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Construction of Supply Chain Risk Identification Model for Digital Economy Background

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SUMMARY: *As the development of the digital economy continues at an astonishing rate, live-streaming e-commerce has emerged as a relatively new business model, where supply chain risk management has become essential. In this paper, supply chain risk management in live-streaming e-commerce is examined using an analytical approach integrating grounded theory, ISM analysis, and ANP to reveal risks in supply chains. The process of grounded theory is used to code the obtained data and determine four major risk types: supply risks, macro-environmental risks, operational risks, and demand risks, including 14 secondary risk factors. These findings form the basis for developing a supply chain risk identification model that is relevant for live-streaming e-commerce. Second, ISM was applied to analyze hierarchical relationships among risk factors, while ANP quantified weight assessments. Findings revealed supply risks as the most significant challenge in live-streaming e-commerce supply chains, accounting for 0.3507 of total weight. Among these, product supply risks exerted the greatest influence on overall supply risks, with a weight of 0.1505.*

KEYWORDS: *Grounded Theory; Interpretive Structural Modeling; Analytic Network Process; Supply Chain Risk Identification; Digital Economy*

1 Introduction

Rapid growth in the digital economy undoubtedly has been a new driver for industry development [1]. By empowering traditional supply chains through data value, digital technology, and network infrastructure, and deeply integrating with them, new digital models and scenarios continue to emerge. This has spurred supply chains toward digital transformation. Leading companies such as Google, IBM, Amazon, and Yahoo have invested significant effort early on in digital technology projects to tap into potential customers[2-4]. Using data as a medium and supported by smart devices, various resources (such as people and machinery) are interconnected to build remotely controllable intelligent networks. This enables enhanced automation management levels and work efficiency under external human intervention and control. While optimizing traditional supply chain structures, it further improves the stability of the entire system [5-7]. The establishment of information platforms also facilitates deeper resource integration, mitigating adverse effects from uncertain demand caused by inaccurate information. Enterprises can flexibly and effectively select and build supply-demand relationships based on their needs, ensuring smooth supply chain operations and mutual benefits for both parties [8-10].

However, enterprises encounter numerous challenges during digital transformation. While

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supply chain value increases, associated risks become harder to predict and control effectively [11]. The first stage of supply chain risk management is the identification of supply chain risks. After specific risks related to supply chains have been identified, actions aimed at minimizing the possibility of occurrence will be taken [12-14]. The concept of supply chain risk management included risk awareness, risk analysis, risk assessment, risk control, and feedback on the effectiveness of these actions [15]. With the development of research on the topic, four key elements were offered, namely risk identification, risk control, risk treatment, and risk monitoring [16, 17]. Risk identification marks the beginning of supply chain risk management. The larger the number of nodes in the supply chain, the more diverse risks can be found in supply chains, and the more necessary the step of risk identification becomes [18]. Against the backdrop of the digital economy, it is crucial to study supply chain risk management problems, risk factor identification, and prevention in practice.

Identification of supply chain risks involves the assessment and determination of both present and potential supply chain risks [19]. The process involves first identifying and understanding the composition and structure of participating entities of the supply chain; secondly, analyzing the risk factors and potential risk factors for the entities as well as assessing the probability of occurrence of the risks and how likely they can harm the parties involved; and lastly, identifying the potential consequences arising out of the risks. In this study, the focus is on supply chain risk types and risk causes as a foundation of supply chain risk identification. Previous researchers classified supply chain risk based on risk actors as six categories of risk. These include supply risk, demand risk, environmental risk, institutional risk, process risk, and preventative risk planning failure [20]. However, further advancement in academic studies and changes in circumstances have led to increased number of risk factors. For instance, one researcher identified seven dimensions of risk as supply risk, process side risk, demand risk, logistics risk, collaboration risk, financial risk and environmental risk [21]. Another researcher identified a conceptual classification of supply chain risk where risks were categorized into four main classes as core risks, infrastructure risk, external risk, and natural risk. This classification made it easy to identify risks at all parts of the supply chain network with negative impacts to performance [22]. For specific areas, literature [23] classifies risk factors in global raw material supply chains into ten categories and analyzes risk scenarios exacerbated by commoditization and geography, aiming to provide references for improving the global supply chain system. In another study, a new risk classification structure was built for cruise supply chain systems. Six risk classifications included: macro-risk, safety risk, security risk, health risk, information risk, and supply risk [24]. Seven risk types for a service-oriented supply chain were found to include: demand risks, supply risks, operational risks, information risks, financial risks, time-delay risks, and external risks, while the service-oriented supply chain was defined as well [25].

Identifying supply chain risks, investigating the sources of identified factors will help managers deal with risks at the root cause level. Drawing on the risk categorization criteria mentioned above, this study continues to further explore a range of specific risk factors and their influencing factors. Literature [26] specifically analyzes for example the sources of risk in the retail segment as unstable economic conditions, poor distribution networks, improper pricing, and product quality risks. A study on risks in the fuel supply chain and its findings include the identification of 34 different risk factors out of which seven risk factors can be termed systemic in nature as they occur almost everywhere in the supply chain and these include "lack of financial support," "policy/regulatory framework changes," and "public concerns" as the three major risk factors [27]. Literature [28] identifies uncertainty factors (e.g., natural disasters, political unrest, and epidemics) as one of the main causes of GSC risk as well, which are severe and can lead to supply chain disruptions, delays, failure of supply to meet demand,

labor shortages, and demand fluctuations, among other effects. Literature [29] identified and assessed supply chain risks in Iranian biopharmaceutical industry and listed 23 important risk factors including regulatory conflicts, sanctions, shortage of domestic suppliers, counterfeit production, and financial problems. A second study suggests that moral hazard is another important supply chain risk factor that results from losses caused to suppliers and customers because of the malpractice of other collaborating firms along with the lack of effective supply chain governance practices in place to check such behavior [30].

Now that supply chain risks types and their causal factors have been analyzed in detail, we move on to the discussion about related research in supply chain risk identification models and methods. In this regard, the domestic and foreign literature predominantly uses expert survey techniques, SCOR model, hierarchical holographic modeling, and similar techniques in conducting relevant researches. One of the studies conducts a systematic investigation of supply chain risks in humanitarian aid logistics using expert survey techniques, thereby discovering six core risks such as material shortage and transportation interruption, and providing a quantitative analysis of the occurrence probabilities and impact levels of these risks to enable risk management [31]. One more research uses SCOR method to identify risks and risk sources within cassava supply chain processes, thereby revealing 47 risks and 34 risk sources that can cause interruptions within the supply chain [32]. Another study combines the scenario analysis technique and SCOR method to identify and prioritize supply chain risks, successfully identifying 20 risks through experimentation and prioritizing them as well, thus allowing a collaborative risk analysis along the whole supply chain [33]. Hierarchical holographic modeling is adopted by one study in developing a methodological approach for supply chain risk identification, suggesting a new approach for the identification, prioritization, and management of supply chain risks from multiple overlapped perspectives [34]. One more study develops a hybrid model by integrating the concepts of fuzzy logic with hierarchical holographic modeling, whereby hierarchical holographic modeling is applied for the purpose of risk identification, while a qualitative risk assessment model and fuzzy-based risk assessment model are applied to analyze these risks [35]. Finally, an approach rooted in hazard and operability analysis (HAZOP) is suggested for the purpose of supply chain risk identification in one research, whereby risk management in chemical processes is utilized to conduct a systematic study of parameter deviations along the supply chain, with the help of oil refinery supply chain being used for verification purposes [36].

With the swift advancement of information technologies, intelligent algorithms are applied to identify risks in supply chains. Specifically, in one study, a model for predicting credit risks in supply chains using the PCA-GA-SVM approach was proposed, where initially, PCA technique was used to reduce the initial index system, followed by GA optimization of parameters for SVM to build a prediction model for identifying credit risks in supply chains [37]. Another research work presented an active risk identification approach based on reinforcement learning techniques that were benchmarked against risks identified by risk managers using manual methods, and the results showed that a good performance of the approach could be achieved in identifying risks in supply chains [38]. Furthermore, another study introduced RL-SCRI, a novel active supply chain risk identification method using NLP and reinforcement learning techniques, and the results of the experiments conducted showed that high performance could be reached [39]. Moreover, one research study proposed an ISCOR model for identifying risks in supply chains, and comparing the effectiveness of intelligent algorithms like support vector machines, k-nearest neighbors, random forests, and decision trees found that the random forest method provided up to 99% accuracy in identifying risks [40]. Literature [41] proposed an intelligent algorithm called IO-SuperPageRank for identifying risks in complex systems and demonstrated its effectiveness through simulation

experiments and a case study involving global supply chain risks. Another research explores risk interaction in an international logistics supply chain using an interpretive structural modeling technique, and presents a dynamic supply chain logistics risk analysis model in order to provide a deeper insight into the risk event interactions [42].

This study focuses on addressing the difficulties of supply chain risk management encountered in live streaming e-commerce, and builds a supply chain risk identification and assessment model using the grounded theory, Interpretive Structural Model, and Analytic Network Process methods. First, the index system of supply chain risk factors in the live streaming e-commerce environment is constructed via open coding, axial coding, selective coding, and the saturation test within the framework of grounded theory. Subsequently, the structure relationship among risk factors is analyzed using ISM. Finally, the weights of risk assessment indexes are calculated using ANP, which makes it possible to effectively assess the risks of the live streaming e-commerce supply chain.

2 Supply chain risk identification and assessment model for live e-commerce

As a new economic type that features the characteristics of the digital economy era, the live-streaming economy can play an important role in promoting consumption in cities and rejuvenation in rural areas. In this research work, the issue of identification of the risk in the supply chain of live-streaming e-commerce will be considered, and a model based on grounded theory, the interpretive structural model, and analytic network process will be constructed for identifying and assessing risks in live-streaming e-commerce.

2.1 Directed E-Commerce and Supply Chain Risk Management

2.1.1 Direct broadcast e-commerce

The live-streaming e-commerce is a new business approach that is carried out via the internet, whereby the host presents the products close to customers online and interacts with them in real-time, thus enhancing customer experience, purchasing intention, and restructuring the relationships between customers, products, and locations.

Compared with conventional e-commerce, the live-streaming e-commerce possesses several distinguishing features.

(1) More intuitivity. The live streaming e-commerce offers a more integrated presentation of the product as compared to the regular e-commerce process. Hosts offer their services by putting the products on trial, through tasting, testing, and describing them to consumers, which helps the consumer get acquainted with them better, offering more intuitivity in terms of the product.

(2) Interaction. The process of live streaming commerce eliminates the one-sidedness in information flow in regular e-commerce. This happens through the means of interaction between hosts and consumers via comments and bullet screen messages. In addition, consumers get to interact among themselves and follow each other, thus creating an interactive atmosphere.

(3) Precision marketing. Live e-commerce also has fan economic benefits, Netflix anchor or star celebrities, can take advantage of their own fan base to bring consumers into the live room, build strong fan viscosity and loyalty, through big data on the shopping group portrait depiction, you can carry out precision marketing. At the same time, consumers' real-time opinions and views on products can also promote merchants to continue to follow up on products and services, recommend more suitable products for consumers, and improve the

conversion rate of sales.

2.1.2 Supply chain risk management

Supplies chain risk management refers to the management of potential risks arising from the occurrence of some events or changes in the supply chains. Identification of risks, assessment of risks, taking actions against the risks, and monitoring and measuring risks are steps followed in supplies chain risk management process.

Some events of different magnitudes shall always happen in the supply chain and affect operations in general. In case an incident occurs or risk is posed, the first thing to do is identify the risk. This involves classification and analysis of different types of risks that may occur in the supply chain and segmentation for more analysis.

After risks have been classified, it will be necessary to assess the risks according to their scale and the possibility of occurring. Risk assessment is known as risk estimation, where there is quantification and evaluation of risks. Different mathematical methods will be employed to analyze past risks and evaluate risks likely to occur in future.

After identification and risk estimation, uncertainties related to a particular risk event can be reduced through different approaches or negative impacts of a risk incident can be reduced.

2.2 Theory of Rooting

Rooted theory [43] is a qualitative research method that takes inductive logic as the core operating principle, in which the researcher performs coding analysis on the collected raw data, implements data organization and inductive refining, and ultimately extracts the theoretical categories of deeper significance. During the research process, the researcher needs to systematically sort out the correlation between different categories, clarify the structural relationship between theoretical elements, and finally form a new theoretical system through continuous comparison and conceptualization.

The rooted theory coding process consists of three core links, namely, open coding, principal axis coding, and selective coding. The open coding process emphasizes the need for the researcher to exclude the influence of subjective cognition, deconstruct and reorganize all the research materials in their initial form, which requires line-by-line parsing and labeling of the textual materials, and then classifying and integrating the labeled units according to the new criteria. The spindle coding session uses inductive deduction to identify and construct logical links between different conceptual categories, and to classify the same type of coding units into higher-level categories. Selective coding involves identifying the coding framework for the core categories within the existing conceptual category system through systematic sorting and integration.

2.3 Interpretive Structural Modeling (ISM)

The specific steps of the ISM method [44] are as follows:

(1) Set up an ISM team to identify the significant impact elements $N = \{S_i, i = 1, 2, 3, 4, 5, ..N\}$.

(2) Based on the mutual reachability of the elements, further construct the adjacency Boolean matrix, defined as A, and let the element a_{ij} of A, represent the direct reachability state between the element i and the element j, where 1 denotes reachability, and 0 denotes unreachability.

Is defined as $A = (a_{ij})_{nxn}$, then it is defined as:

$$a_{ij}=\begin{cases}0, & S_i\bar{R}S_j, \quad \text{The elements } S_i \text{ and } S_j \text{ do not have a direct binary relationship}\\ 1, & S_iRS_j, \quad \text{The elements } S_i \text{ and } S_j \text{ have a direct binary relationship}\end{cases} \tag{1}$$

(3) Calculate the reachability matrix M from the adjacency Boolean matrix.

Reachability matrix is a kind of square matrix, which reflects the direct or indirect reachability between all the elements in the system, in the directed graph to indicate whether there is a path of arbitrary length between any two nodes connected through any length, describes the ternary connectivity state that can be achieved through any number of transitive relationships between the elements in a system. Adjacency simply determines the adjacency of the elements, but if one reaches the other through an intermediate element, it means that the two elements are reachable and that each element can reach itself, hence the value of 1 for the diagonal of the reachability matrix.

Assuming the adjacency Boolean matrix A obtained after steps (1)~(2) above, to which is added the unit matrix I with diagonal I and the rest 0. This step ensures that each element of the matrix is considered as self-reachable at the beginning, i.e., I on the diagonal denotes the reachability of each element to itself. This matrix is then subjected to successive matrix multiplication operations until the matrix no longer undergoes any change, i.e., the desired reachable matrix M is obtained. In matrix M, if there exists some transitive binary relation between elements S_i and S_j, which is equivalent to the existence of a directed pathway between S_i and S_j from node S_i to node S_j in the corresponding directed graph, based on this logic then S_i is said to be reachable to S_j.

The reachability matrix serves as a matrixed representation of this relationship, and its element values have a specific meaning, where when the element of the reachability matrix corresponding to the S_i rows and S_j columns is 1, it represents that there exists a path between the factors of the rows and columns that allows S_i to reach S_j either directly or indirectly, and conversely, when the element of the reachability matrix factor of 0, it represents that there is no direct or indirect relationship of any kind between the factors of row S_i and column S_j. Therefore, the reachability matrix comprehensively reflects the intricate, direct or indirect interrelationships between the factors of the system, which is formulated as follows:

$$M=(A+I)^{n+1}=(A+I)^n\neq(A+I)^{n-1}\neq(A+I)^2\neq(A+I) \tag{2}$$

where n represents the maximum road length or the maximum number of passes under the no-loop condition, i.e., an element changes from 0 to 1, indicating that the corresponding node needs to be reached by n roads.

(4) Obtain the reachable set, prior set, and common set of each influence factor from the reachability matrix.

Using the reachability matrix obtained in step (3), the reachable set, prior set, and common set of each influencing factor can be further decomposed as follows:

Reachable set, denoted $P(S_i)$, is the set of factors represented by all columns corresponding to column elements with a value of 1 in the rows of factor S_i in the reachability matrix, representing the collection of all other factors that are reachable by factor S_i.

Prior set, denoted $Q(S_i)$, is the set of factors represented by all rows corresponding to row elements with a value of 1 in the columns of factor S_i in the reachability matrix, representing

the collection of all other factors that are capable of reaching factor S_i either directly or indirectly.

The common set: $T(S_i) = P(S_i) \cap Q(S_i)$, takes the intersection of the reachable and prior sets obtained above.

(5) Divide the hierarchy and draw the multilevel recursive order structure model

After obtaining the reachable set, antecedent set, and common set of each element according to the above step (4), further hierarchical division is carried out, which generally adopts $P(S_i) \cap Q(S_i) = P(S_i)$ or $P(S_i) \cap Q(S_i) = Q(S_i)$ Two ways to hierarchize, i.e., whether the common set is the same as the reachable set or the common set is the same as the antecedent set. In this paper, the form of $P(S_i) \cap Q(S_i) = P(S_i)$ is taken to carry out the hierarchical decomposition, which is a result-first method, and the core of the method lies in the fact that when the reachable set and the common set of a certain factor are equal, then the factor is regarded as the topmost element of the current hierarchy, and then the highest level of the ranks is removed, and continue to carry out the the same judgment logic, you can get each level step by step.

(6) Remove strongly connected subsets, transgressive relationships and obtain the skeleton matrix

If it is found that there exist two nodes with identical row and column element values respectively, this indicates that these two nodes are completely equivalent in terms of reachability and being reachable in the system, constituting a loop set. In this case, any node from the set of loops is selected as a representative element, which can effectively represent the functions and roles of the other nodes in the loops, so that the complexity of the reachability matrix and the convenience of the subsequent analysis can be greatly simplified. By processing in this way, a simplified reachability matrix can be obtained, called the reduced reachability matrix, denoted as M'.

The most concise among the many matrices capable of representing a particular reachable matrix M', that is, the adjacency matrix containing the minimum number of binary relations, meaning the minimum number of "1" elements in the matrix, is termed the minimum realization of the binary relation matrix of M', or the skeleton matrix.

For the reduced reachable matrix M', a simplified matrix A' can be obtained by removing the transitive binary relations between the elements of the matrix that have been established by the adjacency binary relations.

2.4 Network Hierarchy Analysis (ANP)

ANP (Analytic Network Process) [45] is a decision-making approach introduced as an evolution from the AHP method (Analytic Hierarchy Process). The ANP framework is illustrated in Fig. 1. This decision-making approach takes care of complex problems of decision making which have many elements, levels, and criteria by forming a control layer and a network layer. The control layer normally involves the primary objectives of criteria for the decision problem under consideration, whereas the network layer comprises the decision elements interacting among themselves.

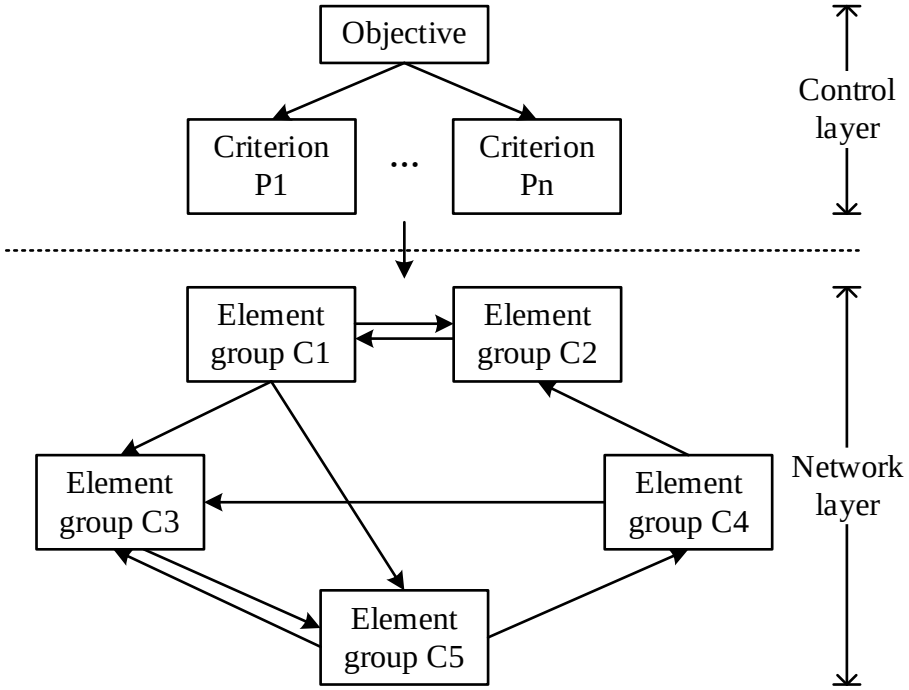

Figure 1: Basic dtructure of ANP

The calculation process of ANP is as follows:

(1) Construct network model

(1) Define the decision problem: define the background and objectives of the problem.

(2) Determine the decision elements: determine the individual criteria, sub-criteria and alternatives.

(3) Structuring the network: organize the decision elements into a network structure, determine the interdependence between the elements and the feedback loop.

(2) Constructing the pairwise judgment matrix.

(1) Construct pairwise judgment matrix: make pairwise comparative judgments on each pair of decision elements P_i and P_j, and use Saaty's 1-9 scale method to assess their relative importance, and the assessment criteria are shown in Table 1.

Table 1: Comparison criteria for importance scoring method

Serial number	A comparison of the importance of the two indicators	Score
1	The former is equally important than the latter	1
2	The former is slightly more important than the latter	3
3	The former is more important than the latter	5
4	The former is much more important than the latter	7
5	The former is extremely important than the latter	9
6	The former is more important than the latter and lies between the above-mentioned importance	2, 4, 6, 8

2) Fill in the matrix:

The result of the comparison is filled in the corresponding position of the matrix, e.g. $a_{ij} = 5$ means that the i th element is 5 times more important than the j th element.

The diagonal element of the matrix is l, since each element is equivalent compared to itself, i.e. $a_{ij}=1$.

The matrices are mutually inverse, if $a_{ij}=5$, then $a_{ji}=1/5$, i.e., the two corresponding positions of the matrices are mutually inverse.

3) Form the pairwise judgment matrix A:

$$A=\begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \tag{3}$$

(3) Conducting consistency tests

In the consistency test, the consistency of the judgment matrix is typically measured by the consistency ratio (CR), which is derived from the ratio of the consistency index (CI) to the random consistency index (RI).

The process begins by applying the eigenvalue decomposition method to the pairwise judgment matrix A, from which the largest eigenroot of the matrix, $\lambda_{\max}$, is calculated. Under conditions of perfect agreement, the largest eigenroot $\lambda_{\max}$ should equal the dimension of the matrix.

The maximum eigenvalue $\lambda_{\max}$ is calculated as follows:

$$\lambda_{\max}=\frac{\sum_{i=1}^{n}\left(\sum_{j=1}^{n}a_{ij}w_{ij}\right)/w_i}{n} \tag{4}$$

where w is the feature vector.

The consistency index (CI) and consistency ratio (CR) are calculated as follows:

$$CI=\frac{\lambda_{\max}-n}{n-1} \tag{5}$$

$$CR=\frac{CI}{RI} \tag{6}$$

By calculating the consistency index (CI) and consistency ratio (CR), potential inconsistencies in the pairwise judgment matrix can be detected, ensuring the reliability and accuracy of the judgment outcomes. A CR value below 0.1 indicates that the consistency test has been passed and the level of consistency is acceptable. Should the CR exceed 0.1, the judgment must be re-examined and revised in order to arrive at more consistent and credible decision results.

(4) Calculate the local priority vector

(1) Finding eigenvectors: the computation of eigenvectors w can be obtained by decomposing the eigenvalues $\lambda_{\max}$ of matrix A, i.e., find the makes:

$$Aw = \lambda_{\max} w \tag{7}$$

2) In order to make the elements in the feature vector w sum to 1, the feature vector is further normalized. The normalized local priority vector represents the relative importance of each element with respect to the other elements and sums to 1. The normalization method usually involves dividing each element in the feature vector w by the sum of all the elements:

$$w_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{8}$$

When the eigenvectors are normalized, a local priority vector will be created for each individual, which is used to express how important the individual is relative to the next level.

(5) Construct initial supermatrix

(1) Define the supermatrix: according to the local priority vector, the results of each pairwise judgment matrix are integrated into the initial supermatrix W. The initial supermatrix W is a matrix containing all the elements in the decision network and their mutual influence relationships. The size of this matrix is $n \times n$, where n is the total number of all elements in the decision system. The initial supermatrix can be divided into submatrices, each of which reflects the influence of a particular element. The structure of the initial supermatrix is as follows:

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix} \tag{9}$$

2) Populated supermatrix: W_{ij} represents the influence of element group i on element group j, as populated by a vector of local priorities computed from the pairwise comparison matrix. The positions of non-related elements are filled with zeros.

(3) Column normalization: after obtaining the initial supermatrix, it is necessary to normalize each column of the supermatrix, i.e., to ensure that the sum of the elements in each column is 1. This is to ensure that the influence of each element can be correctly normalized in the subsequent calculations. The specific method is as follows:

$$W_{ij} = \begin{bmatrix} \frac{W_{11}}{\sum_{k=1}^{n} W_{k1}} & \frac{W_{12}}{\sum_{k=1}^{n} W_{k2}} & \cdots & \frac{W_{1n}}{\sum_{k=1}^{n} W_{kn}} \\ \frac{W_{21}}{\sum_{k=1}^{n} W_{k1}} & \frac{W_{22}}{\sum_{k=1}^{n} W_{k2}} & \cdots & \frac{W_{2n}}{\sum_{k=1}^{n} W_{kn}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{W_{n1}}{\sum_{k=1}^{n} W_{k1}} & \frac{W_{n2}}{\sum_{k=1}^{n} W_{k2}} & \cdots & \frac{W_{nn}}{\sum_{k=1}^{n} W_{kn}} \end{bmatrix} \tag{10}$$

(6) Calculate the limit supermatrix

(1) Calculate the weighted supermatrix: if different groups of elements have different influences on the decision, it is also necessary to transform the initial supermatrix into a weighted supermatrix. The weighted supermatrix is the result of multiplying the weights of the control criteria in the decision by the corresponding parts of the initial supermatrix, thus generating a weighted matrix that represents the influence of each element in the global picture.

2) Iterating the initial supermatrix: a stable matrix is obtained by continuously multiplying the weighted supermatrix by itself until the matrix no longer changes. This process is called the power operation of the matrix, and through constant iteration, each column of the supermatrix gradually converges and converges.

(3) Convergence to the limit supermatrix: after many iterations, the supermatrix will eventually converge to form a limit supermatrix. After this step, every column in the matrix will become identical, symbolizing the final priority of each individual. Every value in the matrix at this step will represent the total weight of each individual compared to other individuals.

The limit supermatrix W^* is finally obtained:

$$W^* = \lim_{k\to\infty} w^k \tag{11}$$

For specific calculations, the iterative calculations are performed by the following equations:

$$W^{k+1} = W^k \cdot W \tag{12}$$

Until $W^{k+1} \approx W^k$. The limit supermatrix W^* represents the prioritization relationship between the decision factors in the steady state.

(7) Comprehensive Prioritization

(1) Extracting the global priority vector: the global priority vector of each element is extracted from the limit supermatrix. The values attributed to these elements depend on their relative importance in the decision-making process; the higher the importance of the element, the more significant the impact of such an element in shaping the decision.

2) Weighted processing of comprehensive priority: if different groups or levels of factors have different weights, the priority vector of each element needs to be weighted. According to the weight of each group, the comprehensive priority of each element is calculated.

3) Sorting by Priority: The final comprehensive prioritization table ranks all the factors according to their weights, helping decision makers to see clearly which factors should be prioritized the most.

3 Live e-commerce supply chain risk identification based on rooting theory

3.1 Experimental Methods and Data Sources

The coding analysis in this chapter is carried out using the NVivo12 program, with a view towards conducting a grounded theory coding analysis at three levels. Prior to undertaking the coding analysis, 25 percent of the interviews were held in reserve for saturation testing in later stages of the study.

The qualitative data needed for the study was sourced through two sources. The first method entailed crawling consumer negative reviews of products offered by live-streaming e-commerce

companies from live streaming sites through big data mining to generate firsthand information. In the big data mining exercise, consumer reviews were gathered separately for the five most popular categories of products offered by live-streaming e-commerce businesses, including daily necessities, beauty care category, clothing, food and fresh food and electronic products category of the twenty kinds of commodities of the poor evaluation information, including the head of the anchor and the tail anchor data, crawling a total of 10,000 pieces of poor evaluation information. The second is to obtain secondary information by searching online news events and so on, including expert interviews, industry-related reports, typical case reports, etc., to supplement and enrich the primary information. A total of more than 120,000 words of textual information were collected this time.

3.2 Coding process

3.2.1 Open coding

Open coding realizes the purpose of interpreting the phenomenon and its data with concepts by breaking down the raw data and naming the raw data with concepts and categories, a process that requires the researcher to abandon personal bias and research stereotypes to compare and analyze the collected raw data word by word and sentence by sentence. At the same time, attention should be paid to the close proximity to the data itself during the coding process, so as to obtain 84 initial categories. After categorization and repeated comparisons based on the intersection between the initial concepts, the 36 most valuable initial categories were finally extracted.

3.2.2 Spindle coding

Based on the results of the open coding, the spindle coding is used to sort out the potential logical relationship between the initial categories, so as to further refine and differentiate the initial categories. In addition, by fully exploring the connotation of each independent category and discovering and establishing the organic connection between each independent category, the purpose of summarizing the initial and main categories in turn is realized. After generalization and abstraction, a total of 14 main categories are obtained at this stage. The results of the main axis coding are shown in Table 2.

Table 2: Spindle coding results

Main category	Preliminary category
Commodity supply risk (S1)	The goods are unsafe (D1)
	The price of the goods is high (D2)
	There is a quality problem with the product (D3)
	Product design issues (D4)
Supplier Risk (S2)	The supplier's production capacity is insufficient (D5)
	The willingness of suppliers to cooperate has declined (D6)
	Quality fluctuation (D7)
Logistics delivery risk (S3)	Risks of loading, unloading and handling (D8)
	Logistics packaging risk (D9)
	Transportation process risk (D10)
	Delivery risk (D11)
The risk of selecting the wrong partner (S4)	E-commerce partner (D12)
	Live streaming platform partner (D13)
	Breach of contract in live-streaming cooperation (D14)
	MCN agency breach of contract in cooperation (D15)
Natural emergencies risk (S5)	Natural disaster (D16)
	Climate change (D17)
Policy and legal risks (S6)	Policy adjustment (D18)
	The relevant laws and regulations are not complete (D19)
	Lack of supervision by relevant departments (D20)
Public event risk (S7)	Public health event (D21)
	Public opinion crisis (D22)
Employee accident risk (S8)	Improper operation by the employee (D23)
	Risk of staff turnover (D24)
Information technology risk (S9)	Live streaming technology failure (D25)
	Data security (D26)
Compliance management risk (S10)	Compliance risks of live-streaming content (D27)
	Product quality and labeling compliance risks (D28)
Consumer behavior risk (S11)	Passive consumer rights protection (D29)
	Crisis of trust (D30)
Risk of demand fluctuation (S12)	Seasonal demand fluctuations (D31)
	Market trend (D32)
Risk of incorrect demand forecasting (S13)	Market emergencies (D33)
	Insufficient data (D34)
Return risk (S14)	Return policy (D35)
	Market fluctuations (D36)

3.2.3 Selective coding

This study adopts a selective coding approach to systematically complete the key steps of theory construction.

First, based on the comparative analysis of the 14 main categories, four core categories with higher explanatory power were identified and refined through theoretical sampling and continuous comparison as shown in Table 3.

Table 3: Selective coding results

Main category	Preliminary category
Supply Risk (B1)	Commodity supply risk (S1)
	Supplier Risk (S2)
	Logistics delivery risk (S3)
	The risk of selecting the wrong partner (S4)
Macro environmental risk (B2)	Natural emergencies risk (S5)
	Policy and legal risks (S6)
	Public event risk (S7)
Operational risk (B3)	Employee accident risk (S8)
	Information technology risk (S9)
	Compliance management risk (S10)
Demand risk (B4)	Consumer behavior risk (S11)
	Risk of demand fluctuation (S12)
	Risk of incorrect demand forecasting (S13)
	Return risk (S14)

Logical associations among the fundamental categories and the other categories are further explored. Macro-environmental risk will impact supply risk, demand risk, and operational risk, while supply risk impacts operational risk, and operational risk impacts demand risk. Additionally, macro-environmental risk, operational risk, demand risk, and supply risk may impact live-streaming e-commerce supply chain risk via the risk transfer process. A conceptual framework based on the above relationships is proposed.

A story is built from the linkages identified above to develop a live-streaming e-commerce supply chain risk identification model as shown in Figure 2 below.

This framework for the risk identification model not only organizes the insights gained in the current research systematically but also links well with the existing theories, thus presenting a new perspective on the theory of live-streaming e-commerce supply chain risk.

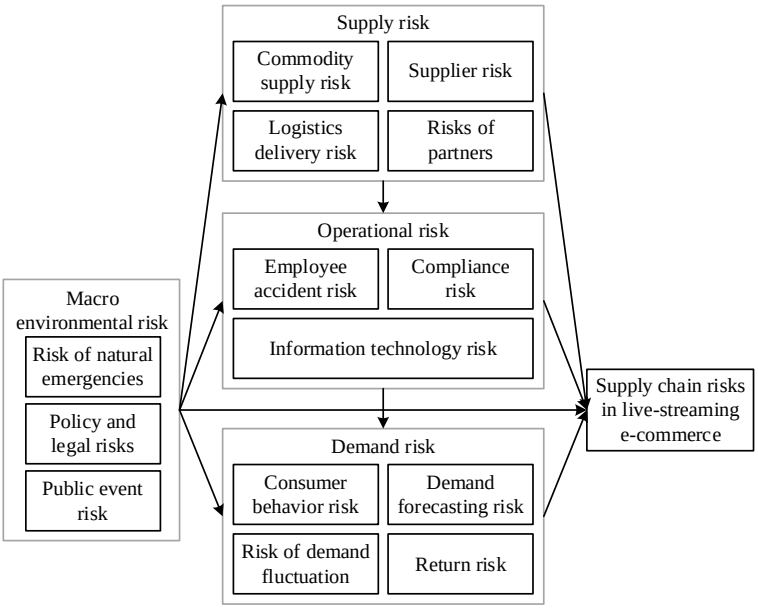

Figure 2: Risk identification model for live-streaming e-commerce supply chain

3.2.4 Saturation test

In order to guarantee the completeness, scientificity, and objectivity of the coding outcomes, it is necessary to carry out a theoretical saturation test to see whether the current risk identification results have attained theoretical saturation. It is suggested that theoretical saturation happens when the researcher finds it no longer feasible to pursue more details of a certain category. The theoretical saturation test is widely adopted as the basis for deciding when to end data gathering, which guarantees that the findings of the research possess high reliability and credibility. To confirm theoretical saturation of the risk identification results, this study also coded the 25% of the interview transcripts that were set aside, and no new categories were found; therefore, it can be assumed that the risk identification results have reached theoretical saturation with a high degree of confidence, and that no further additions to the case data are needed.

4 ISM-ANP based supply chain risk assessment for live e-commerce

By referring to the live-streaming e-commerce supply chain risk identification framework that has been developed by means of the analysis above, this chapter uses the ISM approach to specify the interactive relations between the risk factors individually and incorporate them into the ANP model. Then, using the ANP method, it is possible to calculate the weights of each risk factor.

4.1 ISM-based supply chain risk assessment model construction

In this part, the ISM model will be constructed to investigate the hierarchical relations between the factors that affect the risk in the supply chain of e-commerce by live-streaming in the digital economy era, to reveal the correlations among the risk factors, and also to determine superficial, intermediary, and deep risk factors.

4.1.1 Construction of the adjacency matrix

The adjacency matrix is used to describe the direct logical relationships between elements. Through a questionnaire survey of 16 experts in the field of live-streaming e-commerce, the internal relationships among the factors influencing live-streaming e-commerce supply chain risk are derived. When more than 90% of experts consider that factor S_j has an effect on factor S_j, then factor S_i is considered to have a significant effect on factor S_j, and the matrix element is recorded as 1. Otherwise, it is regarded as having no significant effect, and it is recorded as 0. Neighbor-joining matrix *A* obtained from the survey is shown in Fig. 3, in which dark cyan color indicates the value of 0, and tan color denotes a value of 1, and the latter is the same.

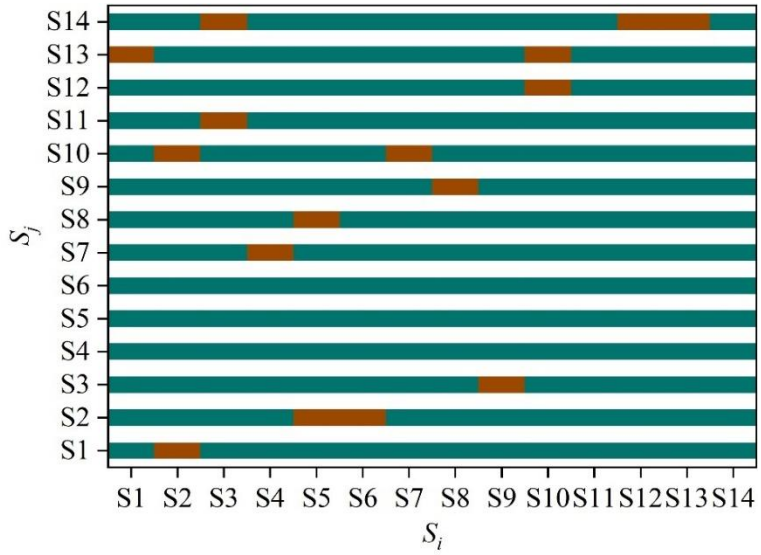

Figure 3: Adjacency matrix A

4.1.2 Construction of reachable matrices

Reachability matrix can be derived by taking repeated powers of the sum of adjacency matrix and the identity matrix (A+I) until matrix M does not change any further. Reachability matrix M is obtained using MATLAB and given in Fig. 4 below.

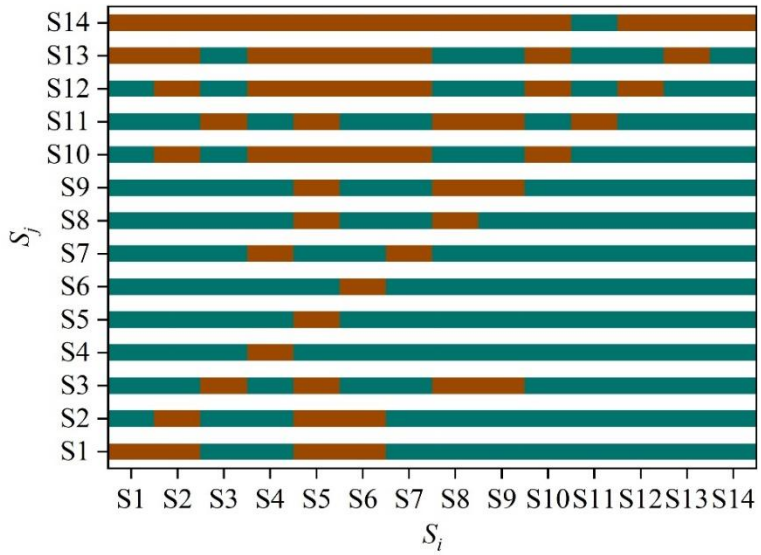

Figure 4: Reachable matrix M

4.1.3 Classification of tiers

Risk factors were sorted into multiple recursive layers through a thorough analysis of reachable set, prior set, and intersecting set so as to establish the hierarchy existing in risks associated with the live-streaming e-commerce supply chain. Reachable set, prior set, and respective intersecting sets have been provided in Table 4.

Table 4: Access sets and advance sets and their intersection table

Element	Access sets	Advance sets	Intersection
S1	S1, S13, S14	S1, S2, S5, S6, S8	S1
S2	S1, S2, S10, S12, S13, S14	S2, S5, S6	S2
S3	S3, S11, S14	S3, S5, S8, S9	S3
S4	S4, S7, S10, S12, S13, S14	S4	S4
S5	S1, S2, S3, S5, S8, S9 S10, S11, S12, S13, S14	S5	S5
S6	S1, S2, S6, S10, S12, S13, S14	S6	S6
S7	S7, S10, S12, S13, S14	S4, S7	S7
S8	S1, S3, S8, S9, S10, S11, S12, S13, S14	S5, S8	S8
S9	S3, S9, S11, S14	S5, S8, S9	S9
S10	S10, S12, S13, S14	S2, S4, S5, S6, S7, S8, S10	S10
S11	S11	S3, S5, S8, S9, S11	S11
S12	S12, S14	S2, S4, S5, S6, S7, S8, S10, S12	S12
S13	S13, S14	S1, S2, S4, S5, S6, S7, S8, S10, S13	S13
S14	S14	S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S12, S13, S14	S14

Since the reachable sets of elements S11 and S14 coincide with the intersection set, the above elements are removed and placed in layer 1, and the remaining factors after removal are shown in Table 5.

Table 5: The result of the first extraction

Element	Access sets	Advance sets	Intersection
S1	S1, S13	S1, S2, S5, S6, S8	S1
S2	S1, S2, S10, S12, S13	S2, S5, S6	S2
S3	S3	S3, S5, S8, S9	S3
S4	S4, S7, S10, S12, S13	S4	S4
S5	S1, S2, S3, S5, S8, S9 S10, S12, S13	S5	S5
S6	S1, S2, S6, S10, S12, S13	S6	S6
S7	S7, S10, S12, S13	S4, S7	S7
S8	S1, S3, S8, S9, S10, S12, S13	S5, S8	S8
S9	S3, S9	S5, S8, S9	S9
S10	S10, S12, S13	S2, S4, S5, S6, S7, S8, S10	S10
S12	S12	S2, S4, S5, S6, S7, S8, S10, S12	S12
S13	S13	S1, S2, S4, S5, S6, S7, S8, S10, S13	S13

Using the accessible set, the prior set, and the table of the intersecting sets, four rounds of hierarchical extraction are conducted according to the principle of priority, and the entire process of stratification after all the extractions is shown in Table 6.

Table 6: Stratification situation

Hierarchy	Factor
Floor 1	S11, S14
Floor 2	S3, S12, S13
Floor 3	S1, S9, S10
Floor 4	S2, S7, S8
Floor 5	S4, S5, S6

4.1.4 Mapping the Directed Topology Hierarchy

The layer topology is drawn according to the hierarchical situation of the reachable set results, firstly, the elements are drawn according to the hierarchical situation, and then connected according to the reachable set of each element, and finally, the cross-layer connections that can have an indirect influence relationship are removed, to get the final layer topology as shown in Fig. 5. Layer 1 forms the surface layer, Layer 5 forms the deep layer, and Layers 2 to 4 form the middle layer. The deep layer influences the surface layer in a directional manner, the surface layer influences the deep layer, and the middle layer influences each other.

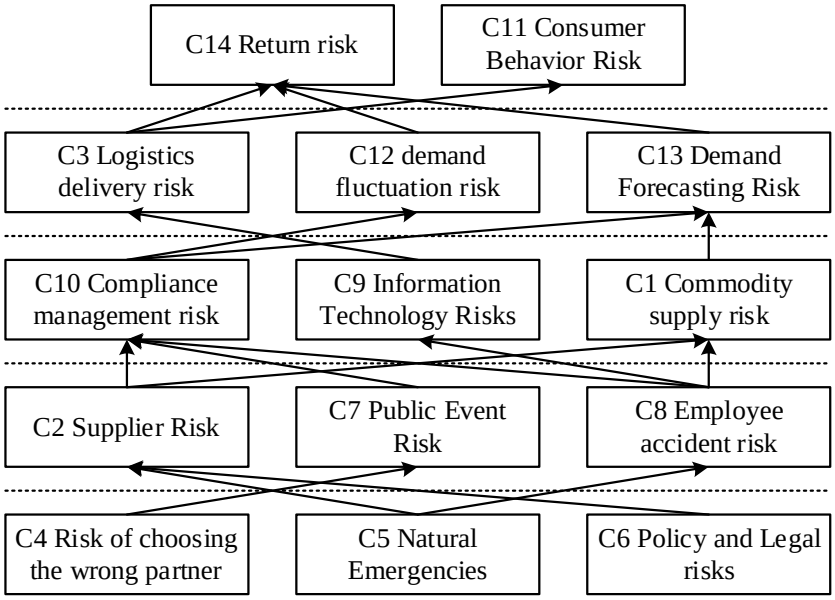

Figure 5: Hierarchical Topology Diagram

4.2 Analysis of ISM model results

4.2.1 Surface direct influence factors

Surface layer direct influence risks include return risk and impulse buying by consumers risk. This pair of risks is the most direct exposure risks and perceived terminal risks of live-streaming e-commerce supply chain risks, and it manifests the real terminal risks caused by supply chain problems.

In the deep factor transmission of return risk, logistics delivery risk of cargo damage, delay and other problems directly trigger returns. Demand forecast errors lead to understocking and delayed deliveries will lead to consumer returns, while overstocking will lead to seasonal merchandise stagnation that fails to meet consumer demand and triggers returns. Supply risk is a direct influence on returns, and quality issues or opaque information, such as false advertising, can lead to a collapse in consumer trust, resulting in a surge in returns. The formation of return

risk depends more deeply on the interaction between L5 deep-rooted risk and L2-L4 middle-rooted risk. In the risk transmission path of "supplier risk (S2) → product supply risk (S1) → return risk (S14)", insufficient production capacity or decreased willingness to cooperate with the supplier will affect the product supply risk, which will then lead to the return of goods by consumers.

In the deep-rooted transmission of consumer behavioral risk, compliance management risk triggers consumer behavioral risk through the risk transmission path of "live broadcast content violation → consumer misinformation → trust crisis". Information technology risk triggers consumer behavioral risk through the risk transmission path of "data leakage, loss of consumer security, and reduced willingness to purchase". Supplier risk triggers consumer behavior risk through the risk conduction path of "decreased willingness to cooperate with suppliers → fluctuations in product quality → inconsistent consumer experience → loss of loyalty". The root cause of consumer behavior risk can be traced back to the deep risk factors, amplified step by step through the middle risk, in the "S6 policy and legal risk → S10 compliance management risk → S14 return risk" risk conduction path, such as live broadcast propaganda regulations tighten policy adjustments will affect merchants to urgently shelve the goods triggered by the consumer trust crisis.

4.2.2 Middle-level influences

The mid-level risks include layers L2-L4, where supply chain risk transmission both takes inputs from the underlying root causes of risk, and through interactions transforms the risk into directly observable surface-level issues. These include S2 supplier risk, S7 public event risk, and S8 employee accident risk in the L4 layer, S1 commodity supply risk, S9 information technology risk, and S10 compliance management risk in the L3 layer, and S3 logistics delivery risk, S12 demand fluctuation risk, and S13 demand forecast error risk in the L2 layer.

In the live e-commerce supply chain risk transmission mechanism, the intermediate layer risk can delay effect amplify the destructiveness of the risk, and such delay effect leads to the failure of the traditional risk assessment model.

4.2.3 Deep Impact Factors

At the fifth level of supply chain risk influence layers, wrong partner selection risk of S4, natural contingency risk of S5, and policy and legal risk of S6 are the fundamental factors causing risks in live-streaming e-commerce supply chain. They manifest their consequences as terminal risks after multilevel transmission; thus, they deserve more attention.

Deep risk has the following characteristics:

(1) Independence, that is, it does not rely on other risk triggers.

(2) Irreplaceable, which cannot be completely eliminated by optimizing the middle layer. Although the probability of occurrence is extremely low, but once it occurs, its destructiveness is huge, which in turn affects a variety of supply chain risk occurrence.

(3) Leverage effect, small perturbation triggers systemic collapse.

4.3 Determination of ANP-based risk assessment weights

With the relationships between the live-streaming e-commerce supply chain risk impact factors being analyzed via grounded theory and the ISM method, the indicator relationship network was generated using Super Decisions software, and the result of ISM-ANP network can be seen from Figure 6 below.

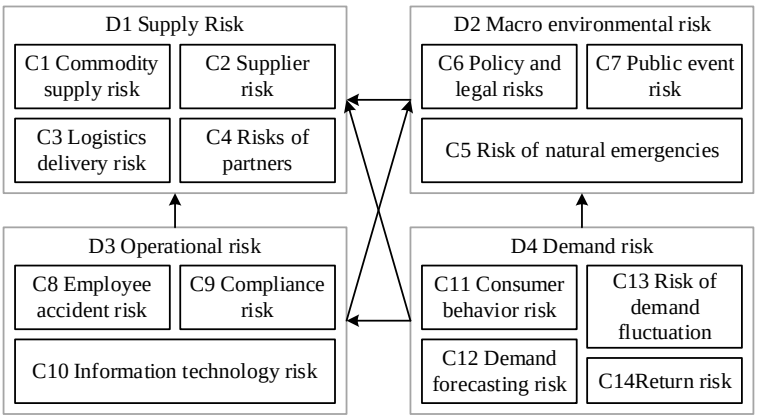

Figure 6: ISM-ANP network structure diagram

By taking the four main factors that affect the risk of live-streaming e-commerce supply chain risk as the criterion layer and taking the other 14 factors as the sub-criteria layer, the judgment matrices among these factors can be built. In addition, based on the pairwise comparison scores of the 16 experts' interviews, all matrices have passed the CR consistency test. After that, an unweighted supermatrix is built according to formula (9). Based on the degree of the influence exerted by factors in each factor group on the sub-criteria layer, the weighted matrix is obtained and then the limit supermatrix can be achieved according to equations (10) and (11). The elements in this matrix represent the weights of these indicators.

Based on the ANP network analysis, the weights of the primary and secondary indicators for assessing live-streaming e-commerce supply chain risks are shown in Figure 7. It shows that among the primary indicators, the influence exerted by the supply risk (B1) on the risk evaluation is the largest, reaching a weight of 0.3507. Next, there are the macro-environmental risk (B2), demand risk (B4), and operational risk (B3), weighing at 0.2900, 0.2313, and 0.1280. On the sub-criteria layer, supplier risk (S2), commodity supply risk (S1), policy and legal risk (S6), natural contingency risk (S5), and consumer behavior risk (S11) are relatively important since their respective weights exceed 0.10. This indicates that among the four kinds of risks in the live-streaming e-commerce supply chain, the supply risk plays the dominant role, especially the commodity supply risk.

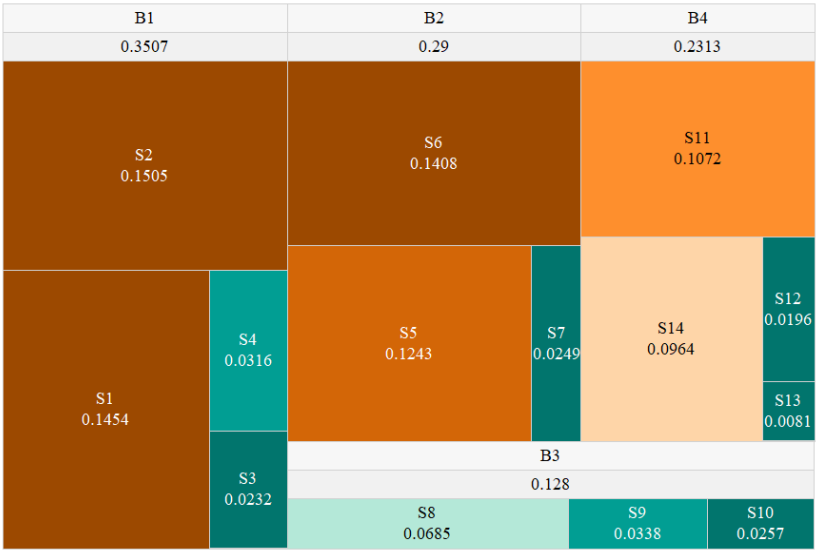

Figure 7: Weights for risk assessment of live-streaming e-commerce supply chain

5 Conclusion

This paper implements the risk identification and risk evaluation of the live-streaming e-commerce supply chain under the background of the digital economy through the use of grounded theory, Interpretive Structural Modeling, and Analytic Network Process together. Grounded theory is utilized as the risk identification technique of the live-streaming e-commerce supply chain, whereby four major risk types and 14 minor risk elements are identified, including supply risk, macroenvironment risk, operational risk, and demand risk, and serve as the foundation for creating the risk assessment indicator system.

The risk factor topology of the live-streaming e-commerce supply chain hierarchy is generated by using the Interpretive Structural Model, consisting of five layers. Layer one comprises the surface layer, layer five comprises the deep layer, and the other three layers constitute the middle layer. Surface layer direct influence factors include return risk and impulsive shopping risk, reflecting the direct exposure risks of the live-streaming e-commerce supply chain. Deep layer influence factors include partnership risk, contingency risk, and legislation risk, which are regarded as the root cause of risks within the supply chain. In addition to the above-mentioned surface layer influence factors and deep layer influence factors, the rest nine influence factors belong to the middle layer, serving as the medium for transformation from the root cause into visible surface issue. Those risk factors include supply risk, public events risk, employee accident risk, commodity supply risk, information technology risk, compliance management risk, logistics and delivery risk, demand variation risk, and demand forecasting error risk.

According to the results of weight allocation in each risk factor, supply risk is identified as the core risk of live-streaming e-commerce supply chain, with a weight of 0.3507. Among the corresponding secondary indicators, Supplier Risk and Commodity Supply Risk have the largest weights of 0.1505 and 0.1454, respectively, indicating that they are both the main drivers and core shortcomings of supply chain resilience, with a combined share of 84.37%, highlighting the high dependence of live e-commerce on supplier stability and commodity quality.

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