Impact Assessment of the outburst public health event on Chinese Tourism Demand for Japan -- a Case study of COVID-19 pandemic

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Abstract. The COVID-19 pandemic has had a huge impact on the tourism industry. This study uses the Baidu index for travel to Japan from 2011 to 2019 to create an ARIMA model and uses geographic spatial analysis methods—seasonal concentration index, geographic concentration index, and coefficient of variation—to explore changes in China's demand for travel to Japan under the impact of major public health events such as the COVID-19 pandemic. The findings indicate that (1) before the pandemic, China's demand for travel to Japan had remained at a relatively high level, with demand peaking in March and July compared to other months. After the pandemic, monthly differences narrowed, and seasonal demand became more balanced, with summer emerging as the relatively peak season for travel demand, while autumn remained the lowest throughout the year. (2) Before the pandemic, the distribution of attention on Japan tourism network varied significantly among provinces, exhibiting an uneven pattern with higher attention in eastern regions and lower attention in western regions. After the pandemic, the gap between regions has widened. (3) Compared to unaffected values, affected values exhibit significantly wider inter-regional disparities and heightened seasonal volatility in online attention to Japan tourism. This study utilizes Baidu index to study Japanese tourism demand through network attention. It can enrich the theoretical system of tourism demand research and provide theoretical guidance for tourism enterprises to adjust their operating models and adapt to the post-epidemic tourism market.

Keywords: Japan tourism, Network attention, Baidu index, ARIMA model, Pandemic.

1. Introduction

In early 2020, the COVID-19 pandemic spread rapidly worldwide, exerting a significant impact on all aspects of society [1]. As an industry highly dependent on human mobility, the tourism sector came to a complete standstill under the pandemic's impact [2]. Japan, one of the most popular overseas travel destinations for Chinese citizens [3], saw a sharp decline in travel demand to Japan owing to the pandemic [4], and a transformation in the tourism industry [5-6]. In January 2023, after the State Council approved the lifting of Category A infectious disease prevention and control measures for COVID-19, China officially entered the post-pandemic era, also known as the "regular epidemic prevention and control." Subsequently, the economy gradually recovered, and the tourism market saw a comprehensive recovery [7]. However, due to a combination of factors, the domestic tourism market to Japan still faces fluctuations after the pandemic [8]. In 2023, the number of mainland Chinese tourists to Japan only recovered to about 25% of the 2019 level (Japan National Tourism Organization). Therefore, investigating the impact of major public health events like the pandemic on China-Japan tourism holds significant academic and practical value. It can enrich the theoretical system of tourism demand research and provide theoretical guidance for tourism enterprises to adjust their operating models and adapt to the post-epidemic tourism market to Japan.

Currently, existing studies have analyzed outbound tourism demand, such as from the perspectives of tourist flow [9-10], tourism preferences [11], and influencing factors [12-13], among others, these studies typically employ methods such as questionnaires and interviews [14-15] to collect data and combine statistica [16] and economic models [17] for analysis. Research on China's outbound tourism reveals distinct characteristics and evolving patterns. Diego Q. and Jianrong Peng systematically reviewed 171 studies from 1995 to 2020, highlighting that existing research is predominantly regionally concentrated (e.g., Hong Kong, Macao, Taiwan), relies mainly on questionnaire-based methodologies, and often fail to connect cultural values with consumption behaviors [18]. LUSHCHY M. V. pointed out that Chinese outbound market exhibits a "high-growth, high-concentration, high-influential" characteristics, where tourist behavior is significantly shaped by digital platforms, creating a dual impact of economic benefits alongside cultural and ecological risks on destinations[19].

The COVID-19 pandemic further altered tourist psychology and behavior. Employing Psychological Distance theory, Zhiyong Li and Shan Zhang demonstrated that the pandemic heightened tourists’ risk perceptions, leading to more conservative and self-contained travel behaviors [20]. Through questionnaires and interviews within the theory of planned behavior (TPB) framework, Zhang S. revealed that post-pandemic travel behaviors were influenced by risk perception, pandemic control policies, and altruistic attitudes (e.g., supporting economic recovery through tourism) [21]. Econometric modeling by Xin Jin and Youzhe Wang indicates the post-pandemic outbound tourism market is characterized by sluggish domestic demand coexisting with a recovering outbound international market, suggesting industry revival is heavily dependent on policy intervention [22].

However, studies leveraging big data analytics for outbound tourism demand are relatively scarce, and studies on the impact of the pandemic on tourism demand changes are also limited. Based on this, this study starts from the perspective of comparing differences in tourism demand, constructs ARIMA models based on Japan tourism network attention data from 2011 to 2019, introduces spatial analysis methods—geographic concentration index, seasonal concentration index, and coefficient of variation—and compares the unaffected tourism demand values before the pandemic with the affected demand values after the pandemic to analyze changes in Japan tourism network attention before and after the COVID-19 pandemic. This study quantifies the impact of the pandemic on Japan tourism and explores the temporal and spatial distribution characteristics of the pandemic's impact on Japan tourism demand in different regions. This will contribute to the development of the Japanese tourism market after the pandemic.

2. Data and method

2.1. Data source

The Baidu index is based on statistics generated from the search volume of citizens on Baidu, which is one of the platforms with the largest number of users in China. It uses keywords as the statistical object and calculates the frequency of web page searches through scientific weighting, which can reflect the intensity of public attention to specific events or things to a certain extent. The network attention to Japan tourism refers to the degree of attention citizens pay to tourism activities with Japan as the destination through the Internet, which can indirectly reflect the demand for travel to Japan.

The data selected for this study are all from the official Baidu index data. Keywords are selected based on the six core elements of tourism—clothing, food, accommodation, transportation, shopping, and entertainment—as well as popular tourist attractions in Japan. These keywords can better reflect the information that tourists are most interested in and their various needs during their travels. Based on this, data from all provinces, autonomous regions, and municipalities directly under the central government (excluding Hong Kong, Macao, and Taiwan due to data availability) from January 1, 2011, to December 31, 2024, were obtained for analysis.

2.2. Research Methods

2.2.1. Seasonal Concentration Index

The Seasonal Concentration Index (SCI) can be used to measure the temporal concentration of attention on Japan tourism networks, quantifying whether attention is evenly distributed across seasons or clustered in specific periods.

$$S=\sqrt{\frac{\sum_{i=1}^{12}\left(x_i-8.33\right)^2}{12}} \tag{1}$$

In equation (1), S is the seasonal concentration index, and X_i is the percentage of Japan tourism network attention in each month relative to the total Japan tourism network attention for the whole year. The closer the S value is to 0, the smaller the time difference in Japan tourism network attention, and the more evenly distributed it is throughout the year.

2.2.2. Geographic concentration index

The Geographic Concentration Index (GCI) can be used to measure the spatial inequality of network attention toward Japan tourism, indicating whether attention is evenly distributed across regions or focused on specific locations.

$$G=100\times\sqrt{\sum_{i=1}^{n}\left(\frac{X_i}{T}\right)^2} \tag{2}$$

In equation (2), G is the geographic concentration index, X_i is the network attention (times) of the i-th region to Japan tourism, and T is the total network attention (times) to Japan tourism. The closer the G value is to 100, the more concentrated the network attention is, and vice versa.

2.2.3. Coefficient of Variation

The Coefficient of Variation (CV) can be used to measure inter-provincial disparities in network attention to Japan tourism.

$$CV=\frac{\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\bar{Y})^2}{n}}}{\bar{Y}} \tag{3}$$

In equation (3), CV is the coefficient of variation, Y_i is the network attention to tourism in Japan in the i-th region(times), Y is the average network attention, and n is the number of regions (provinces, autonomous regions and municipalities directly under the central government). The larger the CV value, the greater the degree of regional differences and the higher the concentration.

2.2.4. Urban primacy index

The Urban Primacy Index (UPI) can be used to assess the imbalance in network attention across Chinese cities, revealing whether one dominant city has a disproportionate share of attention compared to others.

$$P=\frac{X_1}{X_2} \tag{4}$$

In formula (4), X_1 and X_2 represent the provinces with the first and second highest levels of network attention; $P<2$ indicates that the distribution of network attention is relatively balanced, while $P>2$ indicates that the distribution of network attention is unbalanced.

2.2.5. Herfindahl-Hirschman Index

The Herfindahl-Hirschman Index (HHI) can be used to evaluate the degree of spatial concentration in network attention toward Japan tourism, with higher values indicating a monopoly or oligopoly of attention in few locations.

$$H = \sum_{i=1}^{n} P_i^2 \tag{5}$$

In formula (5), n is the number of provinces in the region, Pi is the proportion of the i province in the region's annual network attention; H takes values in the range [0,1], and H tends to 1, indicating that the spatial distribution of network attention is more concentrated, and vice versus indicates that the spatial distribution is more dispersed.

2.2.6. Counterfactual analysis based on the ARIMA model

The ARIMA model, or auto-regressive integrated moving average model, is one of the classic time series analysis methods. Time series analysis methods refer to the theory and methods of establishing mathematical models through curve fitting and parameter estimation based on time series data obtained from actual observations and then using these models to make predictions about the future. These methods have the advantage of being able to easily capture changes in data by relying only on historical network attention data, without the need for exogenous variables.

Counterfactual analysis refers to the process of deducing possible changes in results based on facts that have already occurred, assuming that certain conditions or events are different. Based on this theoretical framework, this study uses the time series prediction model ARIMA to model the network attention data from 2011 to 2019 and simulate the Japan tourism network attention data for 2020 and beyond without the impact of the COVID-19 pandemic to explore the actual impact of the pandemic on Japan tourism.

The ARIMA model can be expressed as ARIMA (p, d, q), where p is the order of the auto-regressive term, d is the number of differences used to make the time series stationary, and q is the order of the moving average term.

(1) Construction of the ARIMA Model

Step 1: Stationarity Test

Prior to ARlMA modeling, the stationarity of the raw time-series data must be verified using methods such as the Augmented Dickey-Fuller (ADF) unit root test. Non-stationarity observed in Japan tourism network attention data (2011-2019) necessitated first-order differencing. After differencing, stationarity was confirmed via Autocorrelation Function(ACF) and Partial Autocorrelation Function (PACF) diagnostics in SPSSPRO, followed by a Ljung-Box test to validate white noise properties of the residuals.

Step 2: ARIMA Model Selection

Parameters (p,q) were tentatively identified based on ACF and PACF plots. Subsequently, the optimal model was determined through multiple comparative analyses based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. This approach facilitated the identification of province-specific ARIMA parameters using SPSSPRO.

(2) Model Validation

The goodness-of-fit (R^2) was calculated to evaluate the optimal model.

As shown in Table 1, most provincial ARIMA models achieved R^2 values exceeding 0.8, while a minority exhibited moderate fit due to data limitations. Critically, the Ljung-Box Q(LBQ) test for all model residuals yielded p-values < 0.05, failing to reject the null hypothesis that residuals constitute a white noise series. This confirms the statistical significance of all models, thereby precluding the need for re-specification

Table. 1 ARIMA Model Parameters and Goodness-of-Fit for Selected Provinces.

Variable	Model	Goodness-of-Fit (R^2)	Ljung-Box Q(LBQ)		
		R^2	statistical measure	DF	P-value
Anhui	(1,1,1)	0.896	63.86	16	<0.001
Beijing	(2,1,1)	0.947	759.591	15	<0.001
Fujian	(1,1,1)	0.912	153.41	16	<0.001
Guangdong	(5,1,1)	0.972	201.215	12	<0.001
Hebei	(2,1,1)	0.91	52.798	15	<0.001
Henan	(2,1,1)	0.915	57.205	15	<0.001
Heilongjiang	(1,1,1)	0.865	33.039	16	<0.001
Hubei	(0,1,3)	0.919	145.555	15	<0.001
Hunan	(5,1,1)	0.899	51.016	12	<0.001

To assess extrapolation capability, an ARIMA model was constructed using network attention data from 2011 to 2017. The calculated values for 2018 to 2019 were compared with the actual observed values. The results showed that the average absolute error (MAE) for most regions was less than 30%, except for Qinghai, Ningxia and Tibet, where the average absolute error (MAE) was 116.67 and the mean relative error (MRE) was 16%. This indicates that the model can reliably capture the spatiotemporal changes in network attention and has high predictive accuracy.

3. Results Analysis

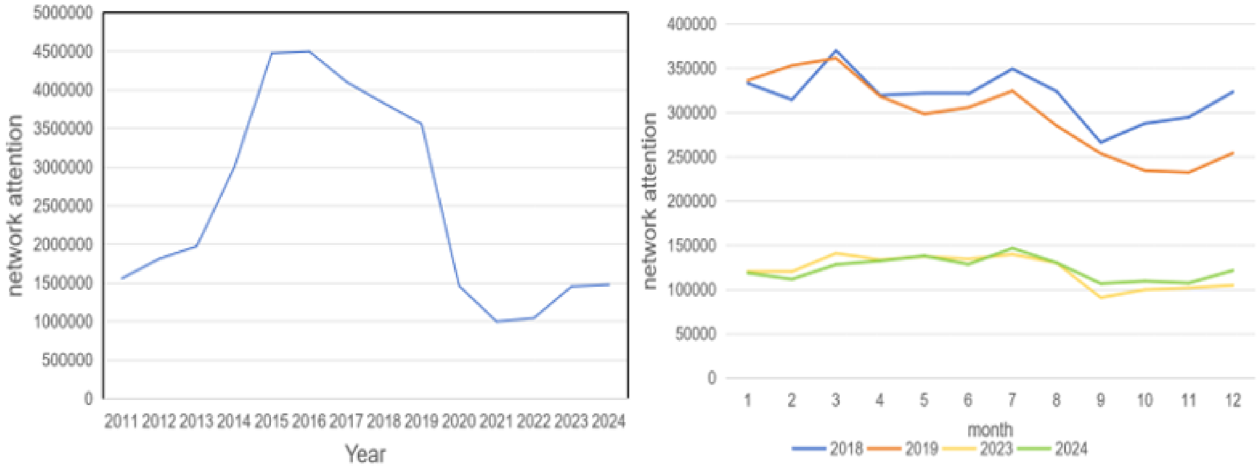
3.1. Characteristics of network attention before and after the pandemic

3.1.1. Temporal characteristics

Analysis of network attention to Japan tourism from 2011 to 2024 reveals a characteristic pattern of initial growth, subsequent decline, and eventual recovery (Figure 1.(a)), with distinct phases shaping the trajectory. The sustained growth period from 2011 to 2016 culminated in a peak of 4.5 million person-times in 2016, primarily driven by Japan's expanded duty-free shopping policies and relaxed visa requirements for Chinese tourists. While moderate contraction followed during 2017-2019, annual attention remained consistently above 3.5 million person-times indicating resilient market demand. The pandemic-induced collapse phase saw attention plummet by 70% year-on-year in 2020 probably due to global travel restrictions and health concerns, reaching its nadir in 2021 before marginally recovering to 1.5 million by 2022.

Although network attention rebounded in the two years after the pandemic, it still did not return to levels before the pandemic. Starting in 2023, network attention rebounded to 2.2 million visits, still some distance from the historical peak of attention in 2016. On the one hand, this phenomenon is probably affected by the COVID-19 pandemic and weak socioeconomic conditions, which have hindered domestic travel and led to flight capacity shortages and service sector constraints. On the other hand, since 2019, short video platforms such as Douyin and KuaiShou have developed rapidly, gradually replacing traditional search engines such as Baidu and becoming an important channel for residents to obtain travel information. Therefore, the network attention statistics of the Baidu index may be lower than the real value.

From a monthly and seasonal perspective, network attention to Japan tourism exhibited uneven distribution across months during 2018-2019 (Figure 1.(b)) network attention peaked in March, forming a spring surge centered on the cherry blossom season, followed by a second annual peak in July. Autumn attention remained relatively lower compared to summer.



(a).Annual changes in network attention to Japan tourism from 2011 to 2024

(b).Monthly variations in network attention to Japan tourism before and after the pandemic

Figure 1. Changes in Japanese tourism network attention.

In 2023-2024, demand for travel to Japan became more balanced across seasons, with reduced monthly fluctuations. Summer tourism demand was more pronounced than in other seasons, while autumn attention remained the lowest annually. From September to December, monthly network attention fluctuated around one hundred thousand visits.

The Seasonal Intensity Index (SII) remains stable at around 8.25, above the baseline value of 1, indicating that there are seasonal differences in interest in Japan tourism. Additionally, the SII shows little fluctuation across years, suggesting that the seasonal pattern is highly stable.

3.1.2. Spatial characteristics

As shown in Table 2, the network attention for travel to Japan in 2023-2024 is significantly lower than that in 2018-2019. Among them, the decline in East China is particularly significant, from 4,725,415 in 2018 and 4,491,871 in 2019 to 2,337,782 in 2023 and 2,364,178 in 2024, with the North and Southwest regions also experiencing substantial declines.

Table 2. Spatial differences in network attention to Japan tourism(2018–2019 vs. 2023–2024, unit: 10,000 times).

Region	2018	2019	2023	2024
Northeast China	127.30	125.04	54.47	52.51
North China	260.07	248.49	117.73	114.86
Central China	147.83	143.18	69.01	66.88
South China	161.05	156.42	79.69	76.92
East China	472.54	449.19	233.78	236.42
Northwest China	106.06	98.09	39.37	39.44
Southwest China	170.97	168.71	74.60	71.52

Although the attention in each region has declined, the difference in attention between different regions remains relatively stable in different years (Figure 2). The East China has always maintained the highest network attention for Japan tourism, and even after the decline, its value is still far higher than other regions. This may be related to factors such as the relatively developed economy, frequent population movement, and strong tourism consumption capacity of residents in this region. The Northeast China and Northwest China have always been at a relatively low level among all regions.

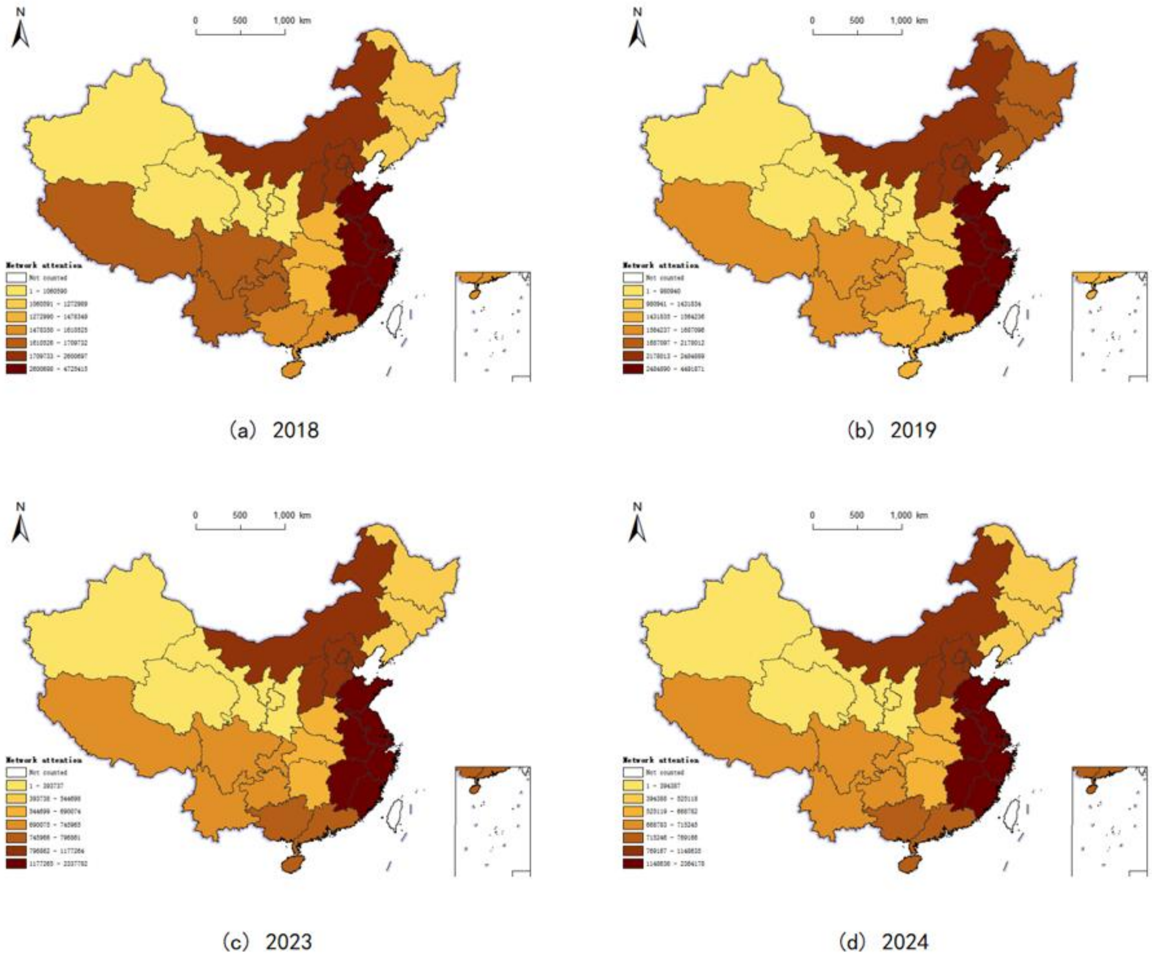


Figure 2. Spatial disparities in network attention to Japan tourism (2018–2019 vs. 2023–2024).

Note: This figure is based on a standard Chinese map (Approval No. GS(2023)2767) downloaded from the Standard Map Service website of the National Administration of Surveying. The base map has not been modified.

Four indicators, namely the coefficient of variation (CV), the Herfindahl-Hirschman Index (HHI), the urban primacy index (P), and the geographic concentration index (G), were used to analyze the spatial differences in network attention to Japan tourism before and after the pandemic (Table 3). In South China, the CV values during 2023-2024 consistently exceeded 0.9, ranking highest nationwide, indicating the most pronounced regional disparities in network attention. The HHl value fluctuated between 0.511 and 0.571, while the G index peaked at 75.553, reflecting an extremely unbalanced distribution pattern. This is probably primarily attributed to Guangdong's economic dominance, robust outbound tourism demand and role as a transportation hub to Japan, resulting in significantly higher attention levels than Hainan and Guangxi.

Table 3. Spatial differences in network attention to Japan tourism (2018–2019 vs. 2023–2024).

Region	Indicator	2018	2019	2023	2024
Northeast China	CV	0.322	0.343	0.424	0.471
	H	0.356	0.360	0.373	0.383
	P	1.656	1.684	1.973	2.101
	G	59.697	59.962	61.100	61.855
North China	CV	0.612	0.583	0.698	0.724
	H	0.260	0.254	0.278	0.284
	P	2.214	2.084	2.271	2.459
	G	50.987	50.444	52.720	53.272
Central China	CV	0.116	0.104	0.083	0.091
	H	0.359	0.336	0.335	0.335

	P	1.047	1.042	1.019	1.083
	G	57.992	57.945	57.869	57.893
South China	CV	0.876	0.893	0.962	1.034
	H	0.534	0.511	0.539	0.571
	P	3.033	3.296	3.224	4.083
	G	70.991	71.461	73.411	75.553
East China	CV	0.375	0.357	0.430	0.455
	H	0.160	0.159	0.166	0.168
	P	1.146	1.115	1.259	1.222
	G	40.008	39.812	40.682	41.017
Northwest China	CV	0.678	0.767	0.945	0.952
	H	0.273	0.294	0.343	0.345
	P	2.002	2.323	2.633	3.012
	G	52.296	54.224	58.557	58.734
Southwest China	CV	0.644	0.661	0.712	0.733
	H	0.266	0.270	0.281	0.286
	P	1.445	1.463	1.561	1.643
	G	51.608	51.944	53.010	53.483

The Northwest China and Southwest China showed similar situations. In Northwest China, the CV value increased from 0.678 in 2018 to 0.952 in 2024, and the P value rose from 2.002 to 3.012. The imbalance is similar to that in South China but with a slightly weaker concentration, possibly due to inter-provincial disparities in economic and tourism development among northwest provinces. In the Southwest region, the G value increased to 53.483, with Sichuan Province's contribution rate rising, reflecting disparities in provincial attention levels.

In Northeast China, CV indicated inter-provincial variations, while moderate HHl and G values suggested no "oligopolistic" dominance, with spatial concentration trends remaining limited. Conversely, Central and East China maintained relatively balanced distributions, evidenced by lower CV and G values alongside P approaching 1, signifying uniform attention across provinces.

3.2. Comparison of network attention to Japan tourism under regular epidemic prevention and control

The post-epidemic era refers to the era after the COVID-19 pandemic has passed. Under regular epidemic prevention and control, the tourism industry has recovered, and consumers' travel patterns and values have undergone tremendous changes, which have had a huge impact on the market. This study discusses the impact and influence of public health events such as pandemics on tourism demand by comparing the affected value of network attention to Japan tourism after the pandemic with the difference in unaffected network attention under the ARIMA model prediction based on historical data.

3.2.1 Comparison of Temporal Differences

(1) Annual Differences

Comparative analysis reveals significantly lower actual online attention to Japan tourism post-pandemic versus ARIMA-predicted unaffected values, with minimal fluctuation in actual values during 2023–2024 contrasted against substantial growth in projected values, resulting in a widening forecast gap (Figure 3). Specifically, 2023 actual attention reached only 35.4% of unaffected value, while 2024’s marginal increase to 1.4807 million—lagging far behind the projected growth rate—represented merely 33.1% of unaffected projections. This shows that the pandemic has had a significant impact on network attention to tourism in Japan, suppressing tourism demand and causing it to remain in a slump. Even in 2024, there will still be a large gap between the actual value and the unaffected level. At the same time, it also reflects that without the impact of the pandemic, network attention to tourism in Japan should have shown good growth.

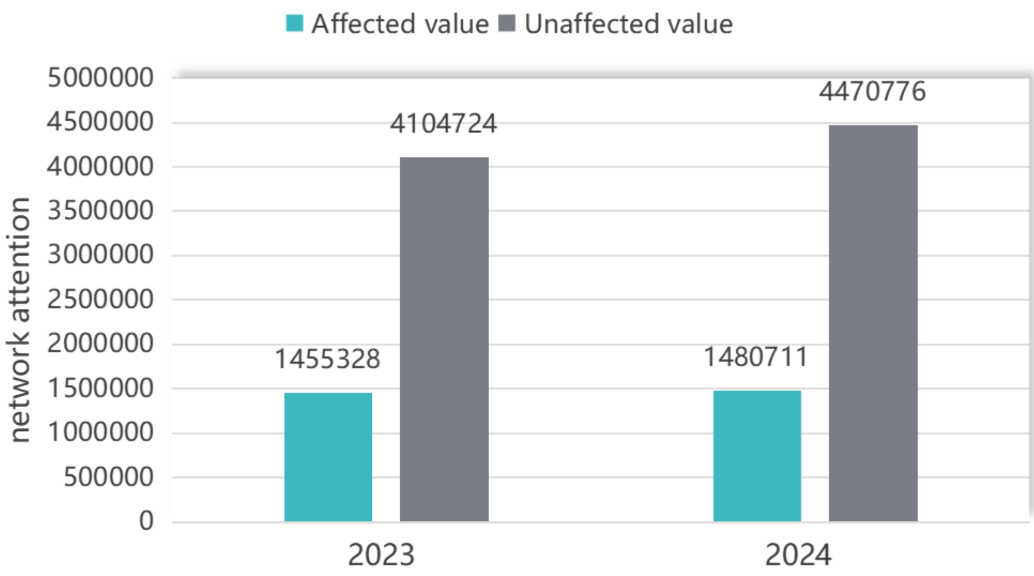


Figure 3. Comparison of affected values and unaffected values by year.

(2)Monthly Differences

As can be seen from Figure 4 there is a clear gap between the network attention of Japan tourism affected by the pandemic and the unaffected value, with the affected value for each month being lower than the unaffected value. The unaffected value trend remained stable, with monthly attention fluctuating between 300,000 and 400,000 times, with little difference between months, and the 2024 value showing stable growth compared to 2023. The values affected show obvious fluctuations, with no significant growth in attention between 2023 and 2024, stable monthly attention fluctuations between March and July, and a significant decline between August and September. The data reflects the continuing impact of the pandemic on the stability of network attention, which not only causes a loss in total volume, but also enhances the differences between seasons.

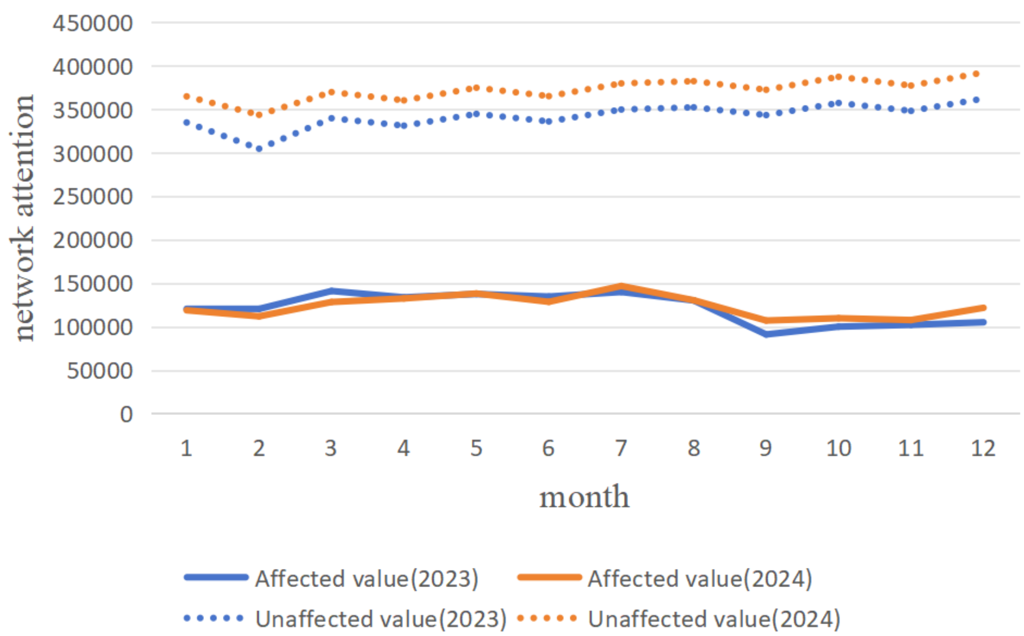


Figure 4. Monthly Comparison of Affected and Unaffected Values.

3.2.2. Spatial characteristics

Table 4 shows that the pandemic had a significant impact on the spatial distribution of network attention to tourism in Japan. The actual CV value for Central China in 2024 is much lower than the predicted value, and attention is more evenly distributed among provinces. Conversely, South China exhibited an inverse pattern, with the actual CV exceeding predictions and the P index reaching significantly elevated levels. This suggests extreme concentration of attention in a few provinces (e.g. Guangdong), likely attributable to inter-provincial economic disparities accelerating post-pandemic recovery divergence, further widening the gap in network attention between regions.

The P-value for the East China region under the influence is lower than the value without influence. The CV value for the Central China region in 2024 is 0.091, lower than the value without influence of 0.401, with the actual distribution being better than the situation without influence. This may be due to strong coordination in tourism promotion among provinces and smaller economic disparities within the region. In Southwest China, affected G values exceeded predictions in both years, confirming stronger spatial concentration than modeled—attention increasingly clustered in a few regions.

Table 4. Spatial differences in network attention to Japan tourism from 2018-2019 to 2023-2024.

Region	Indicator	2023		2024	
		Affected value	Unaffected value	Affected value	Unaffected value
Northeast China	CV	0.424	0.341	0.471	0.343
	H	0.373	0.359	0.383	0.359
	P	1.973	1.721	2.101	1.722
	G	61.100	59.935	61.855	59.957
North China	CV	0.698	0.725	0.724	0.755
	H	0.278	0.284	0.284	0.291
	P	2.271	2.696	2.459	2.833
	G	52.720	53.296	53.272	53.958
Central China	CV	0.083	0.357	0.091	0.401
	H	0.335	0.362	0.335	0.369
	P	1.019	1.593	1.083	1.708
	G	57.869	60.142	57.893	60.754
South China	CV	0.962	0.941	1.034	0.944
	H	0.539	0.530	0.571	0.531
	P	3.224	3.796	4.083	3.827
	G	73.411	72.813	75.553	72.892
East China	CV	0.430	0.482	0.455	0.514
	H	0.166	0.171	0.168	0.175
	P	1.259	1.579	1.222	1.665
	G	40.682	41.387	41.017	41.856
Northwest China	CV	0.945	0.813	0.952	0.809
	H	0.343	0.306	0.345	0.305
	P	2.633	2.458	3.012	2.459
	G	58.557	55.297	58.734	55.203
Southwest China	CV	0.712	0.453	0.733	0.453
	H	0.281	0.233	0.286	0.233
	P	1.561	1.255	1.643	1.251
	G	53.010	48.251	53.483	48.254

The pandemic has caused network attention to Japan tourism in various regions to be generally lower than the ARIMA model calculation values, but there are differences in the characteristics of the gaps between regions (Figure 5). The values affected in each region account for 30% to 45% of the predicted values. Among them, network attention in South China has recovered to 45% of the level before the pandemic, which is the highest among all regions, while the Southwest region has only recovered to 35% of the predicted value, which may be due to differences in the level of economic development between regions. Southwest China recovered only recovered to 35% of the unaffected value. This divergence likely stems from regional economic disparities: Economically advanced regions such as East China and South China maintained larger absolute attention volumes, narrower relative gaps, and faster recovery speeds due to mature tourism infrastructure and higher resident consumption capacity. In contrast, less developed regions such as Northwest and Southwest China faced lower attention and wider relative gaps, exacerbated by intraregional economic imbalances.

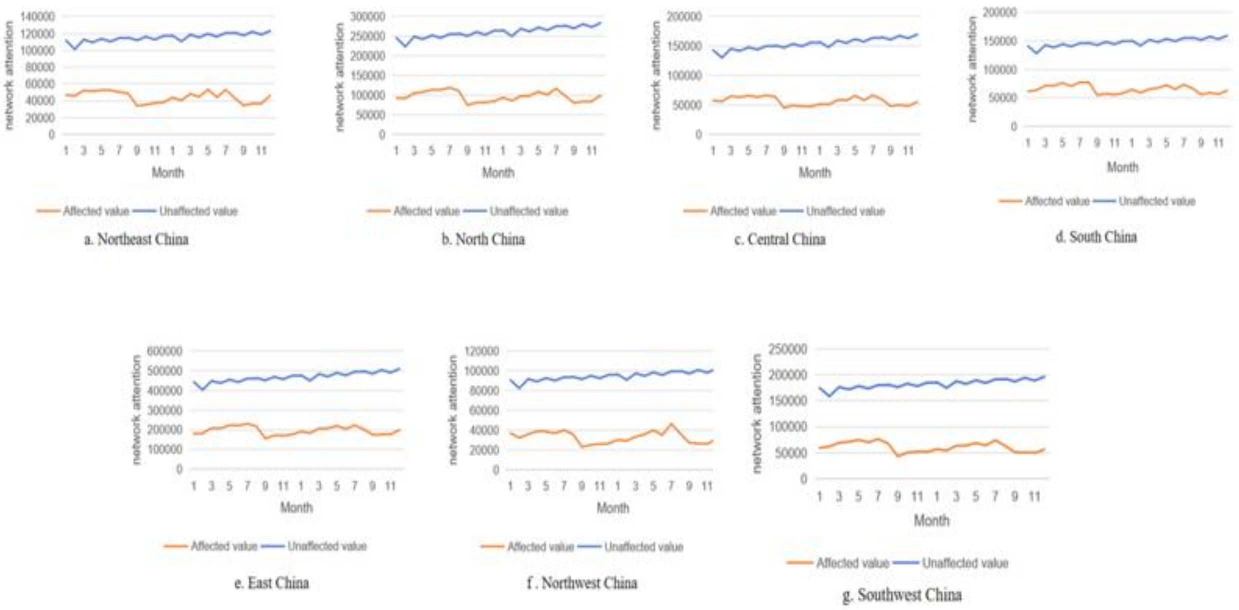


Figure 5. Monthly comparison of affected and unaffected values in each region(2023-2024).

Notably, attention gaps narrowed during summer but widened markedly in winter, reflecting that the pandemic has caused a significant increase in seasonal differences in network attention to Japan tourism, possibly due to the impact of vacation policies and seasonal differences in tourism resources.

Tourism demand is usually affected by the level of regional economic development and the consumption capacity of residents. The tourism industry in East China and South China is more mature than in the western region, and tourism revenue is also higher than in western China, resulting in stronger outbound travel intentions. In less economically developed regions, the demand for travel to Japan is relatively lower, resulting in differences in network attention to tourism between regions.

Based on the values and proportions of network attention to Japan tourism in 31 provinces of China from 2023 to 2024, it can be concluded that there is a clear regional divide in network attention to Japan tourism. Jiangsu, Zhejiang (East China), Guangdong (South China), and Beijing (North China)—these regions maintain a high level of attention due to their economic strength, robust outbound demand, and frequent bilateral exchanges with Japan. Some provinces in the northwest and southwest, such as Ningxia Hui Autonomous Region, Qinghai Province, and Tibet Autonomous Region, do not receive much network attention probably due to their weak economic foundations, limited promotion of tourism to Japan, and inadequate cultivation of demand for outbound travel.

The calculated values of the ARIMA model reflect the development of network attention to Japan tourism without the impact of the pandemic, while the deviation comes from the impact of the pandemic on travel restrictions and psychological expectations. After the pandemic, economic disparities led to greater differences in tourism demand. As Table 5 shows, most provinces maintained stable actual-to-predicted attention ratios; however, Hubei and Chongqing declined in national share due to economic uncertainty, whereas Henan, Hunan, and Guangxi increased their shares. Possible reasons are that economically advanced regions demonstrated stronger tourism resilience, while less developed areas experienced significant attention declines post-crisis.

Table 5. Spatial differences in network attention to affected and unaffected Japan tourism.

Region	2023					2024				
	Affected value	Percentage	Unaffected value	Percentage	Percentage difference	Affected value	Percentage	Unaffected value	Percentage	Percentage difference
Northeast China	181566	8.15%	1346316	8%	0.03%	525118	7.97%	1420449	8.04%	0.07%
North China	235453	17.61%	3002467	18%	0.63%	1148635	17.44%	3245552	18.37%	0.93%
East China	333969	34.96%	5423368	33%	-2.02%	2364178	35.90%	5814668	32.92%	-2.98%
South China	265620	11.92%	1709625	10%	-1.53%	769166	11.68%	1825214	10.33%	-1.35%
Central China	230025	10.32%	1760593	11%	0.37%	668782	10.16%	1929627	10.92%	0.77%
Northwest China	78747	5.89%	1098165	7%	0.78%	394387	5.99%	1169901	6.62%	0.63%
Southwest China	149193	11.16%	2120686	13%	1.73%	715245	10.86%	2258603	12.79%	1.93%

4. Conclusions

Based on Baidu index data from 2011 to 2019, this study uses the ARIMA model to simulate the demand for travel to Japan in 2023-2024 without the impact of the pandemic and compares it with the affected network attention in the real environment. Using research methods such as the seasonal intensity index, coefficient of variation, and geographic concentration index, this study analyzes the temporal and spatial characteristics of the demand for travel to Japan after the pandemic to understand the impact of this major public health event on the demand for travel to Japan.

Research findings: (1) From a temporal perspective, pre-pandemic demand for Japan travel maintained a high baseline, exhibiting two distinct seasonal peaks in March and July. After the pandemic , tourist demand has become more balanced seasonally, summer has emerged as a relative peak period, though autumn remains the annual low point. (2) Spatially, pre-pandemic network attention exhibited pronounced regional disparities between eastern and western China, where eastern regions demonstrated higher demand levels than western regions with this gap widening post-pandemic: East China and South China consistently maintain high network attention, while Northeast China and Northwest China lag significantly behind. (3) Crucially, actual network attention in 2023 reached only 35% of the ARIMA model's simulated unaffected value, confirming the pandemic's persistent suppression effect. Comparative analysis further reveals that the affected value exhibits more pronounced regional disparities and stronger seasonal volatility compared to the unaffected value. By comparing the network attention of different provinces, the following recommendations can be made:

First, tourism enterprises should leverage spatial disparities in network attention to Japan tourism to implement differentiated marketing strategies, innovating products and services tailored to regional demand characteristics. In high-demand regions such as eastern and central China, develop culturally specific offerings aligned with local preferences. For low-attention areas such as northwest and southern China, optimize one-stop services including visa processing and flight-hotel bundles to reduce decision costs, while cultivating market potential through innovative designs to enhance profitability.

Second, tourism service providers should align promotions with temporal attention patterns. During high-demand summer peaks, intensify advertising in key regions such as East and South China via social media marketing matrices to promote popular Japan itineraries and capture traffic dividends. During periods of low attention, such as autumn, companies can deploy strategic pricing incentives to launch special packages during the off-season to stimulate travel demand.

This study still has some shortcomings. First, due to the rapid development of the Internet, users have a variety of options when searching, and analysis based solely on the Baidu index may result in incomplete data coverage, which may lead to bias in the analysis of areas with low Internet usage and penetration rates. Data collection platforms should continue to be expanded to reduce errors caused by a single data source, thereby making the analysis results more accurate. Second, this study focuses on comparing and analyzing the temporal and spatial differences in network attention to Japan tourism under the impact of the COVID-19 pandemic, but there is insufficient discussion of the underlying mechanisms of influence.

For future research: (1) Future research can overcome the limitations of relying solely on Baidu index by constructing a comprehensive analytical dataset. This approach reduces methodological bias from a single data source, thereby enhancing the accuracy of analysis results. Furthermore, big data methodologies should be employed to research tourism. (2) Future studies should delve deeper into the specific factors influencing demand for travel to Japan, examining multifaceted causes such as economic, socio-cultural and political dimensions. Establishing a refined indicator system of influencing factors will provide a theoretical foundation for optimizing outbound tourism strategies and promote the development of outbound tourism.

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