Research on the Formation and Operating Mechanism of College Students' Network Circle Group Subculture: Based on the Perspective of Big Data Management

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Abstract. With the network circle group becoming the mainstream form of college students' online social communication, the accompanying subculture phenomenon has attracted the attention of researchers and business managers. The spread of big data collection and analysis technology has helped operators shape and guide subcultures and capture more revenue. Based on the decision-making trial and evaluation laboratory (DEMATEL) and interpretive structural modeling (ISM) composite model, this paper analyzes the interaction mechanism among enterprise big data management capabilities, network circle group information communication attributes, user's personal factors and subcultures. The results show that the privacy and professionalism of the network circle group provide a unique shaping environment for the subculture, forming a "behavior-emotion-behavior" subculture generation and feedback process. The capability to push unstructured data plays an important role in the formation of subcultures. Comparatively speaking, the influence mechanism of user screening capability and big data value enhancement capability on subcultures is relatively complex. Therefore, the capability to pay full attention to and make use of the characteristics of network circles groups is the key for operators to improve their data profitability. The influence of college students' family environment and information literacy on subculture is more direct, and college students' willingness to share information and sense of identity is easier to realize in the context of network circle group.

Keywords: Network circle group, Subculture, College students' network socializing, Big data, DEMATEL-ISM

1 Introduction

In the era of Internet social networking, the explosive growth of information scale has triggered simultaneous changes in the way users socialize and the way social media operate. In terms of users, the improvement of information retrieval and use ability enables network social communication to exchange information in the form of small groups [1]. Users based on specific purposes or identities gather into "circles", forming network circle groups [2]. For enterprises, the social media management model based

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on big data mining, analysis and push is becoming more and more popular [3]. Due to the lack of social experience and the greater emphasis on trust, college students become loyal followers of network circle groups [4]. In the process of online social communication, college students rely on the natural boundary between network circle groups, and it is easier to form subculture phenomenon than before. For the purpose of profit, network circle group operators often push user preferences based on big data analysis results, so as to improve the efficiency of user information acceptance and network circle group dependency [5]. However, a hidden danger is that it may lead to the rapid and hidden spread of false news, rumors, and negative emotions within the network circle group [6]. For college students, a positive network social environment helps them to form a good attitude of study and life, to face various challenges, and to improve the efficiency of knowledge acquisition and use [7]. However, the habit of blindly following the trend makes college students vulnerable to the negative impact of network subculture [8]. Under the background of big data management, this paper explores the formation and operating mechanism of network circle group subculture, which has both theoretical innovation and practical value.

As a relatively independent and minority cultural form, subculture has a significant impact on the behavior of young people [9]. Subculture is a double-edged sword. In the early stage, more scholars believed that the existence of subculture was a confrontation against the mainstream culture, and although it did not necessarily lead to negative emotions and behaviors, "rebellion" was its essence. With the increase of subculture phenomenon, some scholars began to believe that subculture is a supplement and derivative of mainstream culture, and a cultural form that coexists with mainstream culture, and its mechanism is relatively complex [10]. Many scholars have discussed the process of the emergence and spread of subculture. For example, the origin and function of subcultures [11], antecedents and associated factors of the formation of subcultures [12, 13], subculture differences in different regions [14, 15], the relationship between subculture and corporate management activities [16, 17, 18] and so on. However, there is obvious room for improvement in the existing literature. On the one hand, the evolution mechanism of college students' network circle group subculture in the context of Internet social communication is still unclear. On the other hand, few scholars have analyzed the shaping and guiding process of subculture based on the perspective of big data push. In view of this, this paper comprehensively considers the big data push and user management process of the network circle group, the network social characteristics of college students, the inducement factors and manifestations of subculture, extracts the antecedents and outcome variables of the network circle group subculture of college students, uses the DEMATEL-ISM model and verifies the categories of variables on the basis of expert research and judgment data. Explore the correlation structure and relative importance, and form the corresponding management implications.

2 Conceptual Model Design and Variable Selection

Network circle group subculture is a personalized expression of user emotions [19]. Operators of social networking sites or mobile applications use big data analysis and application technology to attract users into the network and shape the differences between the network circle groups, in order to facilitate diversified profit opportunities [5]. College users find like-minded social partners and seek identity through social networking [4]. Therefore, the shaping process of college students' network group subculture needs to comprehensively consider operators' big data management capabilities, network circle group information communication attributes and users' personal factors. In addition, Subculture representation includes users' extrinsic behavior and internal emotion. After the formation of subculture, it may also have an impact on the behavior of operators and users. The conceptual analysis model of subculture formation and operating mechanism proposed in this paper is shown in Figure 1.

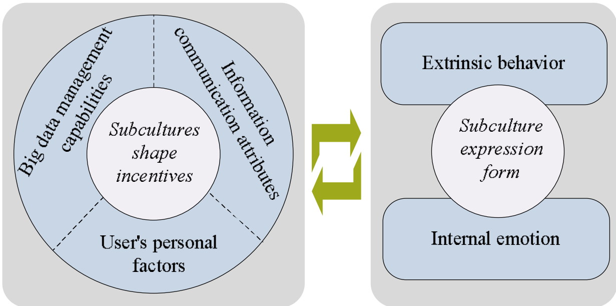

Fig. 1. Conceptual Analysis Model

Big data management capabilities. Identifying accurate information from a large amount of online data and using it to screen users with differentiated communication demands and help them gather in the network circle group is the basis of operators' big data management [20]. The diversified information expression forms of the network circle group, such as text, pictures, voice, video, etc., require operators to have the ability to push unstructured big data [21]. Big data is often characterized by a relatively "low value density." That is, data received in its raw form usually has a low utilization value relative to its size [22]. Operators that can provide high value density information are more likely to help network circle group users generate emotional resonance. Therefore, user screening capabilities, unstructured data push capability, and big data value enhancement capability are important prerequisite for operators to shape network circle group subculture through big data management.

Network circle group information communication attributes. Compared with the more open and clear information push criteria of public channels, the dissemination of information in network circle groups has the characteristics of privacy and professionalism [23, 24]. It is the semi-open communication environment that provides a suitable network environment for the generation of personalized subcultures, and also increases users' sense of belonging and security [25]. There is reason to believe that the privacy and professionalism of the communication channels contribute to the formation of a personalized and stable subculture among users.

User's personal factors. For college students' network circle group users, information reception and dissemination behavior are not only affected by information characteristics and social environment characteristics. Different personal experiences, abilities, and personalities are characterized by differentiated lifestyles, musical preferences, shared values, and behaviors [26]. Family constraints and support will have an impact on young users' Internet use behavior [27]. Being easily influenced by peers or friends makes it easier for users to fit into the network circle group subculture [28]. With the deepening of the application of network technology and information technology in university campuses, in the context of big data, the cultivation degree of information literacy affects the level of information collection and response of college students [29]. Therefore, the degree of lack of family security, information sharing tendency and information literacy affect college students' reaction attitude to all kinds of information.

Subculture representation. The measurement of subculture has always been a complicated problem. Bonds, emotions, and solidarity are essential features of subcultures [14]. The external manifestations of subcultures are easier to grasp. Demonstrating commitment and individuation of consumption mode are the most typical explicit ways of subcultural behavior [30, 31]. Relatively speaking, the internal emotions contained in subcultures are not easily perceived by the outside world. Based on long-term research, vicarious satisfaction and common feeling have been identified as psychological factors that maintain the internal cohesion of specific subcultures [32, 33].

Based on the literature review and conceptual analysis model, the causal variable library of subculture shaping of college students' network circle group proposed in this paper is shown in Table 1.

Table 1. Causal Variable Library

Variable name	Variable code	Variable meaning
User screening capabilities based on big data	DA1	The capability to identify and accurately recommend information to users based on big data technology
Unstructured data push capability	DA2	Text, picture, voice, video and other data push capability
Big data value enhancement capability	DA3	The capability to meet user requirements with "high value density" information
Information dissemination privacy	IA1	The dissemination of information is confined within the network circle group
Specialization of information exchange	IA2	College student users have sufficient professional knowledge and clear communication purposes
Lack of family security	PF1	The degree to which family members ignore the psychological needs of college students
Information sharing tendency of college students	PF2	College students originally intended to share information with their peers on the Internet
College students' information literacy	PF3	The ability of college students to learn and use Internet data information

Demonstrating commitment	SR1	College students express their identification with a particular content or style through actions or words
Individuation of consumption mode	SR2	College students consume specific types of music, clothing, food, or other goods
vicarious satisfaction	SR3	Network communication status, content and rules help college students realize their social desires
Common feeling	SR4	College students share similar values, emotions, rules, sanction mechanisms, or habits

3 Research Method

This paper uses the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Interpretive Structural Modeling (ISM) performs quantitative processing of data. As two types of quantitative analysis methods based on graph theory and matrix operation, DEMATEL can measure weighted directed correlation structures among variables, while ISM is good at mining complex hierarchical relationships between antecedent and result variables [34]. The combination of the above two methods can be realized through a specific matrix operation. Therefore, DEMATEL-ISM has been favored by scholars in the field of big data application and big data technology evaluation in recent years [35, 36]. The quantitative analysis process is shown in Figure 2.

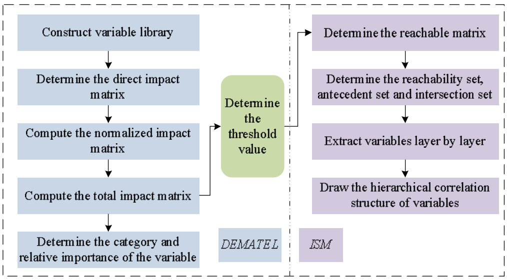

Fig. 2. Quantitative Analysis Process

After the variables are identified and the panel members are screened, the relevant calculations are completed in six steps. Step 1: Build a direct impact matrix based on expert assignment. The expert scores after multiple rounds of coordination constitute a direct impact matrix X between variables, which is shown in equation (1). Each element of the matrix is an integer between 0 and 4, expressed as x_{ij}, reflects the binary relationship between variables, and the variables themselves do not need to be compared, that is, the value on the diagonal of the matrix is "0".

$$X = \begin{bmatrix} 0 & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & 0 \end{bmatrix} \quad (1)$$

Step 2: The direct impact matrix is converted into a normalized impact matrix. After taking the maximum value of the row sum as the normalized base, turning the matrix X into a normalized impact matrix N , as shown in equation (2).

$$N = \frac{1}{\max_{0 \le i \le n} \sum_{j=1}^{n} x_{ij}} \tag{2}$$

Step 3: Calculate the total impact matrix. The normalized impact matrix is calculated with the identity matrix to obtain the total impact matrix T , as shown in equation (3), where I is the identity matrix.

$$T = N(1 - N)^{-1} \tag{3}$$

Step 4: Calculate the influence degree, influenced degree, centrality degree, and causality degree of the variables. Set D_i as the sum of the values of i row in the matrix T , taking into account the direct and indirect effects of variable i on other factors, D_i indicating the comprehensive impact of variables on other variables i . Similarly, set R_j to the sum of the values of j column in the matrix T , R_j representing the sum of the direct and indirect effects of all other variables on the variable i . When $i = j$ is used, $(D_i + R_j)$ indicates the sum of impact and impact of variable i , that is, the centrality. This represents the importance of variable i . $(D_i - R_j)$ represents the net effect of variable i . If it is positive, then variable i is the antecedent variable, if it is negative, then variable i is the result variable.

Step 5: Generate the reachable matrix. The matrix $H(H = T + I)$ is formed by adding T to the identity matrix I , and the basic condition of transformation into the reachable matrix of ISM model is obtained. Since the range of values assigned in the reachable matrix is 0 or 1, a reasonable threshold λ needs to be set to convert the elements of the matrix H to a value of 0 or 1. Let h_{ij} be an element of matrix H , and according to equation (4), value h_{ij} can be converted to k_{ij} , and finally an reachable matrix K can be formed.

$$k_{ij} = \begin{cases} 1, h_{ij} \ge \lambda \\ 0, h_{ij} \le \lambda \end{cases} \tag{4}$$

Step 6: Determine the hierarchy association structure of variables. By extracting the elements of the reachable matrix whose value is 1, the reachable sett, the antecedent set and the common set can be determined. Where, the reachable set is the set of variables corresponding to all columns of matrix element value 1 in row i of the reachable matrix, represented by $R(i)$. The antecedent set is the set of variables corresponding to the row of all matrix elements with value 1 in column i of the reachable matrix, represented by $Q(i)$. $C(i)$ is the intersection of the reachable set $R(i)$ and the antecedent set $Q(i)$. When $C(i) = R(i)$ is satisfied, the corresponding variable is a peer variable, then the row i and the column i in the reachable matrix K can be extracted. This step is repeated until all variable levels are confirmed.

In the process of data collection, 5 file grading criteria are set, and the evaluation criteria of each score are: "0-no impact", "1-little impact", "2-average impact", "3-great impact", and "4-very great impact". According to the research purpose, the 10 experts selected in this paper include researchers of big data analysis, network circle group operation, college student management, and senior enterprise managers. Through multiple rounds of scoring and point of view communication, a unified evaluation result is finally formed.

4 Analysis of Relative Importance of Variables

Through DEMATEL model operation, category judgment and relative importance indicators among variables are shown in Table 2. According to the calculation result, the influence degree of DA1, DA3, PF2, SR1, SR2, SR3, and SR4 is smaller than the affected degree. Proving that an enterprise's capability to use big data to screen users and accurately push the information they need can only be effectively formed through long-term interactions between the enterprise and users. The tendency of college students to share information is influenced by the social process of the network circle group and cannot be regarded as an innate attitude of online social communication. The variables' causalities related to the subculture are all negative, which proves that the subculture of the network circle group does not exist at the early stage of the establishment of the group, but is the result of the data push behavior of the operator and the online social interaction behavior of the user.

Table 2. Key Indicators of DEMATEL Model

Variable	Influence degree	Affected degree	Centrality	Causality
DA1	2.729	2.900	5.629	-0.171
DA2	3.033	1.342	4.376	1.691
DA3	3.182	3.815	6.997	-0.633
IA1	3.562	2.596	6.158	0.966
IA2	4.196	1.861	6.057	2.335
PF1	3.048	0.976	4.024	2.073
PF2	3.867	4.513	8.380	-0.646
PF3	4.119	1.536	5.655	2.583
SR1	2.700	5.583	8.283	-2.883
SR2	2.921	4.335	7.256	-1.414
SR3	2.086	3.973	6.060	-1.887
SR4	3.530	5.543	9.073	-2.013

The influence degree of DA2, IA1, IA2, PF1, and PF3 is larger than the affected degree. The above calculation results show that the capability of enterprises to push unstructured data will affect the adoption attitude and subsequent behavior of network circle group users, which is an important antecedent of the formation of subculture. The privacy and professionalism of the network circle group provide distinct situational conditions for shaping the subculture. It is the relatively private communication environment that helps build trust and a sense of belonging between users. The lack of family care and the improvement of college students' ability to use network information jointly drive college students to go to the network world, find their peers in the virtual environment, and then build "minority" cultural symbols.

With zero value of causality and mean value of centrality as classification criteria, the distribution of relative importance and functional positioning among variables is shown in Figure 3. The distribution of variables shows that the importance of variables that promote the formation and play a role in subculture is low, which means that there is no strong influence factor in the process of subculture shaping. Relatively speaking, the enterprise capability to enhance the value of big data plays an important mediating role in the formation of network circle group subculture and the feedback of subculture on user behavior.

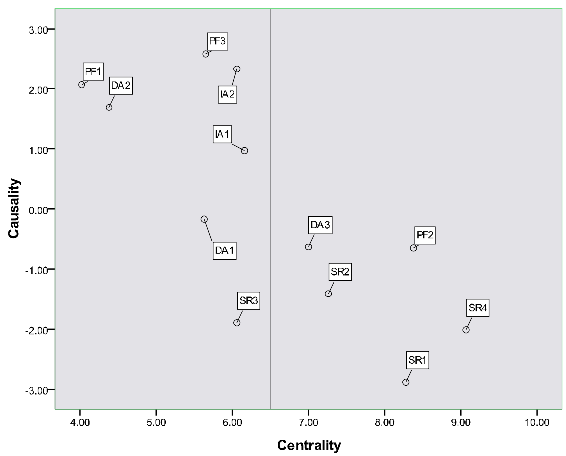

Fig. 3. Distribution of Variable "Causality-Centrality"

5 Analysis of Hierarchical Correlation Structure of Variables

According to the results of total impact matrix data in DEMATEL's calculation process, the sum of factor means and standard deviation (0.4158) are selected as the threshold value. After adding the total impact matrix and the identity matrix, the matrix elements are converted to "1" or "0" based on the threshold value, and the reachable matrix required for ISM model calculation is generated. Then, the reachable set, antecedent set and common set of various variables are obtained, as shown in Table 3.

Table 3. Decomposition Table of Variable Correlation Structure

Variable	ID	Reachable set	Antecedent set	Common set
DA1	1	[1, 9]	[1]	[1]
DA2	2	[2, 9, 12]	[2]	[2]
DA3	3	[3, 9, 10, 12]	[3, 5]	[3]
IA1	4	[4, 7, 9, 12]	[4]	[4]
IA2	5	[3, 5, 7, 9, 10, 12]	[5]	[5]
PF1	6	[6, 9, 12]	[6]	[6]
PF2	7	[7, 9, 10, 12]	[4, 5, 7, 8, 12]	[7, 12]
PF3	8	[7, 8, 9, 11, 12]	[8]	[8]
SR1	9	[9]	[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12]	[9]
SR2	10	[9, 10, 12]	[3, 5, 7, 10]	[10]
SR3	11	[11]	[8, 11]	[11]
SR4	12	[7, 9, 12]	[2, 3, 4, 5, 6, 7, 8, 10, 12]	[7, 12]

According to the extraction criteria of ISM variables, the hierarchical association structure of variables with 5 levels is constructed, as shown in Figure 4. According to the hierarchical relationship between variables, all variables can be divided into three categories, including antecedent variables, intermediate variables and result variables. It should be noted that in terms of explaining causal logic of variables, DEMATEL model focuses on category judgment and relative importance analysis, while ISM model focuses on multi-level decomposition of causal logic of variables. Therefore, the variables defined by ISM as intermediate effects may be judged as result variables or antecedent variables in DEMATEL model.

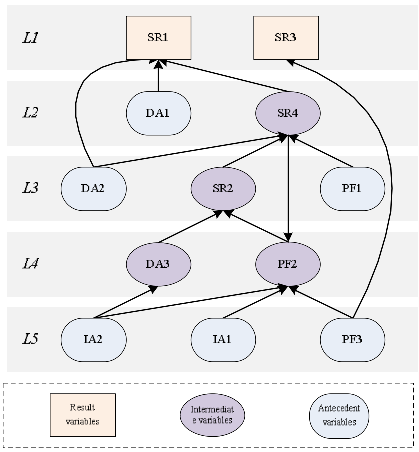

Fig. 4. Hierarchical association structure of variables

The variable hierarchy association structure indicates that, different from other social modes, network circle group builds a relatively independent social environment for college students. The highly professional content of the communication provides the conditions for enterprises to quickly grasp the needs of users and provide high-value information. At the same time, professionalism and privacy bring college students a sense of environmental security and stimulate the desire to share information within the network circle group. The improvement of information literacy accelerates the process of college students' adoption of information in network circle groups and arouses more willingness to share information. Relatively speaking, the effect of enterprises using big data to identify users and push unstructured data mainly depends on the enterprise's big data management capabilities. The user's personal factors and family upbringing are of limited importance to network circle group operators.

The relationship between internal emotions and external behaviors of college students' network circle group subculture is complicated. Individuation of consumption mode is the primary sign of subculture formation. It is different from the "attitude determines behavior" principle that is common in social activities. After the acceptance and implementation of a specific consumption mode, there will be a strong emotional resonance among college students' network circle group users, and finally express their identity and style of a certain subculture through language and action. In college students' network circle group, the formation process of vicarious satisfaction is relatively special. Only with a higher level of Internet data usage ability can college students form a higher level of social status in the network circle group, and then help them realize the desire that is difficult to satisfy in offline communication.

6 Managerial Implications

Based on the analysis of variable function positioning, relative importance level and interaction relationship, it can be found that network circle group situation poses new challenges for operators' big data management capability. These new situations also apply to the understanding and management of college students' social network. The management implications of this research are as follows:

If operators want to improve the effectiveness of information push and seek profit opportunities by influencing the shaping process of subcultures, the push capability of unstructured data should be given sufficient attention. Subculture is a comprehensive expression of users' internal psychological emotions and external social behaviors. Unstructured information helps college students understand and express personalized cultural symbols. Whether the unstructured data can be collected and utilized effectively will become the key for network circle group operators to grasp user resources. Not only that, different from user screening capability and data value enhancement capability, the impact mechanism of unstructured data push capability on users is relatively simple, and it is more beneficial to operators from the perspective of operational costs.

Enterprise big data push and marketing should pay attention to the situational characteristics of network circle groups. The result of privacy and professionalism is that the exclusion of external members of the network circle group is more obvious. The advantage is that the information transfer speed within the network circle group is fast, the value recognition is high, and the user stickiness is strong. On the downside, the unique discourse system and relatively strict access regime build communication barriers, making it more difficult for operators to judge user needs. Therefore, whether the differences between network circle groups can be successfully identified is the key to improve the efficiency of operators' big data utilization.

Different from the interactive way of public platform, the shaping logic of subculture is "behavior-emotion-behavior". This requires enterprises to adopt more direct digital marketing methods. Enterprises can make use of obvious subcultural symbols, such as stories, music, sports, animation, tools, etc., to increase the willingness of college students to adopt advertising and product information. Similarly, the attention and guidance of college students' online social behaviors can also start from the recognizable subcultural symbols, without paying too much attention to the psychological activities of college students.

7 Conclusions

Network circle group has become one of the main forms of college students' online virtual socializing, and the accompanying subculture not only embodies the social attitudes and behaviors of network circle group users, but also provides opportunities for operators to promote marketing information and enhance profitability. By constructing DEMATEL-ISM comprehensive analysis method, the relative importance and hierarchical correlation mechanism of variables are systematically analyzed. The interaction mechanism among enterprise big data management capability, network circle group information attribute, user personal factors and subculture is clarified. Based on the results of data analysis, the emphasis on improving the enterprise's big data management capability is clarified, the opportunities and challenges brought by the exclusive communication situation of network circle groups are found, and the role of family factors and personal preferences in the process of college students' acceptance and presentation of subcultures is further clarified. There are still some limitations in this study. On the one hand, network circle groups have a variety of categories, this paper only selected the basic attributes for analysis, and did not consider the differences in the shaping process of subcultures within various circle groups. On the other hand, the data information based on expert experience judgment still cannot completely eliminate the error. In the follow-up research process, data collection and analysis can be carried out at the user level, and further exploration can be made by other statistical methods.

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