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INTERNET OF THINGS-ENABLED TOURISM ECONOMIC DATA ANALYSIS AND SUPPLY CHAIN MODELING

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Abstract. The purpose is to cut the costs of Supply Chain enterprises in Ice-Snow Tourism (IST) and improve the intelligence and automation of Supply Chain Management (SCM). First, the spatial-temporal characteristics of economic data of the IST Supply Chain are analyzed based on the Internet of Things (IoT). Second, the annual Online Public Attention (OPA) data to IST in domestic cities and regions are collected. The quarterly concentration index and Gini coefficient are used to analyze their spatial and temporal characteristics. Then, the weighted fusion algorithm used for the Supply Chain scenario modeling is improved to solve data redundancy and improve information accuracy. Finally, the framework of the IST-oriented Supply Chain scenario ontology model is proposed. The experimental results show that Internet users give much attention to IST from 2011 to 2021. OPA to IST increased first and decreased and peaked in 2016. The final fusion value of the proposed data fusion algorithm is 20.0221, and that of the adaptive Weighted Average Method (WAM) is 20.0724. Thus, the proposed algorithm outperforms the adaptive WAM. The traditional scenario-based ontology model takes people as the center. In contrast, the Supply Chain scenario-based ontology model centers around product state and scenario. Therefore, the proposed Supply Chain scenario-based ontology model is entirely new. The proposed scenario-based ontology model using polymorphic IoT lays the foundation for developing an intelligent and automatic SCM. It has great practical significance in realizing efficient tourism industry management and SCM.

Keywords: Internet of things, big data, spatial and temporal characteristics, scenario modeling, supply chain, tourism economic data.

JEL Classification: D43, L13, L51.

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Introduction

Ice-Snow Tourism (IST) has been the prioritized tourism industry in the past decade in China. It features resource orientation and spatial-temporal characteristics. Some define IST as an eco-friendly sports tourism, integrating services like enjoyment, leisure, and experience based on ice and snow resources conveying local cultures. IST cities are administrative units with IST scenic spots. In particular, the efficient operation of an IST depends heavily on all links in the Supply Chain. Originally, Supply Chain meant "expanded development". Since then, Supply Chain has become a heated topic because of its increasing importance in enterprise development and product supply. Meanwhile, in the era of the Internet of Things (IoT), Artificial Intelligent (AI), and big data, Supply Chain Management (SCM) drives industrial upgrading toward digital and intelligent development and integration. As computer and Internet technology further advances, IoT enables human society's intelligence and high-efficient operation (Chan & Elsheikh, 2019). Today, tourism has become the leading tertiary industry in the national economy. Thanks to IoT technology, the tourism industry flourishes globally and can easily publicize scenic spot images. Simultaneously, governments are encouraging IoT-based infrastructure construction for tourism sites. At present, the domestic IST is still at its primary stage but is rapidly catching up with the support of the Chinese government.

In terms of research on Online Public Attention (OPA), foreign researchers focus on tourism, disease prediction, and unemployment. In contrast, domestic researchers pay attention to tourism demand analysis and the connection between OPA and passenger flow. Few have analyzed OPA using IoT technologies. Accordingly, this work studies IoT-enabled feature analysis of the IST economic data and Supply Chain scenario modeling. The innovation resides in exploring the spatial and temporal characteristics of the OPA to IST Supply Chain scenario modeling based on the quarterly concentration index and Gini coefficient.

IoT is a combination of computer technology and Internet technology, and it is one of China's strategic emerging industries. IoT sees wide applications in the Supply Chain cycle and thus improves SCM. However, Supply Chain enterprises produce huge amounts of data that bring both benefits and challenges when using IoT. The benefits lie in providing sufficient data for efficient and stable Supply Chain operations. The challenge is rationally using these data. At present, SCM encounters two major problems. The first problem is standardizing multi-source heterogeneous data. The second problem is reducing data redundancy in polymorphic IoT, which is the key to obtaining effective data (Sun et al., 2019; Sang et al., 2020). Further, as IoT perception and processing capacity hike, it is possible to make SCM more intelligent. In order to do so, this work makes an in-depth analysis of polymorphic IoT data to utilize IoT sensor data effectively. In particular, scenario-awareness technology can help mine sensor data, and scenario modeling is the basis of scenario awareness and application and personalized service recommendation and implementation. For example, scenario modeling can visualize the scene and data perception and processing. The seamless integration of polymorphic IoT and scenario modeling can effectively solve the SCM problems and promote intelligence and automation of the Supply Chain. Therefore, it is necessary to study Supply Chain scenario modeling.

The research significance is explained below: Given that domestic IST develops rapidly, but the research on the IST online publicity is scarce, this work discusses the IST based on big data. Specifically, it analyzes the temporal and spatial distribution characteristics of IST. This provides a new research perspective, enriches the research content of IST, and deepens the application of big data. At the same time, it provides a basis for the IST-oriented flow prediction. Following a case analysis of IST's temporal and spatial characteristics in Harbin, the peak season and off-season of the OPA to IST attractions are summarized according to OPA. Then, tourist flow prediction and corresponding reception measures are made. The findings and suggestions help tourism sectors better prepare for peak season, enrich off-season tourism products, implement effective IST management, and promote sustainable IST.

The innovations are: (1) since there is little research on OPA, the OPA to IST is discussed to analyze OPA's temporal and spatial characteristics and influencing factors; (2) the temporal and spatial distribution and influencing factors of IST cities are analyzed to reveal the impact of OPA on tourism towns.

The introduction presents the research background of IST and Supply Chain scenario modeling. Section 1 summarizes the relevant literature. Section 2 analyzes the temporal and spatial distribution of OPA to IST cities and implements the scenario ontology Supply Chain model. Section 3 analyzes the experimental results, and the last Section summarizes the conclusions.

1. Literature review

Many studies have analyzed the temporal and spatial characteristics of tourism economic big data and Supply Chain scenario modeling. Chinese researchers have paid extensive attention to Supply Chain scenario modeling in recent years and have made some achievements. Here, the research on the temporal and spatial characteristics of the OPA to tourism and the Supply Chain scenario modeling is reviewed.

There are great differences in IST research in and outside China. IST research originated in Europe and the United States (Sang et al., 2020), focusing on the ski market and the impact of climate on skiing. Domestic research on IST began in 2006, concentrating on customer satisfaction with IST and the relationship between IST and economic development. Ye et al. (2019) tested the relationship between expectation, service performance, perceived value, and tourist satisfaction using the adjusted Structural Equation Model (SEM) and three-year survey data of the tourism industry. The results showed that tourism expectations had a regulatory effect on the accommodation industry. The higher tourists' expectations of accommodation services were, the more sensitive they were to service quality (Ye et al., 2019). Jia (2020) compared tourists' consumption motivation and satisfaction in China and the United States by investigating online tourists' evaluations. Zeng (2019) analyzed the temporal and spatial characteristics of Tengwang Pavilion, a historical, scenic spot in Nanchang, from 2011 to 2019. The results revealed that the OPA to Tengwang Pavilion was increasing, but the annual growth rate was different. OPA peaked in April and October and plummeted to the lowest point on Friday. The OPA on weekends is greater than on weekdays (Zeng, 2019).

Some researchers claim that human-based scenario modeling aims to realize a system that can understand the contexts around users. Scenario modeling realizes scenario description through digital means and is the basis of scenario perception. A high-performance scenario modeling can improve the analysis, expression, and speed of context information and hardware devices. Many researchers studied IoT and mobile devices-based scenario awareness, with the MyMap system being the most famous application. In particular, MyMap could recommend customized user information. The Compass system improved MyMap by obtaining the scenario information around the user's axis. Then, it inferred and queried the obtained information to match user interest with the existing items and recommended them to the user. Yazdani et al. (2020) reasoned that uncertainty and risks were inevitable in the Supply Chain system. Thus, many concepts and methods could identify, analyze, and eliminate uncertain conditions in the knowledge-based community. Fuzzy logic was an intelligent tool to reduce imprecision and provide an acceptable accuracy level. As a result, a new fuzzy multicriteria decision strategy was proposed. The fuzzy interval expanded the decision-making experiment and evaluation laboratory and integrated them into the input of Quality Function Deployment (QFD) for the first time. The fuzzy decision-making model proposed was applied in actual scenes to eliminate the risks in the agricultural Supply Chain system. Lastly, the sensitivity analysis verified the stability of the model (Yazdani et al., 2020; Yan et al., 2020).

2. Research background

2.1. Basic architecture of polymorphic IoT

IoT can realize the connection and information exchange between things through the Internet. Its essence is to realize the interaction between people and things, things and things. People can control things through the IoT. IoT-connected things can also receive information and act intelligently, achieving the intelligent interconnection in and between people and things. With the continuous development of IoT and information technology, the functions of IoT expand from simple object identification, positioning, and tracking to the application of various sensors, nanotechnology, and intelligent information processing technology (Wang et al., 2020). The IoT content continues to be enriched, and the IoT-native data are massive and polymorphic. Polymorphic IoT involves various fields, information formats, and information collection methods. The common information includes location, temperature, humidity, gas concentration, illumination, audio, image information, and video (Oliveira et al., 2019). Similar to the traditional IoT, the polymorphic IoT also has three levels: the perception layer, the network layer, and the application layer. However, the polymorphic IoT can collect more comprehensive information. The network layer processing information becomes more complex than the traditional IoT. In the polymorphic IoT, the key technologies are Radio Frequency Identification (RFID) and WSN (Wireless Sensors Network) (Thaithatkul et al., 2019).

2.2. Analysis method and data source of spatial and temporal characteristics of OPA

Baidu index is a platform used to share Internet users' behavioral data. It counts each keyword's search frequency and displays the relevant information (Tong et al., 2020; Li, 2021; Wang & Lee, 2021; Han et al., 2020). The data platform is widely used as an important data analysis tool. Moreover, it is scientific and reliable to take the Baidu index as a statistical analysis tool in the era of big data (Sun et al., 2021, Yaacob et al., 2021). Therefore, the search indexes on the Baidu index platform are selected here as the OPA data. The keyword selection follows three principles: firstly, the words are accessible: the keywords are included in the Baidu platform and kept for some time. Secondly, the keywords attract much public attention with high search frequency. Lastly, the keywords are representative. Then, the primary keywords are searched on the Baidu platform following the principles, and unaccessible keywords are deleted.

Moreover, the Baidu platform ranks the research results from high to low frequency to determine the primary keywords. The Search Engine Optimization (SEO) tool uses the remaining words for keyword expansion. In this work, the keywords with higher OPA, such as Yabuli

Ski Resort, IST, and weather, are selected as the target keywords. Then, from January 1, 2011, to April 1, 2021, the keyword search is conducted quarterly, monthly, and on holidays on a provincial basis.

The interannual variation index, seasonal concentration index, and Herfindahl index analyze the temporal characteristics of the OPA to IST cities. The Gini coefficient and the geographical concentration index measure the spatial distribution of OPA, and the correlation analysis method reveals the temporal and spatial characteristics and the influencing factors of OPA.

$$G = 1 + \frac{1}{n} - \frac{1}{n^2 \bar{x}}(x_1 + 2x_2 + 3x_3 + \dots + nx_n). \tag{1}$$

In Eq. (1), G is the Gini coefficient. The closer the value is to 0, the smaller the relative difference is. And x_1, x_2, x_3... is the OPA of each province in descending order.

$$G = 100 * \sqrt{\sum_{j=1}^{n} (p_j / p)^2}. \tag{2}$$

In Eq. (2), p_j is the OPA to the IST in the region j, and p is the total OPA.

2.3. Ontology-based Supply Chain scenario modeling

Ontology is an important tool for knowledge reuse and sharing, widely used in information integration, information retrieval, information storage and sharing, and scenario modeling (Singh et al., 2018; Fang et al., 2019). Researchers believe that ontology contains four layers. The first is conceptualization. That is, the concepts related to certain objective phenomena are abstracted into models, but the model's performance has nothing to do with the specific environment (Won & Sim, 2020; Chen et al., 2021; Qin et al., 2021). The second is clearness. The constraints between concepts have an unambiguous definition. The third is formalization. The computer can read and process the ontology encoded by ontology language. The fourth is sharing. The ontology should reflect a collection of commonly recognized concepts within the domain. In conclusion, ontology can organize knowledge in the domain, and modeling should have clear and specific application methods (Zhang et al., 2020). The ontology-based modeling generally follows the "completeness, clarity, objectivity, consistency, scalability, and minimum commitment" principle by Gruber in 1995 (Hugeng et al., 2020). The collected original polymorphic association data cannot be directly used for scenario modeling. Data fusion technology can eliminate redundancies and improve information quality (Atiqur, 2021). This work focuses on Supply Chain scenario modeling using data fusion for redundancy reduction and information accuracy improvement. Specifically, the calculation-based data fusion technology is mainly studied by considering node energy, delay, accuracy, and network topology. It is challenging to design an efficient and comprehensive data fusion technology in WSN. Thus, a research-specific design should be made (Li, 2021; Sahebi et al., 2019).

A typical data fusion algorithm includes fuzzy theory, Bayes estimation, neural network method, clustering analysis, and Weighted Average Method (WAM) (Zang et al., 2020; Li et al., 2020). The Back Propagation (BP) neural network is widely used in neural networks or artificial neural networks. Applying BP neural networks to fuse multi-state association data can effectively reduce the data feature dimension and improve the data fusion efficiency (Puche et al., 2019). BP neural network is shown in Figure 1.

The WAM in the data fusion algorithm is simple and effective, suitable for simple scenarios. Its calculation is given in Eq. (3):

$$X = \frac{\sum_{i=1}^{n} w_i x_i}{n}. \tag{3}$$

In Eq. (3), X is the fusion result, x denotes the data before fusion, w represents the weight of data, and n means the number of data.

An adaptive AWM can automatically allocate weights according to the data quality by calculating the data's Mean Square Error (MSE). The larger the MSE is, the smaller the weight is. The smaller the MSE is, the larger the weight it is. In the adaptive WAM, nodes' sensing data can only be used to get high-quality fusion estimation (Hou et al., 2020). Based on BP neural network, WAM, and adaptive WAM, this work proposes an algorithm to fuse the sensing data of the Supply Chain node, as illustrated in Figure 2.

The proposed algorithm can be divided into four steps, as detailed in Figure 3.

Step 1 preprocesses the original data. A careless error is incurred in data acquisition when the network error exceeds a threshold (Calisaya-Azpilcueta et al., 2020). Generally, a careless error can be removed by the distribution method, Laida's law, and Grubbs' rule (Peterson et al., 2019). The experimental results show that Grubbs' rule produces a higher data accuracy when removing careless errors. Therefore, this work employs Grubbs' rule. The specific calculation reads: the data obtained by a node within the period of A is $x_1, x_2, x_3, \ldots, x_i, \ldots, x_z$. The mean of the data obtained by the node is counted by Eq. (4). Then, the residual error of the i-th measurement value is expressed in Eq. (5). The standard deviation of the data is manifested in Eq. (6).

$$\overline{x} = \frac{1}{z}\sum_{i=1}^{z} x_i; \tag{4}$$

$$V_i = x_i - \overline{x}; \tag{5}$$

$$\sigma = \sqrt{\frac{1}{K-1}\sum_{i=1}^{K} V_\mathrm{i}^2}. \tag{6}$$

According to $g_0(n, a)$ of Grubbs' rule, the following is obtained. If the measured data x_i satisfy Eq. (7), the quantity data will be eliminated.

Step 2 estimated the data collected by a single sensor in a period. After Step 1, data are divided into n groups, with more than 4 and less than 7 pieces of data in each group. The mean of group j is calculated in Eq. (7), and the variance of group j is counted in Eq. (8).

$$\overline{X_j} = \frac{1}{n_j}\sum_{i=1}^{n_j} x_{ji}; \tag{7}$$

$$\sigma_j^2 = \frac{1}{n_j - 1}\sum_{i=1}^{n_j} (x_{ij} - \overline{X_j})^2. \tag{8}$$

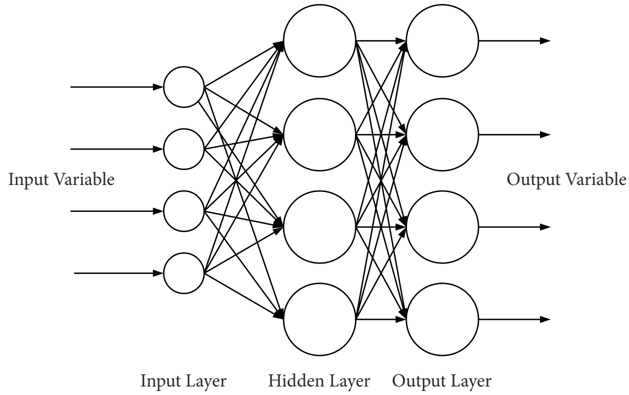

Figure 1. Structure of BP neural network

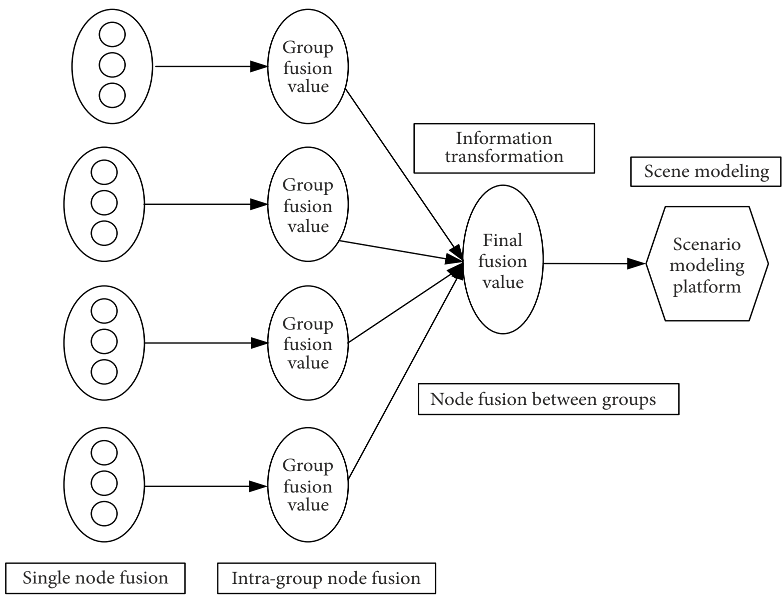

Figure 2. Structure of the data fusion of the proposed algorithm

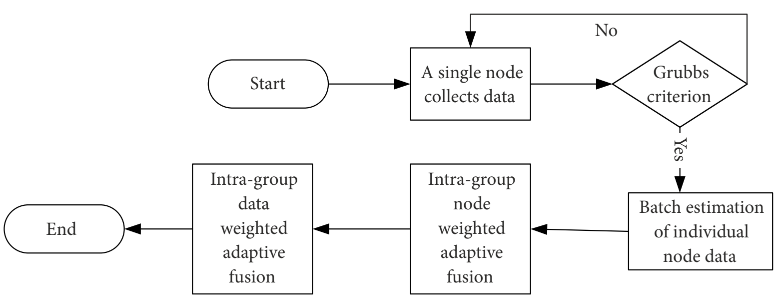

Figure 3. Flowchart of the proposed algorithm

According to the batch estimation theory, the optimal fusion variance of the i-th node is calculated by Eq. (9). The fusion value of the i-th node is calculated using the variance and mean of each group, as in Eq. (10).

$$\sigma_i^2 = \left(\sum_{j=1}^{n} \frac{1}{\sigma_j^2} \right)^{-1}, \ i = 1, 2, \ldots, m; \tag{9}$$

$$X_i = \left(\sum_{j=1}^{n} \frac{1}{\sigma_j^2} \right) \sum_{j=1}^{n} \frac{1}{\sigma_j^2} \overline{X_j}, \ i = 1, 2, \ldots, m. \tag{10}$$

The measurement data are divided into two groups. The first group is the variance of the node, expressed in Eq. (11), and the second is the estimated value of the point data expressed in Eq. (12).

$$\sigma^2 = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2}; \tag{11}$$

$$X = \frac{\sigma_1^2 X_2 + \sigma_2^2 X_1}{\sigma_1^2 + \sigma_2^2}. \tag{12}$$

Step 3 is the adaptive average weighted fusion of the estimated values of the nodes. The estimated value of a single node is obtained after Steps 1 and 2. Suppose there are m nodes in each group, the data fusion of a single node is recorded as X_i, and the variance is recorded as σ_i^2. Then, the estimated value of the nodes is adaptively weighted fusion. The optimal weight W_i of the estimated value of each node is calculated according to the optimal weight allocation rule. The data fusion value X_i of a single node calculated by weighted fusion is the weight of the data. The optimal fusion value and the corresponding variance are described in Eqs (13), (14), and (15).

$$W_i = \left(\sigma_i^2 \sum_{i=1}^{m} \frac{1}{\sigma_i^2} \right); \tag{13}$$

$$Y_q = \sum_{i=1}^{m} W_i X_i, \ q = 1, 2, \ldots, p; \tag{14}$$

$$\sigma_q = \sum_{i=1}^{m} W_i \sigma_i, \ q = 1, 2 \ldots, p. \tag{15}$$

Step 4 is the weighted adaptive data fusion between groups. Based on the first three steps, the weighted adaptive fusion is carried out again. The adaptive weighting factor W_q can be calculated by the group data variance σ_q. The optimal value of the measured data in this period can be obtained based on the adaptive weighting factor and the group data fusion value.

2.4. Framework of tourism Supply Chain scenario modeling based on IoT

The scenario modeling is based on polymorphic IoT. The multiple links of the tourism Supply Chain are the research object, and the top-down ontology construction method is used to respond to multiple Supply Chain links. First, the upper ontology of the tourism Supply Chain is constructed, and the specific mapping of each link is realized. Meanwhile, most model information will be collected from sensor devices. The primary data cannot be used directly. Thus, data fusion technology removes redundancies and obtains more accurate results. Based on the above analysis, the modeling framework proposed is depicted in Figure 4.

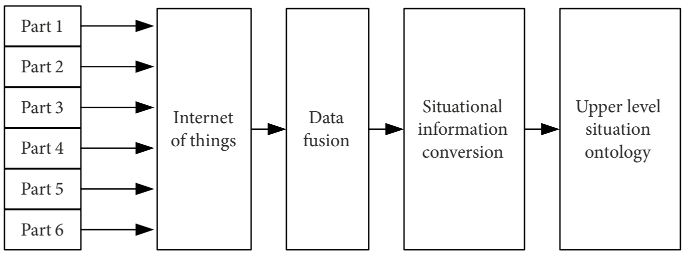

Figure 4. The framework of tourism Supply Chain scenario modeling based on polymorphic IoT

2.5. Analysis and test conditions of the proposed algorithm

MATLAB is used to simulate and verify the proposed algorithm. The methods are as follows: the normal function is used to simulate the data of three groups of sensors in MATLAB 2020, each group including five sensors. The standard deviation of the normal function of the first group is 0.05, and that of the other groups increases by 0.05 in turn. The benchmark value of the data is 20. Then the discrete random function is used to simulate the interference of sensors during data collection. In a single test, each sensor collects ten pieces of data, and the fusion value of the data will be calculated. Overall, 30 tests are taken in this work.

3. Temporal and spatial characteristics results of the IST-oriented Supply Chain scenario model based on the IoT

3.1. Influencing factors of OPA

Figure 5 compares the daily OPA data on IST in all provinces of China from March 1, 2011, to April 1, 2021.

Apparently, the OPA to IST is more from 2011 to 2021, and the overall trend increases at first and then decreases. OPA peaked in 2016 and fell after 2016. Specifically, the interannual change from 2011 to 2015 is significant, and that from 2016 to 2021 is slight. The interannual difference gradually decreases. Presumably, the number of domestic IST cities is gradually increasing, and the attention of tourists is distracted, which leads to the decline of OPA. Then, the interannual variation index is calculated to explore IST characteristics in Harbin, as in Figure 6.

The annual change indexes of the OPA to tourism from 2011 to 2021 are listed in Table 1.

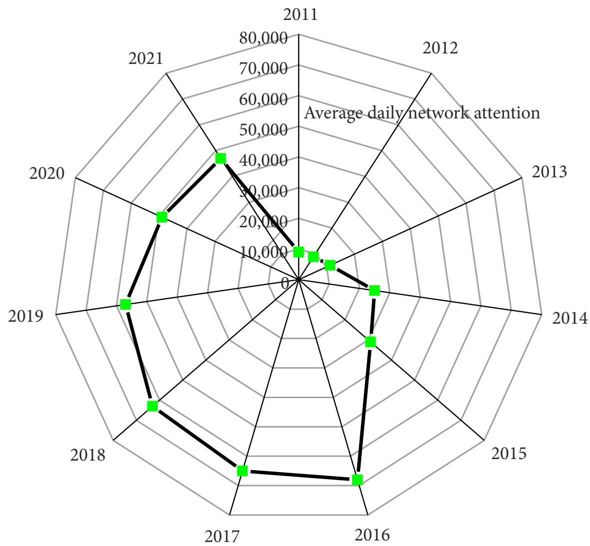

Figure 5. Average daily OPA from 2011 to 2021

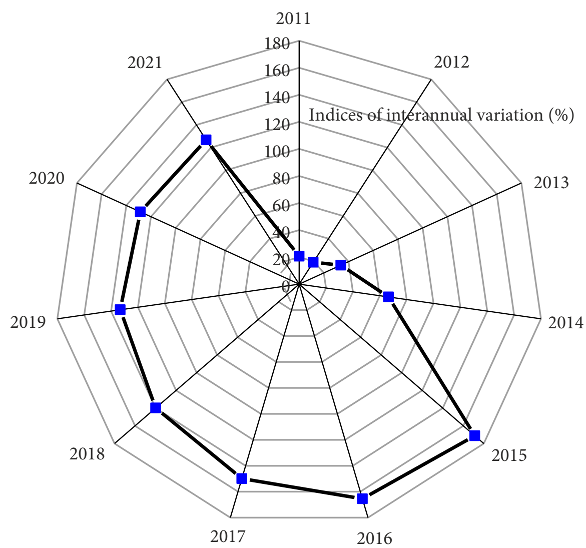

Figure 6. Indices of Interannual variation

Table 1. Annual change indexes of the OPA to tourism from 2011 to 2021

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Change Index	20.12	19.1	33.61	66.51	170.36	161.27	153.58	139.01	133.89	130.21	137.21

Table 1 shows the interannual change in the OPA of 31 provinces (cities and autonomous regions) in China to Harbin's IST.

Figure 6 tells that the interannual change of OPA to the IST in Harbin is not stable. Specifically, the interannual change was less than 100% from 2011 to 2014, while 171.28% in 2015. The interannual change was great from 2011 to 2015 but less than 100% from 2016 to 2021.

Figure 7(a) shows the monthly specific gravity index of Harbin from March 1, 2011, to April 1, 2016, and Figure 7(b) shows that from March 1, 2017, to March 1, 2021.

Figure 7 shows that the annual OPA to Harbin from 2011 to 2021 has the following characteristics. From 2011 to 2014, October, November, and December received the most OPA. From 2015 to 2019, January, February, May, August, October, November, and December received the most OPA. The OPA declined in March, April, June, and September. In addition, the trend of OPA to Harbin in the past 11 years is similar, forming a "W" curve. The OPA peaks appear in January, May, and December. Therefore, the IST model in Harbin has expanded to a tourism model with the characteristics of winter ice and snow and summer vacation.

The seasonal concentration index and Hafendar coefficient are used to study the quarterly variation characteristics of OPA, as plotted in Figure 8.

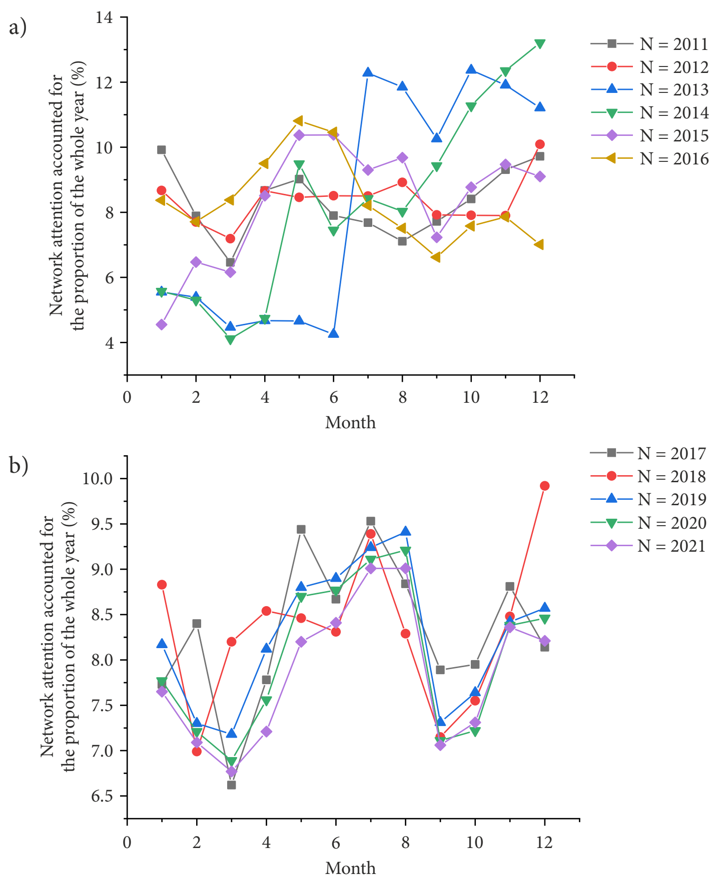

Figure 7. Monthly change of OPA (n – "year") (a. 2011–2016; b. 2017–2021)

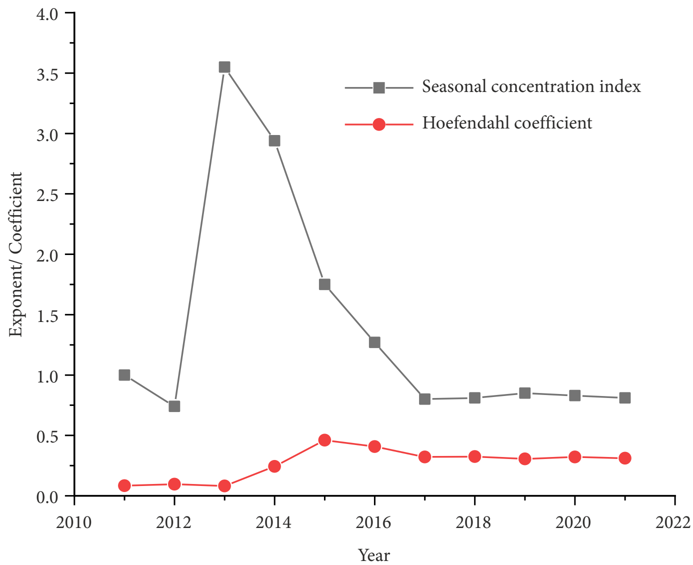

Figure 8. Seasonal concentration index and Hafendar coefficient

Figure 8 implies that the minimum seasonal concentration index of OPA is 0.82, and the maximum value is 3.61, which means that the value fluctuates greatly. In 2013, the seasonal concentration index was 3.61, reaching the maximum. In this case, the concentration of OPA is the largest, and the seasonal difference is obvious. From 2017 to 2019, the seasonal concentration index of the OPA to Harbin is small and has a continuous downward trend. OPA distribution is relatively uniform, and the increase and decrease trends of the Hofendar coefficient and seasonal coefficient in Figure 8 are the same. From 2011 to 2021, the OPA to Harbin's IST shows a trend of concentration before dispersion, which indicates that the seasonal difference in OPA is great. Possibly, the IST attractions are more dependent on resources and climate and have a greater seasonal difference than natural tourist destinations. Besides, November and December are the city's IST seasons. In this period, tourists can experience high-quality IST activities, such as watching ice lanterns, skiing, and ice fishing. In the peak season, Harbin should improve the quality of the IST products and diversify product types to provide a unique experience for tourists.

Tourists' travel motives vary greatly, and most of them travel during holidays, but a few choose their leisure time. This tourist distribution causes obvious fluctuations in the OPA to IST during holidays. Therefore, the OPA to IST during national holidays from 2011 to 2021 is analyzed, and the results are presented in Figure 9.

As in Figure 9, the OPA to IST in Harbin fluctuates with national holidays. From 2011 to 2021, OPA peaked just before the holiday, and the fluctuation was most obvious before Labor Day and Dragon Boat Festival. Since the Spring Festival from 2011 to 2021 lasted for 6–8 days, the peak OPA appeared in the week before the festival, and the lowest OPA was 3–5 days after the festival.

Next, the Gini coefficient statistically analyzes the OPA to IST in all the provinces from 2011 to 2021, as in Figure 10.

Figure 10 suggests that five provinces and cities pay the most attention to the IST on the network: Heilongjiang Province, Beijing City, Jilin Province, Liaoning Province, and Guangdong Province, roughly divided into two groups. Group 1 includes provinces near Harbin geographically. Apparently, there is a decreasing trend of OPA to Harbin's IST as the geographic distance extends. Tourists prefer short-distance tourism attractions that cost less time and money than long-distance attractions. Group 2 is the provinces and regions with higher economic development levels. Tourists from this group have more funds to spare for tourism.

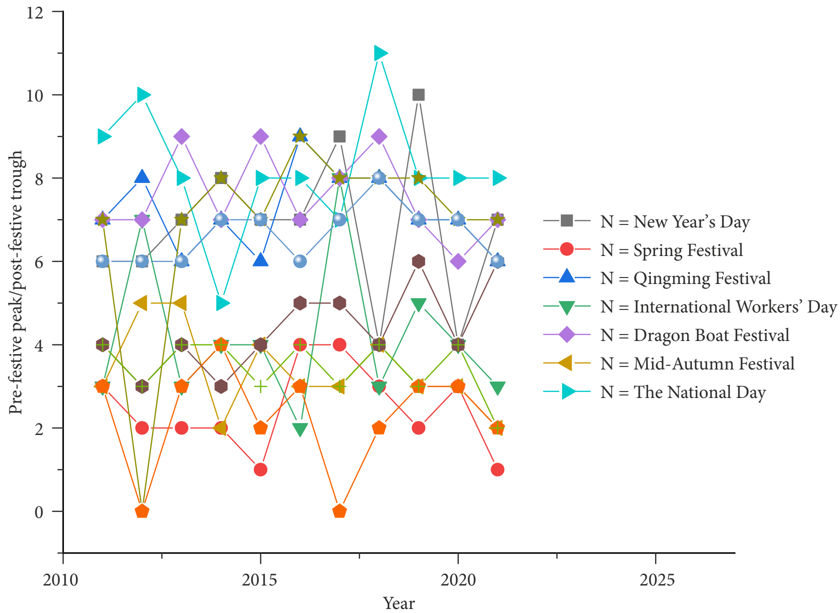

Figure 9. OPA to IST during national holidays (n refers to national holidays)

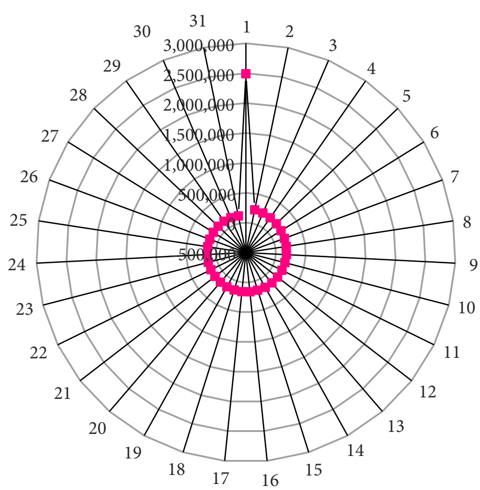

Figure 10. Radar chart of OPA to IST in Harbin from 2011 to 2021

Harbin's OPA increases first and then declines. It reached the maximum in 2015 and decreased slightly in 2016 and 2019. The interannual variation index from 2011 to 2015 was the largest, and it tended to stabilize from 2016 to 2019. The OPA in the off-season and peak season has different characteristics: in 2011–2014, October to December was the OPA peak season, and the OPA off-season was from February to April. In 2015–2021, the OPA peak season was from November to December, and the OPA off-season was in March. This shows that Harbin has developed from winter-centralized IST into snow entertainment in winter and summer.

3.2. Analysis of the improved algorithm

The collected data are analyzed. Table 2 explains the test results of the unit root of first-order differential sequences Dy and Dx. Then, Figure 11 signals the fusion value, variance, and weight of sensor data using the improved algorithm. Figure 12 showcases the fusion value and weight of sensor data using the adaptive weighting algorithm.

Table 2. First-order differential sequence Dy and Dx unit root test results

Samples	ADF test statistics	1% horizontal critical value	5% horizontal critical value	10% horizontal critical value
DY	−27.84365	−3.438521	−2.865040	−2.568689
DX	−28.91714	−3.438529	−2.865040	−2.568689

Table 2 shows that the ADF test statistics of Dy is −27.84365, and that of Dx is −28.91714. The 1% horizontal critical value of Dy is −3.438521, and that of Dx is −3.438529.

From Figures 11 and 12, compared with the adaptive WAM, the proposed algorithm can remove abnormal data, estimate the data of a single sensor, and assign weights according to data quality. Furthermore, the proposed algorithm is more reasonable for distributing data weights and has smaller absolute errors than the adaptive WAM. Thus, the data accuracy of the proposed algorithm is improved. The proposed algorithm is better than adaptive average weighted fusion. Although the ordinary adaptive WAM can automatically allocate the weights according to data quality, it does not eliminate the abnormal data, resulting in a large calculation deviation. By comparison, the proposed algorithm first eliminates the abnormal data, performs adaptive weighted fusions several times, reduces the errors layer by layer, and ensures data accuracy and stability. The proposed algorithm removes the error with significant deviation and reduces fusion information loss. It effectively processes the application data in practical application, fuses data accurately, and has great robustness.

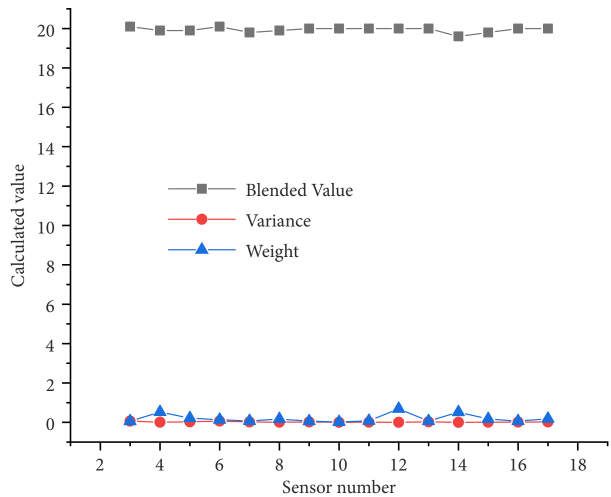

Figure 11. Fusion value, variance, and weight of the data of sensors based on the proposed improved algorithm

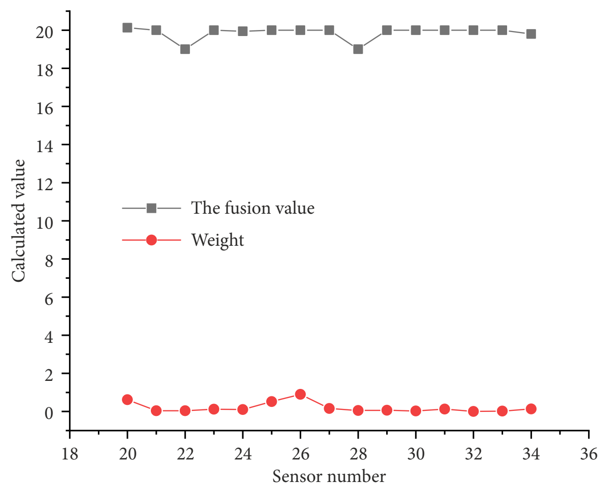

Figure 12. Fusion values and weights by adaptive WAM

Conclusions

The economic data of IST based on the Supply Chain scenario ontology model and OPA are discussed. First, the OPA data of IST in Harbin from 2011 to 2021 are collected. Then, temporal and spatial characteristics of OPA to IST are analyzed. Finally, a data fusion algorithm is proposed to model the Supply Chain scenario. The IST-oriented Supply Chain scenario ontology model is implemented. The OPA to IST first increases and then decreases, with a similar interannual change index in terms of the temporal characteristic. By comparison, OPA to IST is significantly different and becoming much more concentrated in spatial characteristics.

Nevertheless, the difference in OPA to IST between the east and west is slight. Finally, the adaptive WAM is applied to scenario modeling in the Supply Chain because it can remove useless data. This work has achieved the expected research results and has drawn valuable conclusions.

There are still some shortcomings: (1) the temporal and spatial characteristics of OPA to IST are only analyzed in one IST city. The future work will compare the tourist flows of different IST cities to reveal the temporal and spatial characteristics of OPA to tourism. (2) only a preliminary IST-oriented Supply Chain scenario-based ontology model is proposed. In the future, the ontology model will be improved. Additionally, unstructured data will be applied to the ST-oriented Supply Chain scenario-based ontology model. More research methods will be innovated to analyze better the influencing factors of the temporal and spatial distribution of the OPA to IST cities.

Conflict of interest

The authors declare that they have no conflicts of interest.

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