Base on the Public Scientific Quality Improvement Research on Risk Early Warning of Online Shopping

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Abstract
In order to improve the scientific quality of the public, the Chinese Association for Science and Technology has put forward a call to combine popular science education with leisure and entertainment. In view of the fact that online shopping involves a wide range of areas, and the people pay more attention to it, the paper completed the innovation of online shopping risk warning science knowledge, the design of popular science mechanism and the dissemination of popular science knowledge. The paper used complex network’s knowledge discovery methods and decision theory to design online shopping risk warning science knowledge; Using the complex network public opinion dissemination trust analysis realize the dissemination of popular science knowledge and promote the improvement of the public’s quality of popular science. The spread of risk early warning science knowledge in the network shows that the risk early warning mechanism designed can achieve the purpose of improving public science knowledge when the reward and punishment measures are appropriate.

Keywords Public scientific quality · Risk warning method · Online shopping · Complex network

1 Introduction
In recent years, the nationwide science popularization work has achieved remarkable results, and the scientific quality of citizens has been greatly improved, providing important support for social development and economic construction. Doing a good job in science popularization has become a social and universal work [1]. The latest results in 2020 show that the gap in scientific literacy between urban and rural areas and various professional groups is decreasing. From the perspective of its development law, the improvement of scientific literacy of citizens in China has entered a stage of rapid growth. In order
to actively respond to and thoroughly implement the spirit of General Secretary Jin Ping Xi’s important speech on "science and technology innovation and scientific popularization are the two wings of innovation and development, and scientific popularization should be placed as important as scientific and technological innovation", the Chinese Association for Science and Technology proposes to popularize scientific knowledge, and by 2020, the proportion of Chinese citizens with scientific quality will exceed 10% [2–4] believe that the problems and challenges in the development of popular science education in China are manifested in the following aspects: first, insufficient attention has been paid to the lack of a good atmosphere; Second, the lack of popular science education diversity, lack of professional teachers; Third, the investment in popular science education is still insufficient, which affects the effect of popular science education. Relevant experts believe that to deal with these problems in the development of popular science education, we must first eliminate false knowledge, because it is easier to mislead the public; Secondly, scientists and scientific and technological workers should take more responsibility for popular science, and innovation is the first element on development of popular science. Finally, science popularization service projects must be more grounded, and the combination of popular science education with leisure and entertainment will achieve practical results. In view of the fact that online shopping has entered the homes of ordinary people, it involves a wide range of areas and people’s attention is relatively high. Moreover, the current research related to third-party payment risks has no systematic research results on online shopping risk early warning methods. This paper uses innovative research on online shopping risk warning science knowledge, science popularization mechanism design, and research on popular science knowledge dissemination to improve the public’s popularizing scientific knowledge of risk early warning such as tourism economy and network economy.

2 The Current Situation and Challenges of Third-Party Payment Platform Network Early Warning

2.1 Overview on the Risks of Third-Party Payment Platforms Economy

In recent years, due to the thin profit margins, fierce market competition, regulatory and credit issues in third-party payment platform transactions, the risk early warning problems of payment platforms have become more prominent. Literature [5] divides the risks of third-party payment platforms into operational risks and managing risks, and managing risks are further divided into benefit risks and customer mining risks; Operational risks are risks in the traditional sense, including market risks and legal risks, financial risks, credit risks and network technology security risks. On this basis, this paper uses complex networks as the carrier to study the knowledge and dissemination of popular science knowledge and early warning of risks in third-party payment transactions.

2.2 Early Warning Status and Challenges

Due to the existence of many complex and uncertain factors, the operation of third-party payment is always accompanied by diversified risks. The previous research on risk early warning mainly focused on the early warning of legal and systemic financial risks, and mostly ignored the issue of benefit risk early warning and the issue of customer mining risk early warning [6, 7].
At present, many financial institutions use neural network technology and logistic regression analysis. These unstructured technologies are introduced into early warning models to predict the possibility of a crisis by monitoring a set of leading indicator systems. But the amount of information processed is relatively large, the information changes instantaneously, and it has data redundancy and indistinguishability. When it comes to information, they are all slightly inferior [8–11].

Obviously, third-party payment transaction network risk early warning has a large workload, risk factors are intricate and mutually restricted, and are greatly affected by the network structure. Most of the information in the network is uncertain and indistinguishable. There are great drawbacks to the single use of a certain qualitative or quantitative early warning method. Therefore, in the environment of big data and incomplete information, the risk early warning of third-party payment transaction networks is facing huge challenges. Mainly manifested in the following aspects [12–14]:

① The multilateral platforms (banks, merchants, customers, and third parties) fight each other, prevarication, and early warning efficiency is compromised;
② Data barriers and segmentation hinder the cooperation of various departments in risk early warning;
③ Risk early warning has the disadvantages of insufficient experience, low technology, and untimely early warning;

The new challenges faced by these risk warnings reflect the current need to organically unify the rationality of big data with knowledge warning, comprehensive warning, and skill warning. In this way, the paper designs different early warning methods for different risks.

3 Popular Science Knowledge of Online Shopping Risk Early Warning

3.1 Operational Risk Early Warning Method Based on the Importance of Nodes

Due to the large randomness of the node connection of the third-party payment network, the newly added node is easy to link with the node with high degree, and the status and role of different nodes in the network are also different. Therefore, the paper proposes a sorting method of node importance—an important node sorting method based on improved information entropy.

A subjective weight $\mu = (\mu_1, \mu_2, \cdots, \mu_n)^T$ is given according to the position of the node in the network and the revenue it brings to the merchant. Suppose the degree distribution of the network is $p(k)$, then the entropy value is as formula (1):

$$d_{ik} = \frac{t_k p(k) \ln p(k)}{\sum_{k=1}^{k_{max}} (t_k p(k) \ln p(k))}, \quad k = 1, 2, \cdots, k_{max},$$

Among them $i = 1, 2, \cdots, n$, $k_{max}$ represents the maximum value of the network degree $k$, and $t_k$ represents the nodes’ occurrence frequency with degree $k$; Let

$$d = (d_1, \cdots, d_i, \cdots, d_n)$$
$$= (d_{11}, d_{12}, \cdots, d_{1m_1}, d_{21}, \cdots, d_{2m_2}, \cdots, d_{k_{max}1}, d_{k_{max}2}, \cdots, d_{k_{max}m_k})$$

(2)
Take the weight of the $i$th node as $w_i$,

$$w_i = \frac{\mu_i \cdot d_i}{\sum_{i=1}^{n} \mu_i \cdot d_i},$$  \hspace{1cm} (3)

Then the weight of all nodes in the network is $w$,

$$w = (w_1, w_2, \cdots w_n)$$ \hspace{1cm} (4)

The advanced point of this method is, that firstly, it uses the degree distribution of the third-party payment network to calculate the weight, without understanding the network structure, and no need to construct the decision-making matrix on the third-party payment network; The second, to avoid the defect of the entropy method being too objective, the subjective weight of the decision maker is added for modification. With the sorting algorithm of node importance, an early warning method of operational risk can be given.

*Early warning method 1* Operational risk early warning method.

According to the principle of quarter quantile, the risk assessment function value is calculated for the nodes ranked in the top quarter quantile, and then label the nodes with the ranking of the risk assessment function value in the first quarter quantile. These marked nodes are those that need to be strictly controlled in accordance with operational risk control measures.

### 3.2 Early Warning Method of Online Shopping Benefit Risk Based on Rating Method

Literature [6] constructed a new benefit risk indicator system, realized the evaluation of the benefit risk, and used the formula (5) to determine the risk evaluation level:

$$rate_{benefit} = \begin{cases} 
\text{very small} & D \geq 115\% \cdot \cos t \\
\text{smaller} & 115\% \cdot \cos t > D \geq 110\% \cdot \cos t \\
\text{general} & 110\% \cdot \cos t > D \geq 105\% \cdot \cos t \\
\text{higher} & 105\% \cdot \cos t > D \geq \cos t \\
\text{very high} & \cos t > D 
\end{cases}$$ \hspace{1cm} (5)

here $\cos t$ represents the operating cost of the network manager, and $D$ represents the result of benefit risk evaluation.

On this basis, this paper creates a benefit risk early warning method:

*Early warning method 2* Benefit risk early warning method.

When the benefit risk level is very high, it is defined as a red warning, and these platforms will be obsolete in compliance with the laws of the Internet; If it is higher, it is a blue warning, and the platform is difficult to operate. Sellers should be cautious before buying; If it is general or smaller, it is a yellow warning, the platform is still operational, and consumers can buy at their discretion; If it is small, it is a green warning. These platforms are very stable and consumers can buy with confidence.
3.3 Customer Mining Risk Early Warning Method Based on Knowledge Discovery Method

In the competition for customers in the third-party payment network, customer mining is to find some customers who have the purchasing power and desire to buy among the registered users. At present, the method commonly used by third-party payment network managers is to classify customers into bronze members, gold members, diamond members, and crown members based on the accumulated amount of purchases or login traffic. Practice shows that the effect of this is not significant. Customer mining risk early warning refers to finding factors that have a significant impact on the purchase amount from customer consumption characteristics, and establishing an early warning method based on knowledge discovery. Generally speaking, the greater the amount the customer spends, the smaller the risk of customer mining. This paper solves the problem of customer mining risk early warning from four aspects: data collection and sorting, the construction of knowledge discovery risk early-warning model, and customer mining risk science knowledge system.

3.3.1 Data Statistics of Customer Mining Risks

According to factor analysis, this paper divides customer consumption characteristics into group characteristics, psychological characteristics and behavior characteristics. Group characteristics include customers’ gender, age, occupation, education, income, etc.; Psychological characteristics mainly refer to customers’ importance of payment security, product evaluation, merchant’s reputation, and whether they tend to sell high-volume products; Behavior characteristics mainly refer to consumers’ behavior perception, learning, values and attitudes, customers value the quality of goods, channels for understanding goods, decision-making standards, frequency of evaluation after shopping, etc. Here, we conducted a questionnaire survey on customers mined by with larger weights nodes in the node importance ranking, distributed network link questionnaires (430 copies) and paper questionnaires (100 copies), and obtained a total of 450 valid questionnaires. Descriptive statistics of the questionnaire survey data found that each option generally conforms to the form of a normal distribution, but since the minimum option for monthly income and online shopping amount setting has no lower limit, the data in the left half of the peak is relatively concentrated, but it is still approximately conform to the normal distribution.

In data sorting, for the attributes in the group characteristics, gender can be represented by 0, 1. Age, monthly income, and online shopping amount are all direct numerical attributes; The two attributes of education and occupation are determined by the corresponding type of social status, assigned values from low to high. Questionnaires on psychological characteristics are all judgmental, and the options are just assigned 0 or 1. The results of questionnaire data collation and qualitative attribute quantification are shown in Table 1.

3.3.2 Knowledge Discovery of Customer Consumption Characteristics and Popular Science Knowledge of Risk Early Warning

Through correlation analysis of variables, the paper gets the consumption characteristics that are more relevant to the amount of online shopping: $X_2, X_3, X_4, X_5, X_7, X_{10}, X_{12}, X_{13}, X_{14}, X_{19}$. Then take $X_2, X_3, X_4, X_5, X_7, X_{10}, X_{12}, X_{13}, X_{14}, X_{19}$ as the independent variable and the
Table 1  Sorting out questionnaire data (sample size is 450)

| Variable                                      | Variable classification | Proportion% | Average value |
|-----------------------------------------------|-------------------------|-------------|---------------|
| Average online purchase amount in recent months | 1 = below 1000          | 81.33       | 3.24 = 0.8133 + 2*0.0822 + 3*0.0578  |
|                                               | 2 = 1000–2000           | 8.22        | + 4*0.0244 + 5*0.0133 + 6*0.0089   |
|                                               | 3 = 2000–5000           | 5.78        |               |
|                                               | 4 = 5000–10,000         | 2.44        |               |
|                                               | 5 = 10,000–20,000       | 1.33        |               |
|                                               | 6 = above 20,000        | 0.89        |               |
| Gender × 1                                    | 1 = female              | 51.56       | 0.52          |
|                                               | 0 = male                | 48.44       |               |
| Age × 2                                       | 1 = below 25            | 43.56       | 2.03          |
|                                               | 2 = 25–35               | 19.78       |               |
|                                               | 3 = 36–50               | 27.33       |               |
|                                               | 4 = 51–70               | 8.89        |               |
|                                               | 5 = above 70            | 0.44        |               |
| Education × 3                                 | 1 = below high school   | 2.67        | 3.64          |
|                                               | 2 = high school         | 14.89       |               |
|                                               | 3 = junior college      | 13.78       |               |
|                                               | 4 = undergraduate       | 55.78       |               |
|                                               | 5 = master’s degree     | 10          |               |
|                                               | 6 = PhD and above       | 2.89        |               |
| Profession × 4                                | 1 = student             | 39.33       | 2.95          |
|                                               | 2 = freelance           | 13.56       |               |
|                                               | 3 = private enterprise  | 25.56       |               |
|                                               | 4 = foreign company     | 7.11        |               |
|                                               | 5 = business unit       | 14.44       |               |
| Monthly income × 5                            | 1 = below 2000          | 35.56       | 2.18          |
|                                               | 2 = 2000–5000           | 30.22       |               |
|                                               | 3 = 5000–10,000         | 20.22       |               |
|                                               | 4 = 10,000–20,000       | 8.44        |               |
|                                               | 5 = above 20000         | 5.56        |               |
| Credibility × 6                               | 1 = important           | 91.78       | 0.9178        |
|                                               | 0 = unimportant         | 8.22        |               |
| Payment security × 7                          | 1 = important           | 94.44       | 0.9444        |
|                                               | 0 = unimportant         | 5.56        |               |
| Customer reviews × 8                          | 1 = important           | 88          | 0.88          |
|                                               | 0 = unimportant         | 12          |               |
| Sales volume × 9                              | 1 = important           | 76.67       | 0.77          |
|                                               | 0 = unimportant         | 23.33       |               |
| Brand × 10                                    | 1 = important           | 44.44       | 0.44          |
| Quality × 11                                  | 0 = unimportant         | 82.89       | 0.83          |
| Origin × 12                                   |                          | 8.22        | 0.08          |
| Price × 13                                    |                          | 45.56       | 0.46          |
| Value for money × 14                          |                          | 63.88       | 0.63          |
| only count 1                                  |                          |             |               |
| Product Information × 15                      | 1 = yes                 | 66.44       | 0.66          |
|                                               | 0 = no                  | 34.22       | 0.34          |
| Advertising × 16                              |                          | 70.22       | 0.64          |
|                                               | only count 1            | 55.78       | 0.58          |
| Friend recommended × 17                       | 1 = yes                 | 66.44       | 0.66          |
|                                               | 0 = no                  | 34.22       | 0.34          |
| Product review × 18                           |                          | 70.22       | 0.64          |
|                                               | only count 1            | 55.78       | 0.58          |
| Evaluation frequency × 19                     | 1 = almost not          | 24.44       | 2.07          |
|                                               | 2 = sometimes           | 51.11       |               |
|                                               | 3 = usually             | 17.11       |               |
|                                               | 4 = always              | 7.33        |               |
| Decision-making × 20                          | 1 = conformity          | 8.44        | 2.60          |
|                                               | 2 = Sensibility         | 22.89       |               |
|                                               | 3 = rationality         | 68.67       |               |
amount of online shopping as the dependent variable, through model applicability and fitness test, it is known that the model can only consider multiple linear regression models.

Import the effective data set composed of 450 samples into the SPSS software, select \( X_3, X_5, X_7, X_{10}, X_{12}, X_{13}, X_{14}, X_{19} \) as the independent variable and consumption amount as the dependent variable, and perform multiple stepwise regression. The regression equation is as follows, equation (6), the significance test results of the regression equation are shown in Table 2.

\[
y = 0.672 + 0.201x_3 + 0.677x_5 + 1.224x_7 + 0.546x_{10} + 0.544x_{12}
\]  

(6)

From the significance test of the regression coefficient, it can be seen that the five consumption characteristics of education, monthly income, payment security, brand, and place of origin are the significant factors that affect the amount of customer consumption; the regression equation shows that online payment security has the greatest impact on customer mining risk, and the income is inferior. Among them, the product brand and origin are ranked third. Therefore, the key to customer mining risk early warning is payment security early warning and customer income early warning. It can be seen that the higher the educational background and income, the lower the risk of customer mining; The security of payment, the place of origin and the brand of the product have a greater impact on the risk of customer mining. In view of this, the following risk warning method is derived.

**Early Warning Method 3** Customer mining risk early warning method.

For online merchants, after acquiring the group characteristics of customers, they can recommend high-income and highly educated customers among similar products with higher prices, which is more in line with their buying characteristics; In terms of behavioral characteristics, using importance to the characteristics of the brand and the place of origin, increasing the brand and place of origin promotion of the product, can enable customers to better identify the product. As customers are extremely dependent

| Model | Non-standardized coefficient | Standard coefficient | t   | Sig |
|-------|-----------------------------|----------------------|-----|-----|
|       | B                      | Standard error |       |     |
| B     | Standard error | Trial version |     |     |
| Constant | 0.672 | 0.247 | 2.719 | 0.007 |
| X5   | 0.677 | 0.055 | 0.476 | 12.247 | 0.000 |
| X7   | 1.224 | 0.278 | 0.169 | 4.406 | 0.000 |
| X10  | 0.546 | 0.130 | 0.163 | 4.188 | 0.000 |
| X3   | 0.201 | 0.063 | 0.124 | 3.191 | 0.002 |
| X12  | 0.544 | 0.231 | 0.090 | 2.358 | 0.019 |
on payment security psychologically, it is necessary to ensure the payment security of customers.

4 Mechanism Design and Dissemination of Online Shopping Risk Early Warning Based on the Improvement of Public Scientific Quality

4.1 Mechanism Design of Online Shopping Risk Early Warning

In the previous section, the paper studied the popular science knowledge of online shopping risk early warning, so how to scientifically and rationally popularize this popular science knowledge to everyone through customers’ online shopping. To this end, this paper does the following design:

① The financial regulatory agency institutionalizes the legal culture of online shopping risk early warning;

Government regulatory agencies formulate a clear risk early warning system to stabilize the financial market and implement standards for online shopping early warning. Let all online shopping parties know the types, hazards, and early warning mechanisms of online shopping risks. Let each platform pay for the more important products of enterprises and merchants to mark their level in the risk warning. The specific operations are as follows:

For operational risk, the nodes whose importance is ranked in the top quarter quantile and the risk assessment function value are in the top quarter quantile are the nodes of operational risk supervision.

Benefit risk, mark the risk warning level of each platform, which is red warning, blue warning, yellow warning, and green warning. Red warning, then these platforms will be obsolete in compliance with the laws of the Internet; Blue warning, the platform is difficult to operate, and sellers should be cautious before buying; Yellow warning, the platform is still operational, and consumers can discretion purchase; Green warning, these platforms are very stable, and consumers can buy with confidence.

Customer mining risks: merchants highlight the brand and origin of the product to ensure the safety of third-party payment; At the same time, they pay attention to those with high education and high income. Therefore, as much as possible to capture the customer’s education and income information during customer registration.

② Early warning of benefit risk and customer mining risk on the homepage of the website;

Third-party payment need to make careful design to benefit risk and customer mining risk early warning on their website homepage. If design a logo dedicated to benefits risks, and mark different colors to represent the platform’s benefit risk warning level, it will not only give customers reassurance, but also a propaganda and struggle vane for the platform itself.

On the homepage of the platform, when a customer registers, it is best to add information about the customer’s education, occupation, hobbies, and whether you care about the brand and origin of the product. The more you have a grasp of these significant
factors in the customer’s consumption characteristics, the more favorable for merchants
to carry out early warning of customer mining risks.

③ Early warning of operational risks on the product sales page;

Through the statistical analysis of the historical data of legal risk, market risk, credit
risk, financial risk and network technology risk in operational risk, the risk assessment
function of node operational risk is obtained. According to the first warning method, these
products are evaluated label on the product sales page. Dynamic adjustments are made
every certain period to show customers these marked commodities. They are the key nodes
for merchants and platforms to carry out operational risk early warning.

④ The financial regulators’ incentive mechanism for platform risks early warning.

In order to better implement online shopping risk warnings, in addition to formulating
strict penalties, the financial regulatory mechanism should also formulate corresponding
incentive mechanisms for platforms and merchants that implement better, such as mod-
erately reducing transaction fees and network operation management expenses etc.. The
platform also rewards merchants who implement better, such as reducing advertising man-
agement fees and service fees.

4.2 Dissemination of Online Shopping Risk Early Warning Knowledge Based
on the Improvement of Public Scientific Quality

In the previous sections, different types of risk early warning methods have been studied,
and the mechanism design of risk early warning has been realized. So how to popularize
these risk warning knowledge to the public, here we give two steps to achieve:

① The broadcast of cyber risk early warning knowledge on third-party payment platforms

On the homepage of the third-party payment platform, use more eye-catching fonts and
sections to set up a knowledge link of third-party payment warning methods, click on the
web page, and display the types of online shopping transaction risks, risk warning meth-
ods, and warnings on the online shopping platform in the form of charts. The signal shows
the connotation and other information; When it touches the product, business or platform
benefit risk logo of the risk warning mark, there is also a voice broadcast of relevant sci-
ence knowledge. In addition, each commodity reveals its place of origin and brand; At the
connection point of the commodity payment method, click on each payment method, and
there will be a scientific reminder on the security level of each payment method and pay-
ment preferences. Since business risks involve relatively high-importance products on the
platform, then the products that are identified during product recommendation should be
recommended first. In this way, the probability that customers browsing on third-party pay-
ment platforms will be able to gain popularization of risk warning and popular science
knowledge will be greatly improved.

② Dissemination of public opinions on network risk early warning knowledge in social
networks
In social relations, each individual is regarded as a node, and the communication between people is regarded as a connecting edge, which constitutes a social network. Because the social relationship network belongs to the complex network. If an individual learns the risk early warning science knowledge, then he acts as the source node, this science knowledge will be spread in the social network; If multiple groups learn this science knowledge, then in this social network, multiple source nodes will spread the message at the same time. In this way, the promotion of popular science knowledge in the entire social network has been achieved.

So, can this kind of communication really spread to every node in the network? Below the paper discuss this issue from the social network public opinion communication model.

First look at such a small social network diagram, in Fig. 1, the data on the arrow represents the trust of the receiving node to its neighbor nodes. The greater the trust degree, the more likely it is to spread the message. When all neighbors know the news, the node loses interest in the spread of the news, and the spread of online public opinion ends.

Node 1 is used as the source node to learn the risk warning method, then it may spread to its neighbor nodes 2 and 3, node 2 and 3 will spread to its neighbors 4, 5, 9 with a probability of 0.8 and 0.7 respectively; And then 4, 5, 9 spread to their neighbors with a certain probability, until the end of the spread of public opinion. From an intuitive analysis, when each node propagates to its neighbors, no matter what kind of public opinion propagation model is adopted, the trust of the entire network in the message is decreasing. Then, in the process of public opinion dissemination, is there the possibility of dissemination interruption?

The research of [15] shows that if the rewards and punishment coefficients for nodes and their message sources are appropriate, the trust of the entire network will show an upward trend. Therefore, in the social network, the dissemination of popular science knowledge of online shopping risk early warning and appropriate rewards and punishments can ensure that the news is disseminated throughout the network, which also achieves the improvement of the public’s scientific quality.

**Fig. 1** The social network diagram of public opinion dissemination
5 Conclusion

This paper designs different risk warning science knowledge and an online shopping risk warning mechanism based on the improvement of public scientific quality for different risk categories in third-party payment network transactions, and proves that online shopping science knowledge can indeed be disseminated through public opinion in social networks. The main research conclusions of this paper are as follows:

① Operational risk early warning method based on node importance

The risk assessment function value is calculated for the nodes ranked in the top quartile quantile, and then the risk assessment function value is ranked and marked nodes in the top quartile quantile. These marked nodes are those that need to be strictly controlled in accordance with operational risk control measures.

② Early warning method of online shopping benefit risk based on rating method

The determination of benefit risk indicators and their weights, and the study of benefit risk levels, the benefit risk early warning method was created. According to the benefits risk levels rants, very large, large, average, and very small, the red, blue, yellow and green early warning methods are adopted in sequence, and reasonable suggestions are provided for the platform and consumers at all levels of early warning.

③ The early warning method for customers mining risks based on regression analysis

Customers’ education, income, payment security, and product brands and origins have a significant impact on customer spending. Therefore, the paper designs a customer mining risk early warning method based on these consumption characteristics.

④ The design of online shopping risk early warning mechanism based on the improvement of public scientific quality

In terms of mechanism design, the paper makes the following points: financial regulatory agencies will institutionalize the culture and laws of online shopping risk early warning; Do benefit risk and customer mining risk early warning on the homepage of the website; Do operating risk early warning on the product sales page; Financial regulatory agencies’ incentive mechanism for platform risk early warning.

⑤ Popular science knowledge dissemination of risk early warning based on the improvement of public scientific quality

The paper divides the dissemination of popular science knowledge into two stages. One is the broadcasting of network risk warning knowledge on third-party payment platforms; In this way, customers in third-party payment platforms have a greatly increased probability of getting popular science knowledge on risk warning. The second is the public opinion dissemination of network risk early warning knowledge in social networks, as long as an appropriate reward and punishment system is set up, the knowledge of the entire social network can be promoted.
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Author Contributions XL: conceptualization, methodology. LC: data curation, writing—original draft, software, visualization, investigation. TW and XF: supervision, writing—review & editing.

Data Availability Raw data were generated at the large-scale facility. Derived data supporting the findings of this study are available from the corresponding author upon request.

Declarations

Conflict of interest No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work.

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