there is a significant need to incorporate social network information propagation dynamics models into research related to supportive communication and online support groups.

Methodology

Data collection and reprocessing

Sina Weibo, a Twitter-like microblogging service, is one of the largest microblogging social media in China. By March 2023, more than 593 million active users had access to Sina Weibo. HIV super topic is the largest and only official HIV-related online community on Weibo and was created on December 2nd, 2016, where a cluster of 4,458 members now.

The present research crawls all posts, comments, and reposts, along with their corresponding user IDs, textual content, and timestamps for posting, commenting, and reposting from December 2nd, 2016 to August 11th, 2023. After data cleaning, 1401 posts from 389 users, 2402 comments from 1246 users, and 1415 reposts from 806 users are collected in total. The results of descriptive statistics are presented in the Table 1.

Table 1. Descriptive Statistics Results of Posts, Comments and Reposts

	Total	Mean	Max	Min	Sd
Posts	1401	3.60	470.00	1.00	24.55
Comments	2402	1.93	56.00	1.00	3.11
Reposts	1415	1.76	48.00	1.00	3.46

The research defines commenting on existing posts as the flow of information from users who comment to posters and defines reposting existing posts as the flow of information from posters to users who repost. Based on this definition, the collected dataset forms an asymmetric directed relationship matrix of dimensions 2160 by 2160 with weighted values after applying deduplication to user IDs.

Text binary classification

The social support behavior code identified five types of social support: emotional, informational, tangible/instrumental, self-esteem, and network (Cutrona & Suhr, 1992), but there are overlaps between these types (Maestre et al., 2018). Thus, this research selects the most particular types: emotional and information support to classify textual data. Emotional support is defined as a communicative behavior enacted by one party with the intent of helping another cope effectively with emotional distress. Informational support is understood as behaviors that provide advice, guidance, and facts in order to help someone solve or manage a problem.

To accomplish the binary classification of social support into emotional and informational types, this research utilizes the Support Vector Machine (SVM) algorithm for text classification. The initial step involves labeling all posts and utilizing them as the training dataset. Subsequently, by leveraging the TF-IDF values associated with each post, we proceed to train the SVM model. Ultimately, the trained algorithm's performance is evaluated using comments and reposts, yielding an F1-score of 0.73. And based on the test-passed model, messages are classified into 67.43% emotional support and 32.57% informational support.

Model construction

The time-varying damping motion (TVDM) model is a social network information propagation dynamics model based on physical phenomena. This model regards information propagation as a kind of time-varying damping motion that is a type of motion state where the damping force it experiences changes over time during the motion of an object (Liu et al., 2021). Resting on 4 dimensions of time, space, individual and information, this model considers 7 features displayed in Table 2.

Table 2. Characterization Table

Feature name	Sign	Meaning
Online frequency	ω	Online time habits
Online time difference	φ	The difference in online time
Social relation	m	User network weight
Intimate degree	w	Group closeness
Share willingness	S	Communication initiative
Social reputation	R	User social influence
Information energy	E	Information content value

For operationalization and repeatability, this research chooses feasible methods to measure original features. It defines time intervals between every user posts, reposts and comments every time in HIV online support groups as online frequency, and uses every user's first timestamp to communicate within HIV online support groups as its initial phase in a minimal positive period of propagation. Based on network structural meanings, social relation is estimated by nodes' degree with logarithmic transformation for the smoothing process and intimate degree is estimated by the reciprocal of the normalized shortest distance between two points due to the negative correlation between shortest distance and intimate degree. Share willingness is represented by the out-degree of every node with logarithmic transformation for the smoothing process. Social reputation is estimated by the betweenness centrality of every node. Following the TVDM model, this research still postulates information's own energy is constant.

According to features and definition of time-varying damping motion, the research can denote the propagation distance and propagation acceleration as:

$$x = \sqrt{ESR}\,\sin(\omega t + \varphi)\, r(\omega t + \varphi) \quad (1)$$

$$a = \frac{d^2x}{dt^2} \quad (2)$$

The VTDM model also lays the postulation that information propagation is subject to three forces: (1) Driving force of propagation, signed as F_1, describes the size of the spreader's ability to propagate information, numerically equaling to the product of the spreader node mass and the propagation acceleration. (2) Audience rational repulsive force, signed as F_2, describes the ability of the information audience to identify the information, associating with spreader node mass, intimate degree and F_1. (3) Public opinion force, signed as F_3, is related to the number of nodes and influence factors of government departments or media and F_1. Due to a high level of online support groups collective identification, this research refers opinion influence to influence of top 5 users with the highest centrality. Thus, the resultant force on information from node 1 to node 2 can be denoted as follows as:

$$F = F_1 - F_2 + F_3 = F_1 - \sqrt{\frac{m_2}{m_1+m_2}(1-w)F_1} + \frac{1}{N}\sum_{i=1}^{N} m_i f_i F_i \quad (3)$$

where N, m_i and N_1 refer to the number of corresponding selected nodes, node mass and influence factors, and $F_1 = m_1 a$.

According to the force analysis, the research denotes information propagation probability of information from node 1 to node 2 as:

$$p_{(1,2)} = \frac{F}{m_1} = a(1 - \sqrt{\frac{m_1}{m_1+m_2}(1-w)} + \frac{1}{N}\sum_{i=1}^{N} m_i f_i) \tag{4}$$

Data analysis

The present research delves into supportive communication within HIV online support groups cross-sectionally and longitudinally.

Methods for social network analysis are utilized to describe the distribution of emotional and informational support in HIV online support groups and ascertain differences in their network structure.

Based on the TVDM model, the research calculates the propagation probability of every flow of information and creates a time-varying probability matrix $P_{(i,j,t)}$. In this matrix with 3 dimensions, the matrix element $p_{(i,j,t)}$ refers to the probability of the propagation from node i to node j at time t. Then it applies the T-SC time series clustering algorithms to ascertain propagation patterns of two types of support. Furthermore, the research explores what factors affect the information propagation probability of two types of support by principal component regression analysis.

Results

Social network analysis

Based on the asymmetric directed relationship matrix, the research utilizes Gephi to visualize the social network structure, as shown in Figure 1. In this illustration, nodes represent users, edges symbolize the transmission of support information between two users, and the colors of the edges indicate distinct types of social support. Specifically, red edges represent emotional support, while blue edges signify information support. Relevant metrics for social network analysis are shown in the Table 3.

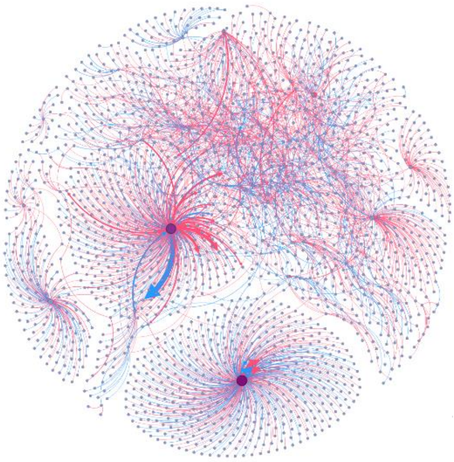

Figure 1. Network Structure of HIV Online Support Groups

Synthesizing the network structure and results of social network analysis, it is found that the structure of information support networks is denser than that of emotional support networks, reflected by the value of the average clustering coefficient. However, the difference in average path length indicates that emotional support networks have higher network scalability. Furthermore, a higher average weighted degree of emotional support networks indicates that more nodes have high influences in emotional support networks.

Table 3. Descriptive Result of Social Network Analysis

	Emotional	Informational
Proportion	67.43%	32.57%
Average clustering coefficient	0.03	0.05
Average path length	4.24	2.28
Average degree	6.92	4.45
Average weighted degree	2.28	1.11
Weakly connected component	603.00	1261.00

To sum up, the internal connections within communities are strong in the informational support network, but the connections between communities are weak. Besides, there are some nodes with high influence in the emotional support networks, and the presence of fewer weakly connected components indicates that there are no significantly isolated nodes or subgroups in the network.

Time series clustering analysis

The T-SC algorithm is designed for clustering time series data. Unlike the K-SC algorithm, which requires specifying the final number of clusters beforehand, the T-SC algorithm initially sets a maximum number of clusters and iteratively performs clustering. This process continues until the distances between cluster centers surpass a predefined threshold, while also dynamically adjusting the number of clusters throughout the iterations (Zhou et al., 2015). To create time series data for propagation probability, the research concentrates on tracking the changes in probability during propagation, using every post's timestamp as the starting point for its corresponding time series. This process integrates both the probability from posters to users who repost and the probability from users who comment to the posters into the time series of every post. This results in the generation of 1,401 time series of propagation probability.

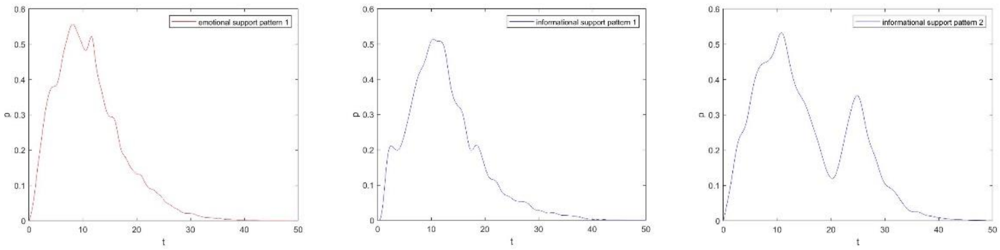

Figure 2. Propagation Patterns of Emotional and Informational Support

According to the clustering result illustrated in Figure 2, it reveals emotional support has one propagation pattern and informational support has two propagation patterns of which one is similar to emotional support. The emotional support pattern and the first pattern of informational support exhibit a rapid increase to a peak within a short period, characterized by a steep slope, followed by a decline towards a stable state where propagation nearly ceases. Notably, although the second pattern of informational support is similar to the first pattern initially, it features a small peak at a later time, which indicates that informational support will propagate again with a little probability after benefiting from visibility endowed by algorithms initially.

Principal component regression analysis

Principal component regression analysis, a statistical method that combines principal component analysis (PCA) and regression analysis, aims at the reduction of multicollinearity and dimensionality of the predictor variables based on differences in their contribution to total variance. Considering social network structure and the TVDM model, there are 5 original predictor variables selected: out-closeness centrality of information source (OCCIS), in-closeness centrality of information target (ICCIT), betweenness of information source (BIS), betweenness of information target (BIT) and time interval (TI). As the result of PCA, the cumulative proportion of the first three components has reached 0.98, indicating they are principal components to represent predictor variables and are supposed to be selected for new predictor variables in multiple regression analysis. And selected components' eigenvectors are displayed in Table 4.

Table 4. Selected Components' Eigenvectors

	OCCIS	ICCIT	BIS	BIT	TI
PC1	0.28	0.35	0.25	0.37	-0.11
PC2	-0.43	0.32	-0.12	—	-0.63
PC3	0.52	0.63	—	—	0.28

Drawing on the PCA result, multiple regression is constructed with selected components as predictor variables, propagation probability as the response variable and types of social support as dummy variables (emotional support = 0; informational support = 1). According to the fit result illustrated in Table 5, it is found that the information propagation probability can be enhanced by nodes with a high closeness and betweenness centrality. Besides, time intervals' effects on information propagation are supposed to be paid attention to, which is presented by PC 2's situation that even if there is a node featuring negative effects from centralities, it tends to improve propagation probability in a short period. Furthermore, while little effect was made by types of social support, there does exist a situation in which emotional propagation tends to propagate compared with informational support.

Table 5. Fit Result

	Estimate	Standard error
PC1	1.22***	0.36
PC2	0.81*	0.46
PC3	-0.42*	0.21
Type of support	-0.03*	0.52

Discussion

Resting on the analysis results from perspectives on social network structure and time series, the research sheds light on information propagation dynamics of supportive communication within HIV online support groups. Particularly, supportive information propagation probability can be simulated and quantified based on the TVDM model considering factors of networks, time and individuals, which proposes a novel perspective differing from research on supportive communication and online support groups by social network analysis and content analysis. Following this clue, it is found that supportive information propagation probability is positively associated with the synergy of source nodes' closeness and betweenness centrality and time interval. Within HIV online support groups, members with a high level of centrality tend to be equipped with high supportive information propagation probability calculated based on the TVDM model. And even if members fail to feature a noticeable level of centrality, their supportive information tends to propagate if other members encounter it within a short period after into online support groups. This finding reinforces correlations between social capital benefiting from network structures and participation behaviors' outcomes and supplements a time dimension for it (Pan et al., 2020).

Differences in types of supportive information are found to affect propagation probability as well. Due to few expertise constraints and much collective identification within online support groups, emotional support is easy to happen between every member. However, the advantages of enhancing its propagation between two members also constrain its broad propagation to more members. Emotional support information is endowed with specificity and privacy which improve the difficulty of its applicability to others. Deconstructing from the perspective of social network structure, the emotional support network features a high level of connection coverage which indicates there is almost no member to be isolated. And viewing the propagation probability reveals that emotional support information features a high probability between two members and can be clustered into 1 propagation pattern indicating it tends to propagate in a short period and fails to propagate further. As for informational support information, it is usually provided by individuals with expertise or related experience. In the informational support network with HIV online support groups, informational support information propagates via weak connections prevailingly. Notably, besides the similar pattern with emotional support, informational support information propagation has another pattern featuring the probability of propagating again after the first time. Valuable informational support information tends to be regarded as knowledge pertaining to online support groups and reserved in networks.

Based on the analysis results, this research provides a theoretical foundation for HIV prevention control efforts and care about HIV-positive patients' mental health as well. According to propagation's features of supportive communication, introducing social media accounts with expertise in HIV and a high level of influence to HIV online support groups can be helpful to garner attention on HIV prevention and duly provide information to help patients ascertain situations they are facing, erase their anxiety and endow them with a high level of self-care self-efficacy in problem-solving. Furthermore, official social media accounts can post HIV-related information periodically in HIV online support groups to reduce the negative effects of asynchronization on information propagation. Considering the emotional support information propagation pattern, it is a nice try to add chatbots geared toward HIV patients to online support groups for direct and private conversations with members, and supportive responses from chatbots can benefit patients' mental health.

As an attempt to employ a social network information propagation dynamics model in supportive communication, this research proposes a novel perspective but has limits as well. Drawing on a high level of collective identification within online support groups, this research defines the force of opinions referring to influences of the top 5 users with the highest centrality, while not considering influences outside the online support groups. Furthermore, this research simply codes textual data with emotional and informational support, lacking further content analysis for a more refined classification to verify the assumption that support information's content contributes to the underlying mechanism of support information propagation. Besides, this research implements a social network information propagation model to bridge propagation networks and individuals' behaviors, but there exists a research gap about a combination of networks and individuals' psychology. The research question about the relationship between what people think, what people say and what people do within supportive communication is not answered clearly.

Conclusion

In conclusion, this research employs the TVDM model in supportive communication within online HIV support groups to simulate the support information propagation process and estimate its propagation probability, based on time-varying damping motions. It is revealed that besides structural social capital' positive association, the time interval between the time users post and users encounter information is negatively associated with support information propagation probability. Furthermore, emotional support information propagation features one pattern near one-shot propagation, while informational one has another pattern with the probability of propagating several times besides one-shot propagation. Ultimately, the result of principal component regression suggests that emotional support information tends to propagate between two users, compared with informational support information. This research answers why support information will propagate within social networks and what factors affect this propagation. And it proposes a novel perspective for researching supportive communication considering information propagation. Also, it provides a theoretical foundation for HIV prevention control efforts and caring about HIV-positive patients' mental health.

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