# Evaluation of Word-of-Mouth Influence of Cross-Border E-commerce Products Based on Social Network Data Analysis

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**Abstract.** To improve the performance of word-of-mouth impact assessment for cross-border e-commerce products, a method based on social network data analysis is proposed for evaluating the word-of-mouth impact of cross-border e-commerce products. Eliminate abnormal users on social networks and establish an evaluation index system for the reputation and influence of cross-border e-commerce products. Based on this system, the basic indicators for evaluating the word-of-mouth impact of cross-border e-commerce products are determined, and an indicator weight judgment matrix is constructed using Analytic Hierarchy Process to calculate the weight of the word-of-mouth impact evaluation indicators for cross-border e-commerce products. Based on the weight calculation results, a word-of-mouth impact evaluation algorithm for cross-border e-commerce products was designed to achieve the evaluation of word-of-mouth impact of cross-border e-commerce products. Case analysis demonstrates that this approach effectively evaluates the impact of word-of-mouth for cross-border e-commerce products with a 95% improvement in evaluation efficiency and reliability, boosting overall performance.

**Keywords:** Social Network Data Analysis · Cross-Border E-Commerce · Product Reputation · Effect · Assessment · Weight Calculation

## 1 Introduction

With the upgrading of China's consumption structure, the domestic market's demand for overseas goods continues to release. In addition to the favorable policy background, import cross-border e-commerce has developed rapidly. At present, import and retail cross-border e-commerce is mainly based on the B2B model, but in recent years, the transaction scale and proportion of import and retail cross-border e-commerce have continued to expand. According to the statistics of Intelligent Research Consulting, the transaction scale of import and retail cross-border e-commerce has rapidly increased


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from 47.8 billion yuan in 2012 to 408.2 billion yuan in 2016, from 19.9% to 34% of the import cross-border e-commerce transaction scale, and is expected to increase to 40% in 2018. With the expansion of consumer demand and the tightening of regulatory policies, import and retail cross-border e-commerce has gradually developed from C2C mode to B2C mode [1]. In 2016, the transaction scale of B2C mode accounted for 56.4% of import and retail cross-border e-commerce.

In domestic research, Chen Yufen [2], conducted risk analysis on four links involving commodity quality, and built a risk identification, evaluation index system, risk measurement. The quality risk assessment system of imported B2C cross-border e-commerce goods is divided into five parts, namely, risk rating and risk cause tracing, and takes Hangzhou imported B2C cross-border e-commerce enterprises as an example for empirical research. The problem of how to maintain the reputation of cross-border e-commerce platform reputation defenders when facing one or more losers was attempted to be solved by Zhan Haoling and others [3], by establishing a multi-objective Stackelberg game model with incomplete information of defenders and losers. In this model, we analyzed the prior probability, damage effect, and the impact of input costs of both sides on the maintainer's strategy in the reputation network game model of cross-border e-commerce platforms, and put forward relevant suggestions. In foreign research, Zhang X et al. [4] mainly studied the mechanism and model of cross-border e-commerce green supply chain based on customer behavior. The green supply chain partners select 24 secondary indicators of the evaluation system as input vectors. Wang F et al. [5] examined the differences in the impact of OL and WOML on consumer decision-making in three stages of online shopping through the theoretical approach of motivation reinforcement. The results indicate that when consumers purchase products with high participation, word-of-mouth has a greater impact on the consumer decision-making process than OL, while when consumers purchase products with low participation, OL has a greater impact on the consumer decision-making process than word-of-mouth. Miremadi A et al. [6] published a topic titled "Evaluation of the Role of Electronic Word of Mouth (EWOM) in Customer Perception and Behavior in Electronic Stores". Then, research hypotheses and objectives were proposed, and samples required for methodology, statistical population, and analytical techniques were introduced to achieve the assumed objectives and results. Miranda S et al. [7] used a mixed method of symmetry and asymmetry. Through SEM, it was found that consumers with high suspicion of behavior, perfectionism oriented towards others, and a lack of recognition of imperfections have a lower tendency to provide positive word-of-mouth due to their higher perception of social risks.

This paper evaluates the word-of-mouth influence by analyzing social network data. Firstly, by removing abnormal users from social networks, the accuracy and reliability of evaluations can be improved. Secondly, a cross-border e-commerce product word-of-mouth influence evaluation index system has been constructed, which includes a series of indicators that can reflect the product's word-of-mouth influence, such as the number of comments and likes. Then, by calculating the weights of evaluation indicators, the importance of each indicator in the evaluation of word-of-mouth influence can be determined. Finally, an algorithm for evaluating the word-of-mouth influence of cross-border e-commerce products was designed, and the product's word-of-mouth influence score was obtained by integrating the weights and values of various indicators. Through this study, the word-of-mouth influence of products can be objectively and accurately evaluated. This helps cross-border e-commerce platforms and merchants understand the reputation and performance of products in the market, thereby improving product improvement and market promotion, enhancing product competitiveness and sales performance.

# 2 Design of Evaluation Method for Word-of-Mouth Influence of Cross-Border E-commerce Products

## 2.1 Eliminate Abnormal Users of Social Networks

The degree of co-occurrence of two commands in social network user login is called tight density. Here, we use the sliding window to measure the tight density of cross-border e-commerce product word-of-mouth evaluation commands. Social networking [8, 9] user history operations are recorded as a sequence of shell commands. The command sequence is collected through the sliding window, and the word-of-mouth evaluation commands often used together will appear in a window. Assuming that the sliding windows are numbered and the windows that appear in each command are counted, each word-of-mouth evaluation command will correspond to a feature vector and represent the window that has already appeared, then the similarity between vectors is the tightness between social network users' word-of-mouth evaluation commands.

Set two parameters related to sliding window: sliding window size $s$, which is the number of commands that the window can hold. Window change step $l$, which is the number of sliding commands per window. When the window is sliding, count the number of times each command appears in the window. Set the training data length to $L$, all commands in training data are $\Sigma$, the number of different commands is $m = |\Sigma|$, the number of windows is $n = \frac{L-s}{l} + 1$. The login characteristic data of social network users can be expressed as $m \times n$ Matrix of $W$, the expression is:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ w_{n1} & w_{n2} & \cdots & w_{nm} \end{bmatrix} \tag{1}$$

Among them, $W$ is the vector values in the columns in indicate the frequency of the corresponding commands in different windows, $W$ is the vector value of each line in indicates the frequency of different commands in the corresponding window.

Setting and $W$ pass the civil examinations $i$. The corresponding command listed is $s_i$, to measure two random commands $s_i$ and $s_j$. For the purpose of compactness $W$. Two matrices are generated, namely:

$$B = \left[b_{ij}\right] \tag{2}$$

$$B^* = \left[b^*_{i'j'}\right] \tag{3}$$

Among them, $B$ and $B^*$ represents a binary matrix, $b_{ij}$ indicates a command $s_j$ in the window $\varpi_i$ whether it appears or not. The same command appears more frequently in the window, which can be seen as the result of the alternate appearance of the command and its twin commands, $b^*_{i'j'}$ representative order $s_j$. Twin command $s_j$ in window $\varpi_i$ whether it appears or not.

According to the above analysis and calculation, we can get the formula for calculating the compactness between the two commands of social network users' evaluation of cross-border e-commerce product reputation:

$$Clo(s_i, s_j) = \begin{cases} \frac{b_i \cdot b^*_{i'}}{\|b_i\| \cdot \left\|b^*_{i'}\right\|}, s_i, s_j \in \Sigma \cap i = j \\ 0, s_i \notin \Sigma \text{ or } s_j \notin \Sigma \\ \frac{b_i \cdot b_j}{\|b_i\| \cdot \|b_j\|}, s_i, s_j \in \Sigma \cap i \neq j \end{cases} \tag{4}$$

The average closeness of word-of-mouth evaluation commands in the window can be called the window convergence degree. Assuming that the word-of-mouth evaluation commands in the window are frequently used by legitimate users, the higher the window convergence degree is; Otherwise, the window aggregation degree is lower.

According to formula (4), social network users evaluate the compactness between the two orders of cross-border e-commerce product reputation $Clo(s_i, s_j)$ the calculation formula can effectively detect the word-of-mouth evaluation order by social network users with low degree of aggregation, and eliminate such users as camouflage users.

### 2.2 Build an Index System for Evaluating the Word-of-Mouth Influence of Cross-Border E-commerce Products

On the basis of fully understanding the concept and characteristics of word-of-mouth influence of cross-border e-commerce products, this paper uses literature search, process analysis and field research methods to identify the word-of-mouth influence in the four links of overseas procurement, warehousing logistics, platform sales and product after-sales under the bonded warehouse and overseas warehouse models. This constitutes a list of word-of-mouth influence of cross-border e-commerce products. At the same time, utilizing the distinct implications of diverse effects and the accessibility of diverse impact indicator information, while adhering to the principles of inclusiveness, feasibility, comparability, and relevance in constructing the indicator framework, a word-of-mouth impact assessment indicator framework for cross-border e-commerce products has been devised, demonstrated in Table 1. The specific construction process of the evaluation indicator system of word-of-mouth influence is shown in Fig. 1.

Based on the principles of comprehensiveness, operability, comparability and pertinence in the construction of the indicator system, the evaluation indicator system of the reputation influence is constructed.

### 2.3 Calculate the Weight of Cross-Border E-commerce Products' Reputation Impact Evaluation Indicators

Based on the evaluation index system of word-of-mouth influence of cross-border e-commerce products, the analytic hierarchy process [10–13] is used to calculate the

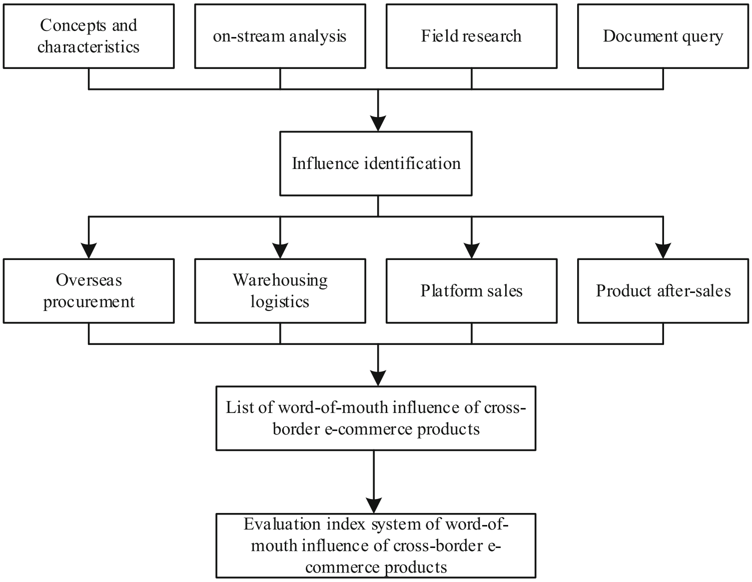


**Fig. 1.** Construction process of evaluation indicator system for word-of-mouth influence of cross-border e-commerce products

weight of the evaluation index of word-of-mouth influence of cross-border e-commerce products. The specific calculation process is as follows:

Step 1: Determine the basic indicators for evaluating the reputation influence of cross-border e-commerce products.

Users can obtain relevant information about cross-border e-commerce products on various social networks. According to the analysis of social network data, the basic indicators for evaluating the word-of-mouth influence are determined, namely:

$$N = \begin{cases} \sqrt{N_w} + \zeta \\ \sqrt{(X_a B_b)^2} + \zeta \end{cases} \tag{5}$$

where, $N_w$ indicates the quality indicators of cross-border e-commerce products, $X_a$ represents the security base in transportation, $B_b$ represents the safety amplitude in transportation, $\zeta$ represents the weight coefficient.

Step 2: Build indicator weight judgment matrix.

After determining the basic indicators for evaluating the word-of-mouth influence of cross-border e-commerce products, the redundant information of the evaluation indicators at different levels is normalized by comparing the evaluation indicators at the same level, so as to improve the accuracy of the weight calculation of the word-of-mouth influence evaluation indicators of cross-border e-commerce products. If the evaluation indicators of different levels are redundant $i$ and $j$ the comparison results of $v_{ij}$, then the indicator weight judgment matrix can be expressed as:

$$v_{ij} = \frac{1}{v_{ji}} \tag{6}$$

**Table 1.** Evaluation index system of word-of-mouth influence of cross-border e-commerce products

| Target layer | Primary indicators | Secondary indicators |
|---|---|---|
| Evaluation index system of word-of-mouth influence of cross-border e-commerce products | Overseas procurement | Cognition of product quality standards |
| | | Supplier qualification and credit level |
| | | Supplier supply defect rate |
| | | Product acceptance mode |
| | Warehousing logistics | Warehouse sanitation and safety compliance rate |
| | | Sampling inspection frequency of product quality in stock |
| | | Rationality of product logistics, transportation and packaging |
| | | Operation error rate of logistics personnel |
| | Platform sales | Number of platform entry assessment items |
| | | Monitoring frequency of platform public opinion |
| | | Lack of product traceability information |
| | | Lack of information displayed online |
| | After sales | Number of after-sales guarantee items |
| | | One time solution rate of after-sales quality problems |
| | | Collection frequency of product after-sales quality information |

Step 3: Process coincidence indicators.

When evaluating the word-of-mouth influence of cross-border e-commerce products, we need to make up for the shortcomings of influence evaluation indicators from different perspectives, which will lead to overlap of evaluation indicators. In order to ensure the rationality of evaluation indicators in the evaluation of reputation influence of cross-border e-commerce products, according to $n_1 + n_2 \leq 2\sqrt{n_1 n_2}$ based on the inequality principle, redundant information of coincidence index is removed.

Step 4: Calculate the weight of the evaluation index of word-of-mouth influence at all levels.

First level evaluation indicators for the reputation influence of cross-border e-commerce products $A_i$ to build a judgment matrix $U_0$ and secondary evaluation indicators $B_{ij}$ judgment matrix of $U_{i1}$, $U_{i2}$, $U_{i3}$ and $U_{i4}$, i.e.:

$$U_0 = \begin{bmatrix} 1 & 4 & 7 \\ 1/4 & 1 & 4 \\ 1/7 & 1/4 & 1 \end{bmatrix} \tag{7}$$

The square root method is used to calculate the weight vector of the evaluation index of word-of-mouth influence of cross-border e-commerce products. The formula is:

$$\omega_i = \frac{x_i}{\sum\limits_{j=1}^{n} x_j} + y_i \tag{8}$$

Among them, $x_i$ represents the square root result of the product of each element in the judgment matrix, $y_i$ represents the weight of matrix elements.

According to the weight vector of cross-border e-commerce product reputation influence evaluation indicators [14], the weight set of cross-border e-commerce product reputation influence evaluation indicators is obtained, namely:

$$\Omega_z = v_{ij}\omega_i \tag{9}$$

According to the above calculation steps, the weight value of the cross-border e-commerce product reputation influence evaluation index is calculated.

## 3 Design the Algorithm for Evaluating the Word-of-Mouth Influence of Cross-Border E-commerce Products

Assume that the nodes for the evaluation of the reputation influence are $B_i$, the importance of reputation influence is $Z$, the impact of cross-border e-commerce product reputation is $O$, the momentum of cross-border e-commerce products' reputation influence nodes is $N_iR$. The word-of-mouth influence is analyzed hierarchically [15], which is described as follows:

$$B_iR = \frac{AS \times OS \times Z}{\Omega_z} \tag{10}$$

In the formula provided, the level of $AS$ information represents the reputation effect of cross-border trading items. On the other hand, $OS$ displays the influence of social media data concerning the cross-border trading products' word-of-mouth effect [16–18]. Following the hierarchical analysis of word-of-mouth impact on cross-border e-commerce products, significant variations are apparent. The particle swarm optimization algorithm is leveraged to describe this connection. Thus, the ensuing formula determines the criteria for evaluating the word-of-mouth influence of cross-border e-commerce products.

$$AS = \frac{Q_i}{S^I} \tag{11}$$

Among them, $Q_i$ indicates the degree of correlation between the word-of-mouth influence level and the word-of-mouth influence, $S^I$ refers to the evaluation criteria.

Hypothesis $N_i$ express the reputation influence target node of $O_i$, $\Delta O$ represents the evaluation time domain of the reputation influence, and its satisfaction $\Delta O = |t_c - t_d|$ the current time period for evaluating the reputation influence is $t_c$, the past period is $t_d$ the time window for evaluating the reputation influence is $[t_d, t_c]$ [19]. Then the reputation influence $O_i$. Target node for $N_i$ stay $\Delta O$ the reputation influence in the period can be divided into $m$ influence links $At_j$, then the influence index of cross-border e-commerce product reputation is:

$$OS_{(t_i,N_i)} = \frac{\chi}{N_i} \cdot 10^{v_i} \cdot G^{n_i} \tag{12}$$

In the above formula, $\chi$ is the influence coefficient representing the reputation, $G^{n_i}$ is Bias information indicating the reputation influence, set $K_i$ for the related information of cross-border e-commerce products' word-of-mouth influence [20], it is necessary to consider the main influencing factors of cross-border e-commerce products' word-of-mouth influence and select the direct influence of cross-border e-commerce products' word-of-mouth $v_i$ as the most influential factor, namely:

$$v_i = \max\left\{\phi K_{i1} \cdot v, \cdots, K_{in_i} \cdot v\right\} \tag{13}$$

Among them, $\phi K_{i1} \cdot v$ represents the smallest factor affecting the reputation of cross-border e-commerce products, $K_{in_i} \cdot v$ represents the biggest factor affecting the reputation of cross-border e-commerce products. The word-of-mouth promotion has a complete strategy, and the specific membership values [21] are $S_C$, $S_I$, $S_A$ according to different levels of influence, we can get the degree of influence subordination of cross-border e-commerce product word-of-mouth:

$$S = \sqrt{\frac{S_C^2 + S_I^2 + S_A^2}{3}} \tag{14}$$

According to the factors affecting the reputation and the proportion of the reputation influence of cross-border e-commerce products, the evaluation weight of the reputation influence is obtained:

$$\omega = \sum_{j=1}^{m} v_j \tag{15}$$

Among them, $m$ indicates the amount of word-of-mouth influence of cross-border e-commerce products, and the weight of word-of-mouth influence of each cross-border e-commerce product is $v_j$ [22–24], any influence can be used $j$ express. In period $\Delta t$ Internal, define the threshold of word-of-mouth influence as $SR_{(\Delta t)}$, the value is calculated by the weight of the reputation influence and the reputation influence weight of each cross-border e-commerce product, namely:

$$SR_{(\Delta t)} = \sum_{j=1}^{n} N_i R_{(N_i,\Delta t)} \times \omega_i \tag{16}$$

Among them, $n$ refers to the number of word-of-mouth influence of cross-border e-commerce products, $NR_{(N_i,\Delta t)}$ means that the reputation is in the period possible influence value in $\Delta t$.

Assuming that there are multiple influence coefficients within the reputation influence level $NR_{(N_i,\Delta t)}$. Indicates the risks in the process of evaluating the reputation influence of cross-border e-commerce products, $\omega_i$ express the reputation influence Evaluation coefficient of $N_i$ [25].

According to the weight vector determined above $V_i$ And judgment matrix $S_j$, calculate the normal vector on the evaluation set, and the formula is:

$$\psi_i = V_i \oplus S_j = (a_1, a_2 \cdots, a_n) \tag{17}$$

In the above formula, $\oplus$ It is a composite operator of cross-border e-commerce product word-of-mouth influence evaluation. On the basis of determining the calculation equation, it designs a cross-border e-commerce product word-of-mouth influence evaluation algorithm, and realizes the evaluation of cross-border e-commerce product word-of-mouth influence.

# 4 Example Analysis

## 4.1 Experimental Data

In order to verify the performance of the method in this paper in the evaluation of word-of-mouth influence of cross-border e-commerce products, eight products of a cross-border e-commerce enterprise were selected as the example analysis samples to evaluate the word-of-mouth influence of cross-border e-commerce products. The weight data of the word-of-mouth influence of eight cross-border e-commerce products are shown in Table 2.

Table 2 is from a cross-border e-commerce enterprise that has settled on the Amazon platform. The company's products cover various fields such as electronic products, fashion clothing, household products, beauty and skincare products, mother and baby products, and food.

## 4.2 Measure the Cumulative Contribution Rate of Cross-Border E-commerce Product Reputation Impact Assessment

Based on the weight data of word-of-mouth influence in Table 2, the evaluation methods in the article, the evaluation method based on the entire process in reference [2], and the evaluation method based on incomplete information in reference [3] are used for comparison, and the principle of cumulative contribution rate greater than 96% is adopted to screen out the main components of the evaluation indicators of word-of-mouth influence of cross-border e-commerce products. The cumulative contribution rates of the three methods are shown in Fig. 2.

According to the results in Fig. 2, the cumulative contribution rate of the first five cross-border e-commerce product word-of-mouth influence evaluation indicators is 96.12% when the evaluation method based on the whole process is adopted, while the

**Table 2.** Weight data of word-of-mouth influence of cross-border e-commerce products

| Product category | A | B | C | D |
|---|---|---|---|---|
| Cognition of product quality standards | 0.12 | 0.52 | 0.16 | 0.34 |
| Supplier qualification and credit level | 0.56 | 0.14 | 0.75 | 0.26 |
| Supplier supply defect rate | 0.74 | 0.35 | 0.97 | 0.18 |
| Product acceptance mode | 0.15 | 0.86 | 0.43 | 0.54 |
| Warehouse sanitation and safety compliance rate | 0.53 | 0.24 | 0.65 | 0.53 |
| Sampling inspection frequency of product quality in stock | 0.25 | 0.42 | 0.68 | 0.94 |
| Rationality of product logistics, transportation and packaging | 0.74 | 0.98 | 0.25 | 0.61 |
| Operation error rate of logistics personnel | 0.69 | 0.76 | 0.27 | 0.98 |
| Number of platform entry assessment items | 0.38 | 0.63 | 0.61 | 0.16 |
| Monitoring frequency of platform public opinion | 0.42 | 0.16 | 0.86 | 0.37 |
| Lack of product traceability information | 0.71 | 0.73 | 0.81 | 0.25 |
| Lack of information displayed online | 0.34 | 0.54 | 0.72 | 0.70 |
| Number of after-sales guarantee items | 0.29 | 0.29 | 0.37 | 0.68 |
| One time solution rate of after-sales quality problems | 0.64 | 0.65 | 0.93 | 0.24 |
| Collection frequency of product after-sales quality information | 0.23 | 0.14 | 0.18 | 0.06 |
| Product category | E | F | G | H |
| Cognition of product quality standards | 0.16 | 0.86 | 0.69 | 0.76 |
| Supplier qualification and credit level | 0.73 | 0.81 | 0.38 | 0.63 |
| Supplier supply defect rate | 0.54 | 0.72 | 0.42 | 0.16 |
| Product acceptance mode | 0.29 | 0.37 | 0.26 | 0.08 |
| Warehouse sanitation and safety compliance rate | 0.14 | 0.75 | 0.26 | 0.08 |
| Sampling inspection frequency of product quality in stock | 0.35 | 0.97 | 0.18 | 0.74 |
| Rationality of product logistics, transportation and packaging | 0.86 | 0.43 | 0.54 | 0.35 |
| Operation error rate of logistics personnel | 0.24 | 0.65 | 0.53 | 0.24 |
| Number of platform entry assessment items | 0.65 | 0.53 | 0.14 | 0.39 |
| Monitoring frequency of platform public opinion | 0.68 | 0.94 | 0.87 | 0.97 |
| Lack of product traceability information | 0.25 | 0.61 | 0.69 | 0.25 |
| Lack of information displayed online | 0.27 | 0.98 | 0.35 | 0.45 |
| Number of after-sales guarantee items | 0.61 | 0.18 | 0.47 | 0.67 |
| One time solution rate of after-sales quality problems | 0.05 | 0.29 | 0.18 | 0.84 |
| Collection frequency of product after-sales quality information | 0.47 | 0.73 | 0.37 | 0.91 |

cumulative contribution rate of the first four cross-border e-commerce product word-of-mouth influence evaluation indicators is 96.13% and 96.87% when the evaluation

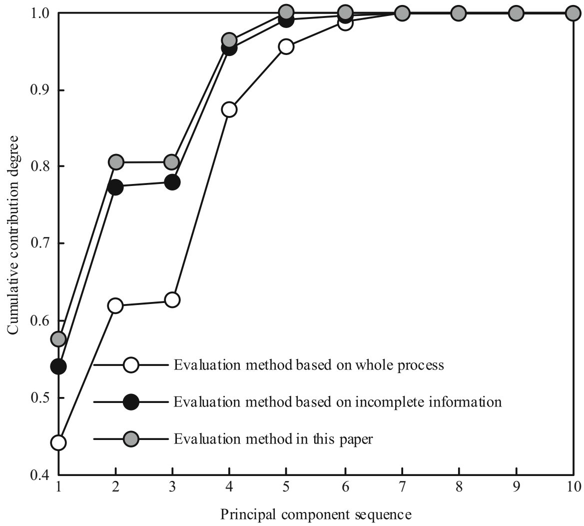


**Fig. 2.** Cumulative contribution rate

method based on incomplete information and the evaluation method in the text are adopted. Therefore, it can be seen that the evaluation method based on incomplete information and the evaluation method in the text have better dimensionality reduction effect. Compared with the evaluation method in the text, the evaluation method in the text based on incomplete information has fast and efficient performance, and is suitable for the impact evaluation of cross-border e-commerce product word-of-mouth.

### 4.3 Evaluation Results

According to the test results of cumulative contribution rate, the word-of-mouth influence evaluation scores and ranking of eight cross-border e-commerce products are obtained by using the evaluation method in the paper. The results are shown in Table 3.

From the results in Table 3, we can see that the cross-border e-commerce products ranking higher are B, H and F. Using the method in the article, we can determine the ranking of eight cross-border e-commerce products of a cross-border e-commerce enterprise in terms of word-of-mouth influence. Therefore, we can get the evaluation method in the article, which can rank the word-of-mouth influence based on the comprehensive scores of cross-border e-commerce enterprises. It has certain application value.

### 4.4 Comparative Analysis

In order to avoid the oneness of the experimental results, an evaluation method based on the whole process and an evaluation method based on incomplete information are introduced to compare and test the efficiency and reliability of the evaluation of word-of-mouth influence of cross-border e-commerce products. The results are as follows.

According to the results in Fig. 3, the evaluation efficiency of the word-of-mouth influence using the evaluation method in the article is higher than that based on the whole

**Table 3.** Score and ranking of reputation influence evaluation of cross-border e-commerce products

| Product category | Comprehensive score | ranking |
|---|---|---|
| A | −0.25843 | 5 |
| B | 0.17854 | 1 |
| C | −0.368 | 6 |
| D | −0.7642 | 8 |
| E | −0.179 | 4 |
| F | −0.0762 | 3 |
| G | −0.7102 | 7 |
| H | 0.0238 | 2 |

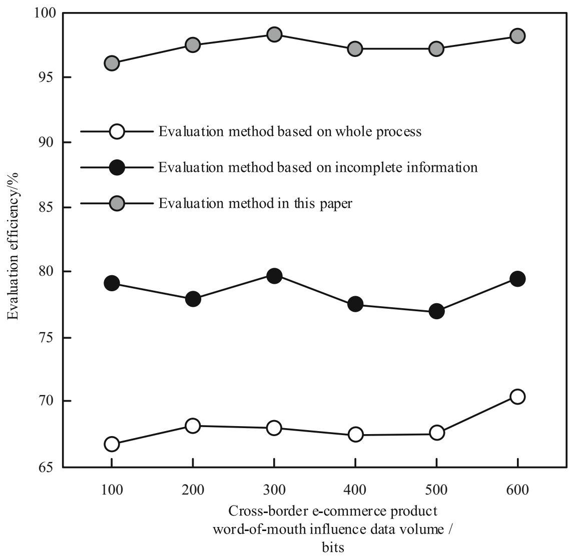


**Fig. 3.** Efficiency of reputation impact assessment of cross-border e-commerce products

process and incomplete information, because the method in the article can eliminate abnormal users of social networks according to the analysis of social network data, Avoid abnormal users of social networks affecting the evaluation results of word-of-mouth influence of cross-border e-commerce products, so as to improve the evaluation efficiency of word-of-mouth influence of cross-border e-commerce products.

The results in Fig. 4 show that compared with the evaluation method based on the whole process and the evaluation method based on incomplete information, the reliability of the method in this paper for the evaluation of the word-of-mouth influence can reach more than 95%, because the method in this paper designs the evaluation algorithm for the

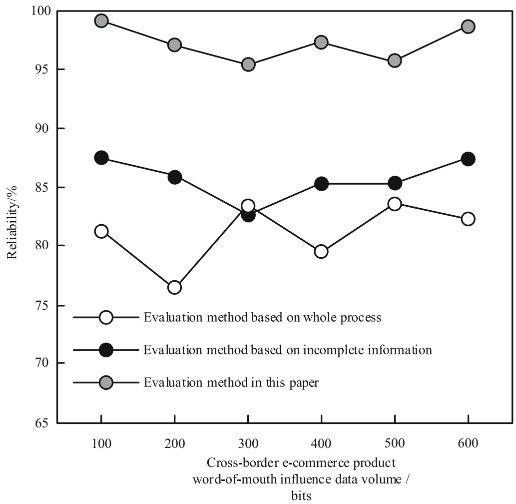


**Fig. 4.** Reliability of reputation influence evaluation of cross-border e-commerce products

word-of-mouth influence by calculating the weight of the evaluation index of the word-of-mouth influence of cross-border e-commerce products, This makes the evaluation of reputation influence more reliable.

## 5 Conclusion

This paper proposes a method for evaluating the word-of-mouth influence based on social network data analysis. Through case analysis, it is found that this method can evaluate the word-of-mouth influence and improve the evaluation performance. Although this research has achieved some results, there are still many shortcomings. In the future research, we hope to introduce the gray correlation analysis to calculate the correlation coefficient between different evaluation indicators, so as to improve the economic benefits of cross-border e-commerce products. The method of evaluating the reputation and influence of cross-border e-commerce products based on social network data analysis has important research value and application prospects under existing technological conditions, but there are also some limitations, such as the reliability of data. The data on social networks may have fraudulent behavior, such as likes and purchases, which can mislead the accuracy of the analysis results. The next step will focus on solving this problem.

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