Designing and Implementing a Digital Management Platform in the Era of Big Data for Enriching Cultural Tourism Experiences

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Abstract. In order to improve the effect of smart tourism management under the background of big data, this paper combines the construction of a smart tourism management platform with big data technology information, and classifies the situational information into sensing situational information and non-sensing situational information. Moreover, this paper proposes an algorithm framework for inconsistency elimination based on contextual information comprehensive quality indicators and DST.Based on the theoretical basis and structural model, this paper seeks to promote the internal and external motives of the integrated development of the smart tourism system, and promote the system integration of smart tourism under the joint driving of the internal and external motives. The experimental research shows that the smart tourism management platform based on big data technology proposed in this paper has a good tourism management effect

Key words: big data; smart tourism; management platform; design; Digital Management
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1 INTRODUCTION

With the gradual improvement of the national economic level, people's pursuit of the spiritual world has gradually increased, and the tourism industry has ushered in opportunities and development. However, as one of the experiences that tourists value, the traditional travel route planning is time-consuming and labor-intensive, and the user experience is poor, so it is in urgent need of improvement. In recent years, the development of science and technology has brought new challenges and opportunities to the traditional tourism route planning, and the smart tourism route planning based on the power of science and technology has emerged as the times require.

Smart tourism, simply put, is to improve the quality of tourism through the rational use of intelligent equipment to effectively transmit or obtain the information required for tourism. Through AR technology, users can experience a novel and unique immersive travel experience without leaving home. Moreover, users can feel AR augmented reality technology using electronic devices, and use computer-generated graphic images and video images to generate visual and auditory cognition, enhance physical experience, and visual impact. This ingenious combination of AR technology and scenic spots is an important opportunity to realize "smart tourism".

Smart tourism is an important part of smart cities and the product of the advanced stage of tourism informatization, which plays a positive role in promoting the transformation and upgrading of my country's tourism industry. Smart tourism originated from the concept of "Smart Earth" and "Smart City". It is against this background that smart tourism came into being. "Smart tourism is to use a new generation of information network technology and equipment to fully, accurately and timely perceive and use various types of tourism information, so as to realize the integration of tourism services, tourism management, tourism marketing, and tourism experience. Intelligent". At present, my country has successively approved the establishment of the first and second batch of national smart tourism pilot cities to meet the needs of tourism market competition, promote the transformation and upgrading of the tourism industry, improve the tourism development system, and enhance the consumption experience of tourists, so as to further realize the needs of the tourism industry. High-quality development. With the continuous development and deepening of technologies such as the Internet, cloud computing, big data, 5G, and artificial intelligence, smart tourism will gradually become the focus of the tourism industry.

Another key point in building smart tourism is tourists. As the object of smart tourism services, providing comprehensive services for tourists has become an important issue. The emergence of smart tourism can solve this problem. Tourists can visit the sub-platform built by Smart Tourism to search, and search for hotel accommodation near the current attractions, tickets for attractions, food recommendations, etc. Before arriving at tourist attractions, you can recommend and optimize traffic routes in real time, preventing traffic jams on the road and wasting time. Even if tourists change their travel plans due to emergencies, the sub-platform can still provide the most cost-effective new travel plans to help tourists spend a pleasant holiday travel experience.

This paper combines big data technology to build a smart tourism management platform, improve the management effect of modern smart tourism, which provide a theoretical reference for the subsequent intelligent development of tourism.

2 RELATED WORK

In the research of tourism system, most of them focus on the exploration of tourism functional elements, spatial structure and development simulation. Literature [1] adds attractive factors to the tourism system; Literature [2] believes that market, travel, destination and promotion are also the main factors that constitute the tourism system; Literature [3] defines the tourism system from the perspective of supply and demand; Literature [5] The tourism system is constructed from the four levels of market, travel, destination and support; Literature [6] believes that the tourism system consists of three subsystems: direct, intervention and support; Literature [7] based on the background of the Internet era, from the tourist-information identification -Acquisition-processing-application-feedback reconstructs the tourism system in six levels. Smart tourism is a new trend in the development of the tourism industry. On the basis of the research on the construction ideas of the tourism system, comprehensive and in-depth thinking on the system integration structure of smart tourism is conducive to more effective and in-depth discovery of the integration and development of smart tourism. Analyze the economic phenomenon of integrated development from different levels to promote the high-quality development of smart tourism [8].

In the tourism system, in addition to the directly related internal systems, there are also some auxiliary supporting subsystems in its periphery. These subsystems develop together to maintain the orderly operation of the entire system. At the same time, there are recessive factors with different functions in each subsystem, and these recessive factors will also have an important impact on the system operation under certain conditions [9].

There are two main ideas for constructing a framework model for the construction and development of smart tourism: one is a framework model based on reflecting the issues of smart tourism; the other is an evaluation model based on the perspective of industrial integration. When the literature [10] studies the theoretical system of smart tourism, it is proposed that the key to building smart tourism is to clearly involve the main body, and divide the main body of smart tourism into development, application and operation. CAA framework system for smart tourism construction.

When studying the system optimization of smart tourism, Literature [12] constructed a smart tourism system with five modules including infrastructure, network layer, data center, application layer and security system based on the perspective of smart tourism application. The integrated development provides a scientific research basis.

Literature [13] builds a system construction strategy model for smart tourism based on four levels: support system, information infrastructure construction and application system, smart tourism resource management and development system, and smart tourism application innovation system, and further proposes specific strategies based on the strategy model. The evaluation index system, but the quantitative processing of some indicators in the index system is too difficult, and the practical guiding significance needs to be improved.

The system integration of smart tourism should not only pay attention to the impact of the development of core elements on the overall operation of the system, but also involve a series of social activities and cultural activities that affect the entire system. Therefore, in the construction of the system structure of smart tourism All aspects of the model should be considered. In addition, smart tourism is a systematic project with strong comprehensiveness and involves all aspects. It needs to solve new problems in tourism development to a certain extent. Its development is closely related to the overall social environment, and it is only considered when evaluating the level of integration and development. The capabilities, attributes, and applications are not comprehensive, and the local social development environment should also be considered, so as to achieve the coordinated and orderly development of the entire system [17].

From the perspective of industrial development, the emergence of the system integration phenomenon of smart tourism is accompanied by the innovation of information technology and the relaxation of government regulation, and it is also an industrial innovation that breaks through the development paradigm of traditional industries. Industrial innovation covers all aspects of industrial development, including innovations in technology, products, processes, organizations, markets, and management. From the fusion point of view, the fusion process itself is not a single, independent process [18]. On the one hand, the demand for information technology in the tourism industry promotes the continuous progress and innovation of information technology, resulting in the emergence of innovations in relevant departments such as software and hardware systems within the information industry; on the other hand, the application of information technology in the tourism industry further promotes the form of tourism products. And the diversification of display methods, and at the same time enhance the sense of interaction and experience, so that there are multiple innovative modes of tourism [19]. From the perspective of industrial innovation, the systematic integration and development of smart tourism is not only a multi-dimensional integration of products, resources, business, market, and policies, but also the integration of smart tourism development and the elements of the entire system from the perspective of the entire social system. Interactive relationship [20]. The integration of resources or product functions involved in the integration of smart tourism enables the integration of multiple resources or functions to form a new form that is different from traditional tourism forms, allowing more tourism resources to be presented in different forms, and at the same time with the help of information resources. Creating a virtual tourism form enriches tourism resources to a certain extent [11]. Each element in the system influences and promotes each other, so that individual resource benefits can be maximized. In addition, the systematic integration and development of smart tourism has changed the competition and cooperation relationship between enterprises and promoted the innovation of the industry in management, operation and organization. Therefore, the new integrated products and new growth points generated by the systematic integration and development of smart tourism can be regarded as expansionary industrial innovations [15].

3 QUALITY EVALUATION INDEX OF CONTEXT-AWARE SMART TOURISM SYSTEM

The reliability parameter represents the degree to which the sensor that collects context information is trusted, and is an objective QoC parameter that is calculated independently of the context information user. Because it can indicate the reliability of a sensor to collect a specific contextual information object, it is often used in scenarios where the choice is made among different sources describing the same contextual information object. Its calculation formula is shown in formula (1):

$$\text{reliability} = \begin{cases} \left(1-\dfrac{d(s,\varepsilon)}{d_{\max}}\right)\times\delta & ,\ \text{When } d(s,\varepsilon)<d_{\max} \\ 0 & ,\ \text{other} \end{cases} \tag{1}$$

Among them, δ represents the sensor accuracy, $d(s,\varepsilon)$ represents the physical distance from the sensor to the target contextual information object, and $d_{\max}$ represents the maximum trusted distance from the sensor to the target object.It can be seen from the expression form of formula (1) that the higher the sensor accuracy δ, the higher the reliability parameter, that is, the more trustworthy the situational information collected by the sensor.

The update degree parameter refers to the freshness of the context information in a given time, and the calculation formula is shown in formula(2)[14].

$$\text{up-to-dateness} = \begin{cases} 1-\dfrac{age}{\text{lifetime}} & ,\ \text{When } age < \text{lifetime} \\ 0 & ,\ \text{other} \end{cases} \tag{2}$$

Among them, age refers to the time difference from the measurement moment to the current moment of the context information, and lifetime is an artificially set threshold, indicating the maximum time limit for the context information to be effectively available. It can be seen from the calculation formula that the update degree parameter decreases with the increase of the context information age.

The correctness parameter refers to the ratio of the situational information to the actual situation, and the formula is shown in formula(3):

$$correctness = \frac{N_{true}}{N_{total}} \quad (3)$$

Among them, N_{true} represents the number of contextual information that conforms to the actual situation, and N_{total} represents the total number of all contextual information.

The completeness parameter refers to the amount of information contained in the context information object, indicating the degree to which context information is available, sufficient and not missing, and is the ratio between the number of available attributes and the total number of attributes of the context information object. The weight of each attribute is considered in the calculation, and the formula is as follows[16]:

$$\text{completeness} = \frac{\sum_{j=0}^{m} w_j}{\sum_{i=0}^{n} w_i} \quad (4)$$

Among them, m represents the number of available attributes, n represents the total number of attributes, and w_i represents the weight corresponding to the i-th attribute of the described target.

The importance parameter refers to the value of the contextual information object, which is often used in emergency situations or health problems. The calculation formula is as follows:

$$\text{significance} = \frac{CV}{CV_{\max}} \quad (5)$$

Among them, CV represents the critical value of a certain context information object, and $CV_{\max}$ represents the maximum critical value that can be assigned to this type of context information object.

A new QoC parameter, contextual information correlation, is proposed. The stored historical contextual information is used to calculate the support degree between contextual information sources. The calculation formula is as follows:

$$relevance(i,l) = \frac{1}{M-1} \sum_{k=1,k\neq l}^{M} rel(i,l,k) \quad (6)$$

$$rel(i,l,k) = \frac{N_{\sup}(i,l,k)}{N_{inc}(i)} \quad (7)$$

Among them, the relevance (i, l) is the context information correlation parameter of the i-th context information collected by the l-th context information source, and M represents the number of context information sources. rel(i,l,k) represents the support degree of the kth contextual information source obtained from the first i contextual information data to the lth contextual information source. $N_{inc}(i)$ is the cumulative number of inconsistent context information in the first i context information data. $N_{\sup}(i,l,k)$ is the cumulative number of information collected from the l-th context information source and the k-th context information source in the $N_{inc}(i)$ -group context information.A simple calculation example of contextual information correlation is shown in Figure 1[4]:

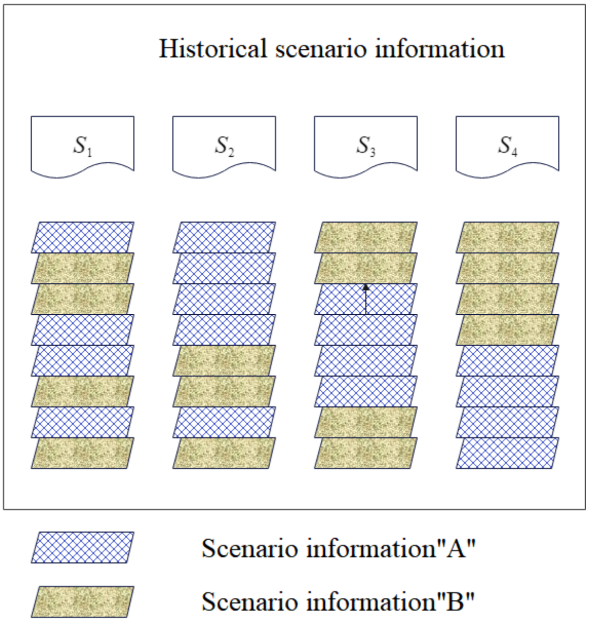

Figure 1: Example of Context Information Correlation Calculation.

We assume that among the first 20 sets of contextual information data, there are 8 sets of inconsistent contextual information data. As shown in Figure 1, there are 8 groups of inconsistent context information collected by four different context information sources, namely S1, S2, S3 and S4.For S1, it can be seen that 5 of the scene information collected by S2 are consistent with S1, so that the support degree $\mathrm{rel}(20,1,2)=\frac{5}{8}$ of S2 to S1 can be calculated. Similarly, $\mathrm{rel}(20,1,3)=\frac{4}{8}=\frac{1}{2}$ and $\mathrm{rel}(20,1,4)=\frac{4}{8}=\frac{1}{2}$ can also be obtained.Therefore, the contextual information correlation between S1 and other contextual information sources is $\mathrm{relevance}(20,1)=\frac{\mathrm{rel}(20,1,2)+\mathrm{rel}(20,1,3)+\mathrm{rel}(20,1,4)}{3}=\frac{13}{24}$.

This paper proposes an algorithm framework for inconsistency elimination based on the contextual information comprehensive quality index and DST, as shown in Figure 2. After receiving the context information input, the specific processing is divided into four stages: context information preprocessing stage, inconsistency detection stage, inconsistency elimination stage and result output stage.

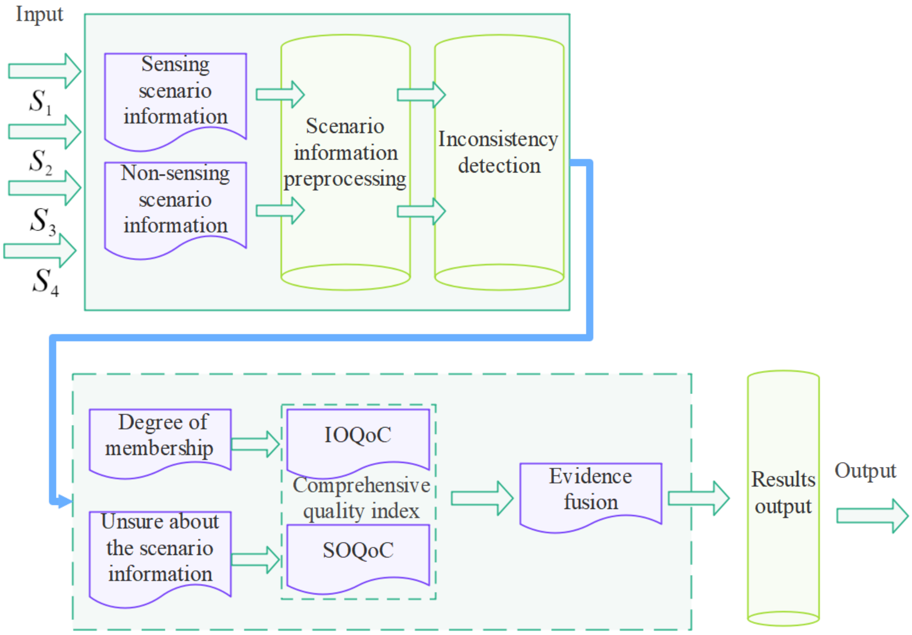

Figure 2: The Framework of the Inconsistency Elimination Algorithm Based on the Comprehensive Quality Index of Contextual Information and DST.

DST is widely used in the field of uncertainty processing and data fusion. The following are some of the more important definitions and concepts in DST.

Definition 1: An identification frame is a set of mutually exclusive event propositions or situational information hypotheses, denoted by $\Theta=\{\theta_1,\theta_2,\ldots,\theta_n\}$ .When the mapping $m:2^{\Theta}\rightarrow[0,1]$ satisfies the conditions of $m(\varnothing)=0$ and $\sum_{A\leq\Theta} m(A)=1$, it is called Basic Probability Assignment (BPA). When $m(A)>0$, A is called the focal element of the recognition frame Θ .

Definition 2: For the recognition frame Θ , the belief function Bel (Belief function) is used to represent the maximum degree of support given to the proposition, and the likelihood function P l (Plausibility function) is used to represent the degree of non-objection to the proposition, respectively expressed as follows:

$$\mathrm{Bel}(A)=\sum_{B\subset A} m(B) \tag{8}$$

$$Pl(A)=1-\mathrm{Bel}(\bar{A}) \tag{9}$$

Definition 3: It assumes that m_1 and m_2 are BPAs under the same recognition frame Θ, $A_1, A_2, \ldots, A_k$ is the focal element of m_1, and $B_1, B_2, \ldots, B_r$ is the focal element of m_2. The Dempster's Combination Rule (DCR) is expressed as follows:

$$m(C)=\begin{cases}\dfrac{\sum\limits_{A\cap B=C} m_1(A)m_2(B)}{1-K} & ,C\neq\varnothing \\ 0 & ,C=\varnothing\end{cases} \tag{10}$$

$$K=\sum_{A\cap B=\varnothing} m_1(A)m_2(B) \tag{11}$$

Among them, $K\in[0,1]$ represents the degree of conflict between the two pieces of evidence. It should be noted that DCR is not limited to two pieces of evidence and can be extended to the fusion of multiple pieces of evidence.

In practical applications, the sources of evidence are affected by different environments and have different degrees of reliability. A commonly used method is evidence discounting, which is important for improving conflicting evidence combinations. We assume that m is a BPA under the recognition framework, and the discount operation is expressed as follows:

$$m^{\lambda}(A)=\begin{cases}\lambda\times m(A) & ,A\neq\Theta \\ 1-\lambda+\lambda\times m(A), & A=\Theta\end{cases} \tag{12}$$

Among them, λ is the discount factor and $\lambda\in[0,1]$. The larger the discount factor, the higher the trustworthiness of the evidence in the exploitation process.

In fuzzy set theory, the set of objects with common properties to be discussed is usually called the domain $X=\{x_1, x_2, \ldots, x_n\}$, and the fuzzy set A is a subset of the domain X completely characterized by the membership function $\mu_A(x)$:

$$A=\left\{\left\langle x, \mu_A(x)\right\rangle \mid\, x\in X\right\} \tag{13}$$

$\mu_A(x)\in[0,1]$ represents the membership degree of the element x to the fuzzy set A. Specifically, $\mu_A(x)\to 1$ represents the high membership degree of x to the fuzzy set A, and $\mu_A(x)\to 0$ represents the low degree. $\mu_A(x)=0.5$ indicates that x is the transition point of fuzzy set A, and the fuzziness is the strongest.

Intuitionistic fuzzy set is one of the generalization theories of fuzzy set, which is characterized by two parameters: membership degree and non-membership degree:

$$A=\left\{\left\langle x,\mu_A(x),v_A(x)\right| x\in X\right\rangle\}$$ (14)

$\mu_A(x)$ and $v_A(x)$ are the membership and non-membership degrees of the element x in the domain X belonging to A, respectively, $\mu_A(x):X\rightarrow[0,1],v_A(x):X\rightarrow[0,1]$, and satisfy $0\leq\mu_A(x)+v_A(x)\leq 1$.

The domain X in the intuitionistic fuzzy set and the recognition frame Θ in the DST are both sets of unspecified objects, so they are equivalent from the perspective of set theory.The basic reliability assignment m is regarded as an intuitionistic fuzzy set A under $\Theta=\{\theta_1,\theta_2,\ldots,\theta_n\}$. At this time, $Bel(\theta)$ is equivalent to the degree of membership of θ to A, and $1-Pl(\theta)$ is equivalent to the degree of non-membership of θ to A. Therefore, the corresponding intuitionistic fuzzy set A can be expressed as:

$$\begin{aligned}A&=\left\{\left\langle\theta,\mu_A(\theta),v_A(\theta)\right| \theta\in\Theta\right\rangle\}\\&=\left\{\left\langle\theta_1,\mathrm{Bel}(\theta_1),1-Pl(\theta_1)\right\rangle,\left\langle\theta_2,\mathrm{Bel}(\theta_2),1-Pl(\theta_2)\right\rangle,\ldots,\left\langle\theta_n,\mathrm{Bel}(\theta_n),1-Pl(\theta_n)\right\rangle\right\}\end{aligned}$$ (15)

This paper proposes a sensing context information inconsistency elimination algorithm based on IOQoC and DST. The flow chart is shown in Figure 3.

First, the original continuous context l information data collected by physical sensors is stored in the domain database, which is used to store historical data measured by sensors and preset data of various smart tourism systems. Next, in order to facilitate subsequent detection and eliminate inconsistency of context information, the original context information needs to be preprocessed. Analyzing the collected scene information, it is found that in a large number of scenes, it is only necessary to know whether the entity monitored by the data is in a normal state.

That is to say, this context information can be classified into two states of normal and abnormal through a certain threshold. Therefore, the context information preprocessing stage converts the original context information data into binary context information according to the threshold binary classification method. Specifically, according to the specific application scenario of the smart tourism system, the threshold interval $[Th_L,Th_H]$ is obtained.Among them, Th_L and Th_H represent the low and high thresholds of the normal state, respectively. Then, the original situational information data is transformed into two propositions: "0" and "1", the data belonging to the threshold interval represents the normal state, that is, transformed into "1", and the rest are transformed into "0".Finally, the preprocessed binary context information is stored in the context information database to facilitate the subsequent use and calculation of historical context information.

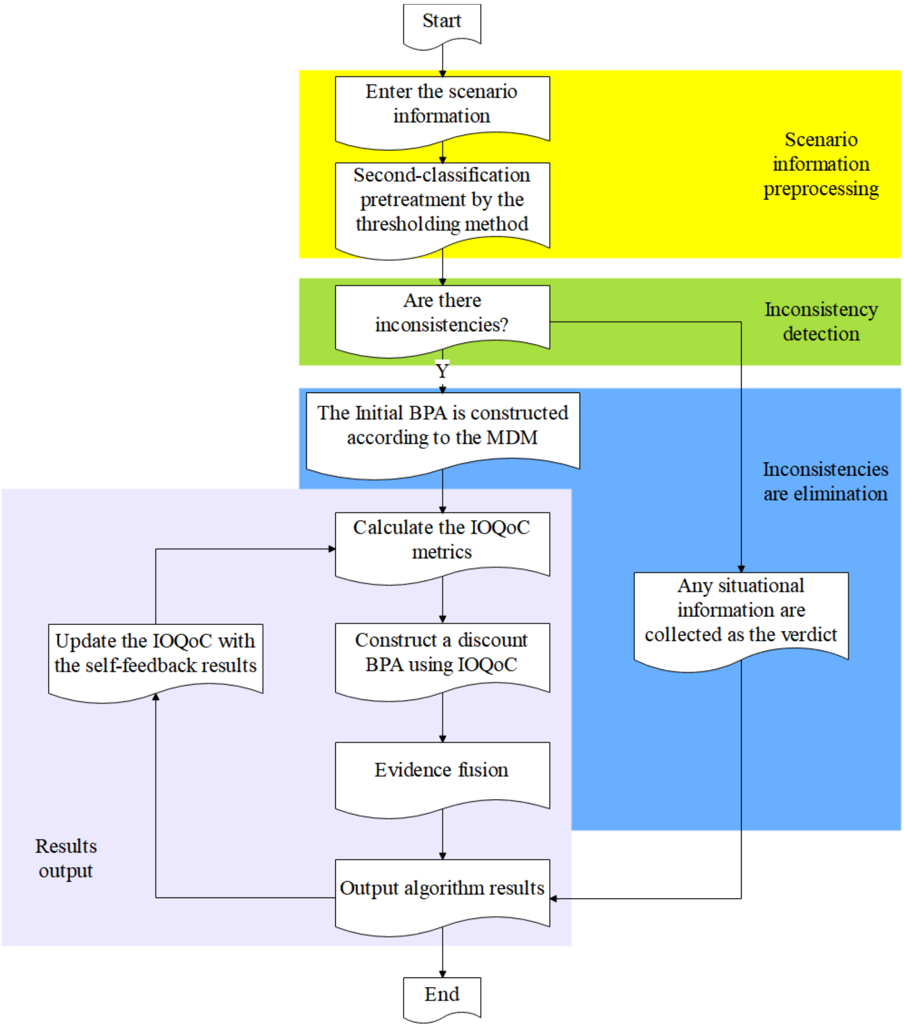

Figure 3: Flowchart of the Algorithm for Eliminating Inconsistency of Sensing Context Information Based on IOQoC and DST.

If there is no inconsistency in a set of context information, the unified state of the context information can be output as the result. Otherwise, inconsistency removal is performed at this stage. In general, the proposed sensing context information inconsistency elimination algorithm constructs the initial BPA from the membership matrix (MDM), fuses multiple QoC parameters to obtain the UIOQoC index, and normalizes the IOQoC into a discount factor. Finally, it performs the discount operation to correct the BPA, and fuses the discount BPA according to the DCR formula to obtain the output. The specific implementation steps are as follows:

Step 1: The algorithm constructs the initial BPA according to the MDM

In order to make full use of the information contained in the original contextual information data, we calculate the MDM according to the theory of intuitionistic fuzzy sets, and construct the initial BPA. In the case of eliminating the inconsistency of the context information, the context information has only two states of "0" and "1".Therefore, the identification frame is $\Theta = \{0,1\}$ and $2^{\theta} = \{0,1,\{0,1\},\varnothing\}$ .The membership function required for state "1" must satisfy the following conditions: the closer to the median of the threshold interval $[Th_L, Th_H]$, the higher the membership, and the farther away from the median of the threshold interval $[Th_L, Th_H]$, the lower the membership.Therefore, we choose the Gaussian membership function with low on both sides and high in the middle, and the calculation formula is shown in 16.

$$membershipp_{ij} = e^{\frac{-(x_y-\mu)^2}{2\sigma^2}} \tag{16}$$

Among them, x_{ij} is the jth scene information collected by the ith sensor, and μ and σ control the center and width of the Gaussian membership function, respectively.Based on this, the membership degree of state "0" can be expressed as ($1 - membership_{ij}$), and the membership degree matrix of the ith sensor can be expressed as:

$$MDM_i = \begin{bmatrix} \mu_1(x_{i1}) & \mu_0(x_{i1}) & \mu_{(0,1)}(x_{i1}) \\ \mu_1(x_{i2}) & \mu_0(x_{i2}) & \mu_{(0,1)}(x_{i2}) \\ \vdots & \vdots & \vdots \\ \mu_1(x_{iM}) & \mu_0(x_{iM}) & \mu_{(0,1)}(x_{iM}) \end{bmatrix}$$
$$= \begin{bmatrix} \text{membership}_{i1} & \text{1-membership}_{i1} & 1 \\ \text{membership}_{i2} & \text{1-membership}_{i2} & 1 \\ \vdots & \vdots & \vdots \\ \text{membership}_{iM} & \text{1-membership}_{iM} & 1 \end{bmatrix} \quad i \in [1, N] \tag{17}$$

Among them, M represents the number of sensors, and N represents the number of contextual information collected by each sensor.

According to the correspondence between the reliability function in the DST and the membership degree of the intuitionistic fuzzy set, the following initial BPA construction results can be obtained:

$$\begin{cases} \text{Bel}(1) = m(1) = \mu_1 = \text{ membership} \\ \text{Bel}(0) = m(0) = \mu_0 = 1 - \text{ membership} \\ \text{Bel}(0,1) = m(0) + m(1) + m(\{0,1\}) = \mu_{(0,1)} = 1 \end{cases}$$
$$\Downarrow$$
$$\begin{cases} m(1) = \text{ membership} \\ m(0) = 1 - \text{ membership} \\ m(\{0,1\}) = 0 \\ m(\varnothing) = 0 \end{cases} \tag{18}$$

Step 2: The algorithm calculates the IOQoC indicator.

The fusion method of each QoC parameter is determined through simulation experiments. The traditional weighted fusion of QoC parameters is used as the base of the function, and the reciprocal of the contextual information correlation is used as the index of the function, and the IOQoC indicator is constructed, as shown in formula 19:

$$\mathrm{IOQoC} = \left(\left[w_1, w_2, w_3 \right] \times \begin{bmatrix} \text{reliability} \\ \text{up-to-dateness} \\ \text{correctness} \end{bmatrix} \right)^{\frac{1}{relevance}} \tag{19}$$

Among them, each QoC parameter can be calculated according to formula 1 to formula 3, formula 6 and formula 7, $\left[w_1, w_2, w_3 \right]$ is the weight factor of reliability, update degree and correctness respectively, indicating the importance of these QOC parameters in the current application scenario.By default, they are $\left[\frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right]$ and can be obtained by expert advice or user settings for flexible processing. For example, when the context information describes the object frequently changing, the weight of the update degree can be adjusted to a slightly larger value.

Step 3: The algorithm uses IOQoC to construct a discounted BPA.

Based on the IOQoC indicator, the evidence discount factor can be calculated by normalization as follows:

$$v(i) = \frac{\mathrm{IOQoC}(i)}{\sum_{j=1}^{M} \mathrm{IOQoC}(j)}, \quad i \in [1, M] \tag{20}$$

$$\begin{cases} m^{\lambda}(1) = v \times \text{ membership} \\ m^{\lambda}(0) = v \times (1 - \text{ membership }) \\ m^{\lambda}(\{0,1\}) = 1 - m^{\lambda}(1) - m^{\lambda}(0) \\ m^{\lambda}(\varnothing) = 0 \end{cases} \tag{21}$$

Step 4: Evidence fusion

The discounted BPA is fused using the DCR formula, the probabilities of the synthesized states "0" and "1" are compared, and the state with a higher probability is selected as the final decision result of the algorithm.

In this paper, the decision rate of context information is used as an index to evaluate the performance of the algorithm, and the calculation formula is as follows:

$$Context - judge \ \text{ rate} = \frac{N_{res}}{N_{inc}} \tag{22}$$

Among them, N_{res} represents the cumulative number of correctly processed context information in inconsistent context information, and N_{inc} represents the total number of inconsistent context information.As shown in Figure 4, the three parts are in clockwise order: the blue part represents the amount of consistent context information, and the orange and gray are respectively the number of correctly processed information and the number of incorrectly processed information in inconsistent context information. Therefore, the orange plus gray is the total number N_{inc} of all inconsistent scene information, and the ratio of the orange part compared with the orange plus gray part is the scene information decision rate.

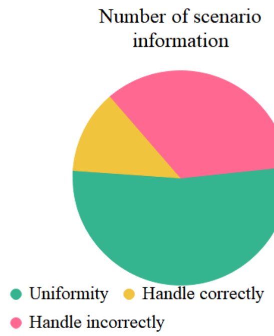

Figure 4: Schematic Diagram of Context Information Decision Rate Calculation.

4 DESIGN AND IMPLEMENTATION OF SMART TOURISM MANAGEMENT PLATFORM IN THE ERA OF BIG DATA

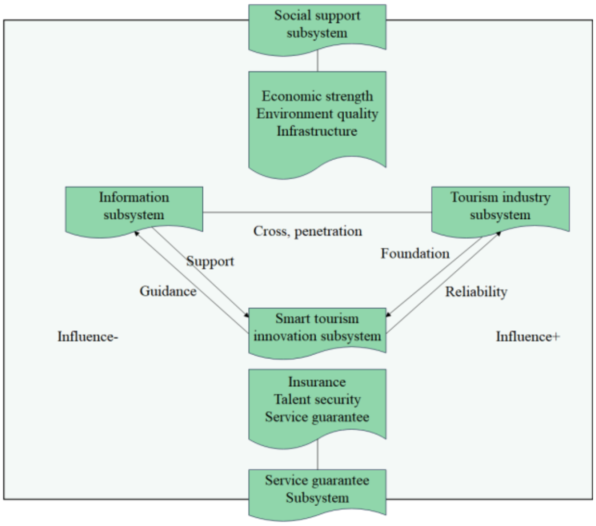

Figure 5: The Integrated System Structure Model of Smart Tourism.

The integrated system structure of smart tourism in this paper is composed of two layers: the system core layer and the system extension layer (as shown in Figure 5).

Based on the theoretical basis and structural model, the internal and external motivations to promote the integrated development of smart tourism systems are sought. Driven by both internal and external motivations, this paper promotes the system integration of smart tourism, and discusses the dynamic system (automatic force subsystem, support force subsystem, driving force subsystem, and resistance subsystem) composed of driving factors, as shown in Figure 6.

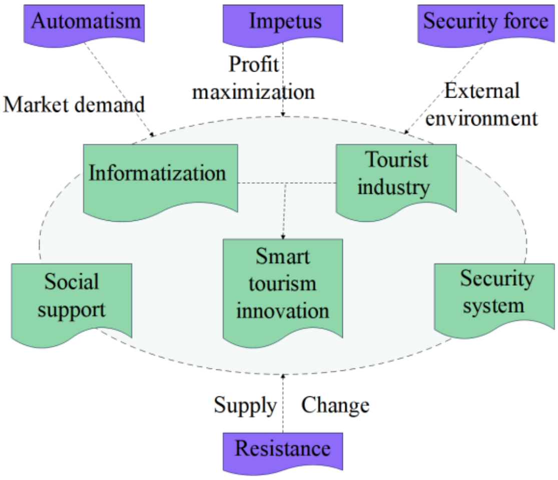

Figure 6: System Integration Power System of Smart Tourism.

The frequency analysis reflects the distribution of the number of research hotspots in smart tourism, and the co-occurrence analysis of high-frequency words can further reveal the relationship between the research hotspots. Figure 7 shows the co-occurrence network map of high-frequency words obtained by the Netdraw program of Ucinet software. Each node in Figure 7 represents a high-frequency word in smart tourism research. The position of the node from the center of the network and the size of the node are proportional to the influence of the high-frequency word. Figure 7 shows that smart tourism is at the center of the co-occurrence network graph. Among them, the nodes of "smart city", "tourism informatization", "big data", "rural tourism" and "smart tourism city" are relatively large, which shows that these keywords have high influence and are the focus of smart tourism research.

Co-word analysis reveals the explicit relationship of research hotspots, and the implicit relationship needs to be clustered. Ucinet software is used for high-frequency word clustering analysis, and the high-frequency word clustering map is obtained as shown in Figure 8. As can be seen from Figure 8, China's smart tourism research is divided into four categories. It includes cluster 1 "smart tourism technology foundation", cluster 2 "smart tourism city construction and development", cluster 3 "smart tourism scenic spot service and management" and cluster 4 "rural tourism intelligence and transformation development".

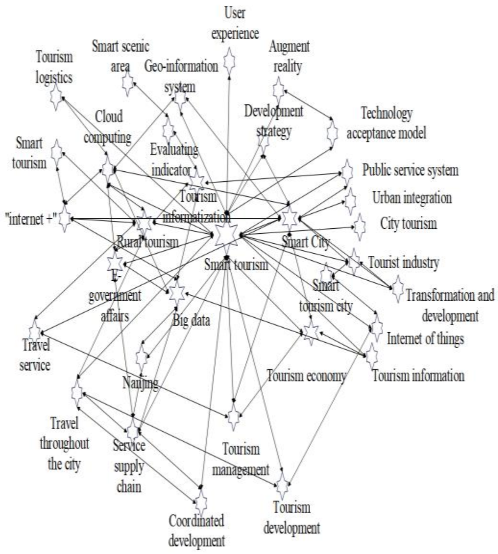

Figure 7: Co-Occurrence Network Map of High-Frequency Words In Smart Tourism Based on Big Data.

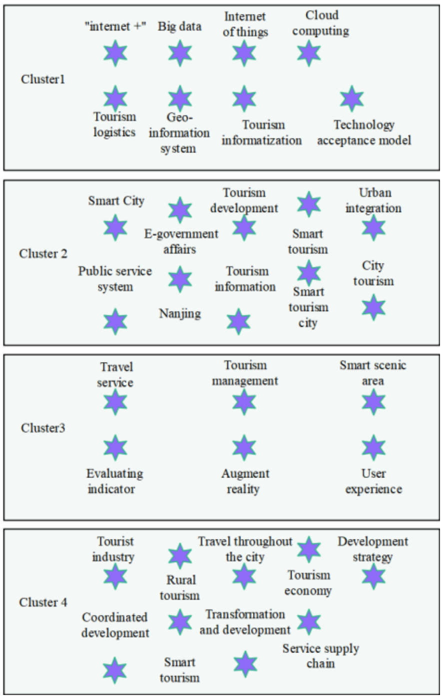

Figure 8: Clustering Map of High-Frequency Words in Smart Tourism Based on Big Data Technology.

On the basis of the above research, this paper verifies the effect of the smart tourism management platform based on big data technology proposed in this paper. This paper obtains a large amount of data from the Internet to verify the effect of the system in this paper. Moreover, this paper uses the online tourism data from January 2019 to December 2021 as the basic input data to count the effect of smart tourism information mining in this system, and obtain the results shown in Table 1.

Num	*Wisdom mining*	*Num*	*Wisdom mining*	*Num*	*Wisdom mining*
1	*95.89*	*25*	*93.39*	*49*	*90.13*
2	*90.40*	*26*	*89.67*	*50*	*94.41*
3	*90.52*	*27*	*90.08*	*51*	*94.13*
4	*89.75*	*28*	*90.15*	*52*	*93.00*
5	*93.31*	*29*	*90.81*	*53*	*91.53*
6	*93.12*	*30*	*89.36*	*54*	*93.81*
7	*90.05*	*31*	*89.32*	*55*	*93.40*
8	*91.10*	*32*	*95.70*	*56*	*95.62*
9	*95.39*	*33*	*91.23*	*57*	*93.84*
10	*92.95*	*34*	*93.77*	*58*	*95.80*
11	*92.67*	*35*	*91.36*	*59*	*91.74*
12	*94.88*	*36*	*95.68*	*60*	*90.16*
13	*92.61*	*37*	*95.02*	*61*	*91.20*
14	*92.01*	*38*	*92.00*	*62*	*91.30*
15	*89.79*	*39*	*89.52*	*63*	*91.43*
16	*95.07*	*40*	*91.80*	*64*	*90.86*
17	*94.90*	*41*	*91.98*	*65*	*93.58*
18	*94.18*	*42*	*89.85*	*66*	*95.85*
19	*91.20*	*43*	*90.36*	*67*	*93.64*
20	*92.01*	*44*	*92.30*	*68*	*91.61*

21	*94.81*	*45*	*90.87*	*69*	*93.09*
22	*91.80*	*46*	*95.73*	*70*	*93.90*
23	*92.22*	*47*	*92.10*	*71*	*89.81*
24	*90.64*	*48*	*89.35*	*72*	*91.46*

Table 1: Information Mining Effect of Smart Tourism System.

From the above research, we can see that the smart tourism management platform based on big data technology proposed in this paper has certain effects. After that, this paper evaluates the system in this paper through the expert evaluation method, and the statistical evaluation results are shown in Figure 9.

Figure 9: System Clustering Effect Evaluation.

From the above research, we can see that the smart tourism management platform based on big data technology proposed in this paper has a good tourism management effect.

5 CONCLUSION

By studying the database constructed by smart tourism construction, it is found that the information in the database has not been fully developed and shared, and the information actually applied to smart tourism is very scarce. The huge amount of data cannot be effectively used, developed and shared, which reduces the utilization rate of big data technology in practice, and it is difficult to form a complete data integration, so it is difficult for information mining in big data to fully play a role.Information collection is a very important link in big data technology. However, in the actual construction, some tourism enterprises and scenic spots did not pay attention to the authenticity and effectiveness of the information in the process of information collection, and did not update the information in time, resulting in some useless information.This paper combines the construction of a smart tourism management platform with big data technology information to improve the management effect of modern smart tourism. The experimental research shows that the smart tourism management platform based on big data technology proposed in this paper has a good tourism management effect.

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