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An Empirical Modelling of New Zealand Hospitality and Tourism Stock Returns

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This paper examines the factor risk premiums of stock returns for the hospitality and tourism companies in New Zealand. The Arbitrage Pricing Theory (APT) approach is used to investigate the expected return for stock portfolio with respect to market, macro (i.e., money supply and discount rate), and tourism factor sensitivities. Monthly stock prices, market index, tourism, and macroeconomic data are used in the study. The results indicate that the risk premiums for international tourism demand and term premium (proxy for discount rate) are positively significant at the 5% level. A one unit increase in tourist arrival sensitivity would result in expected return increase of 10 to 17 percentage point. Similarly, a one unit increase in term premium can increase hospitality-tourism expected returns by 0.2 percentage point. However, the findings for the money supply factor are not significant. As the study shows that investors face high positive tourism demand risk, it is imperative for firms and policymakers in New Zealand to promote inbound tourism through effective marketing and management. This in turn can provide high expected returns and create shareholder value for investors.

1. Introduction

Tourism is travel for recreational/leisure, visiting friends and relatives (VFR), or business purposes. It is vital for the global economy in terms of the production of goods and services, income, and employment generation in the service industries associated with tourism. The real average annual growth of world tourism exceeded the global economic growth during the period 2004–2007 [1]. In 2008 and 2009, international travel demand experienced a tremendous slowdown. Resurgence in international tourist arrivals was evidence of tourism recovery in 2010. Tourism contribution to total global GDP in 2011 was 9% or US$6 trillion [2].

The tourism industry comprises the full scale of businesses which range from large stock exchange listed corporations to small owner-operators. Hospitality business as defined by Hayes and Miller [3, page 5] is "an organization providing food, beverages, lodging, travel or entertainment services to people away from their homes." As the goal of a company is to increase the value of the firm for its shareholders, investors often assess the performance of the firm based on their stock return and variability of return. The stock returns of individual companies and market are commonly used because they are regarded as good indicators of business activities and the data/information are easily available. Chen et al. [4] argued that variations in stock prices and expected returns can be explained by the health of the macroeconomy. If business conditions are expected to improve (deteriorate), company earnings are likely to increase (decrease), and this will have a positive (negative) effect on stock prices [5]. Invariably, studies have shown that macroeconomic factors (such as GDP growth, changes in money supply, unemployment rate, exchange rate, and inflation rate) have significant influence on the fluctuations in stock returns.

The Arbitrage Pricing Theory has been used extensively in the economics and finance literature to explain stock returns. However, this empirical model has not been applied in hospitality and tourism research. The objective of this paper is to examine the factor risk premiums of hospitality and tourism stocks in New Zealand. We use the Arbitrage Pricing Theory approach to investigate the expected return for stock portfolio with respect to market, macro, and tourism factor sensitivities. Our sample includes hospitality and tourism-related companies listed in the New Zealand Stock Exchange (NZX), namely, Auckland International Airport, Air New Zealand, Millennium & Copthorne Hotels, New Zealand Experience, Restaurant Brands, SkyCity Entertainment, and Tourism Holdings. These companies are associated with restaurant/food service, lodging, entertainment, transportation, and so forth. Some of these companies are also listed in the benchmark NZX 50 Index for New Zealand equities, which comprises stocks in the top fifty largest companies on the New Zealand Stock Exchange by market capitalization. The NZX 50 is a gross index, weighed according to the "free float" market capitalization of each company based on the percentage of stocks available for trading. The seven hospitality and tourism-related companies under study belong to the $16 billion services sector of the New Zealand market.

The plan of the remainder of the paper is as follows. In Section 2, we examine the risk-return performance of the selected hospitality and tourism companies for the period 1999 to 2012. Section 3 provides a review of related studies in the hospitality and tourism literature. The methodology used in the study is discussed in Section 4, and the results are presented in Section 5 with some concluding remarks in Section 6. Seasonally unadjusted monthly stock prices, market index, and tourism and macroeconomic data from 1999(3)–2012(9) are used. They are obtained from Datastream, Statistic New Zealand, and the Reserve Bank of New Zealand.

2. Hospitality and Tourism Companies in New Zealand

Auckland International Airport (AIA) was listed in the New Zealand Stock Exchange in 1998. The airport is the busiest international gateway in New Zealand. More than 70% of all international passengers arriving and departing from New Zealand use the Auckland Airport, which handles over 13 million passengers per year. International tourism demand for New Zealand was adversely affected by events such as the September 11 terrorist attacks in the USA, collapse of Ansett Australia which affected Air New Zealand (AIA's major customer), Bali bombings, Iraq War, SARS outbreak, and the 2008 financial crisis. Despite these problems which significantly affected international aviation, AIA still managed to achieve increase in revenue, thus proving its resilience to adversities [6]. AIA was estimated to generate about NZ$19 billion to the New Zealand economy in 2006; and the contribution is expected to grow to $26–$32 billion in 2021 [7].

Air New Zealand (AIR), formerly owned by the New Zealand Government, was privatized in 1987 and it was subsequently listed on the New Zealand Stock Exchange in 1989. In 2000, Air New Zealand acquired full ownership of Ansett Australia. Ansett was a larger airline than Air New Zealand before the merger, and it operated domestic flights within Australia and to several destinations in Asia. The large decrease in AIR stock prices in 2001 was due to the financial collapse of Ansett one day after the terrorist attacks in the USA. The demise of Ansett required the New Zealand Government to bail its flagship carrier out of the financial disaster. Inevitably, the public sector has again become the largest shareholder of Air New Zealand. The airline won the Air Transport World award for 2010. Plunging profits have forced Air New Zealand to embark on cost-cutting measures and large discounting to reduce capacity in response to the downturn in passenger numbers especially on long haul routes [8–10].

Millennium & Copthorne Hotels was listed on the New Zealand Stock Exchange in 1985. It runs thirty hotels in New Zealand under three operating brands: Millenium, Copthorne, and Kingsgate (MCK). The company is the largest owner-operator hotels in New Zealand, with properties in all major cities across the north and south islands [11, 12]. Restaurant Brands Limited (RBD) is the franchise holder of KFC, Pizza Hut, and Starbucks Coffee in New Zealand. Currently, RBD operates over 200 stores, with KFC as the core focus of the company. KFC is also the most competitive and profitable of the three brands [13].

New Zealand Experience Limited, formerly known as Mount Cavendish Gondola Co. Limited, was listed in 1991. Following the acquisition of Auckland Rainbow's End theme park in 1995, the company's name was changed to New Zealand Experience Limited to reflect its diverse business. The company provides entertainment services in the form of amusement rides and various attractions for the public, corporate functions, school, and youth groups [14, 15]. SKYCITY Entertainment Group Limited is a leading entertainment and gaming business. In New Zealand, it operates monopoly casinos in Auckland, Hamilton, Christchurch, and Queenstown. The company also operates restaurants and bars, luxury hotels, convention centres, and cinemas alongside its core business [16].

Tourism Holdings Limited was established in 1986 and the company was originally known as the Helicopter Line Limited, specialising in scenic flights in New Zealand's South Island. Following major business acquisitions and expansion in New Zealand and overseas, the company changed its name to Tourism Holdings Limited (THL) in 1996 to reflect its diverse tourism operations. Its operations in New Zealand include car and motorhome rentals, a specialist caravan and motorhome manufacturing, backpacker transport, and tourism activities. Low interest rates have allowed the company to diversify its range of tourism offerings. However in 2008, THL started to restructure its business by concentrating on its core activities in providing mobile tourist accommodation and disposed its noncore assets for debt consolidation in the challenging business operating environment. Restructuring, discontinued activities, divestments, and downturn in overseas visitor arrivals have negatively impacted the company's earnings [17, 18].

2.1. Risk-Return Performance of Companies. The rate of return on each stock is defined as the proportional change in the monthly stock price (or the monthly percentage return). Figure 1 shows the stock returns of the seven selected hospitality and tourism companies for the period 1999 to

Table 1: Descriptive statistics of Hospitality and Tourism Companies Monthly Stock Returns, 1999(3)–2012(9).

Stock return	Mean	Standard deviation	Normality
Auckland International Airport (AIA)	0.685	5.82	2.38*
Air New Zealand (AIR)	−1.476	11.88	1057.68
Millenium & Copthorne Hotels (MCK)	0.168	7.55	9.64*
New Zealand Experience (NZE)	1.106	13.85	98.23
Restaurant Brands (RBD)	0.358	7.41	6.52*
Sky City Entertainment (SKC)	0.576	6.25	14.56
Tourism Holdings (THL)	−0.402	10.06	6.86

Note: *indicates 5% significance level.

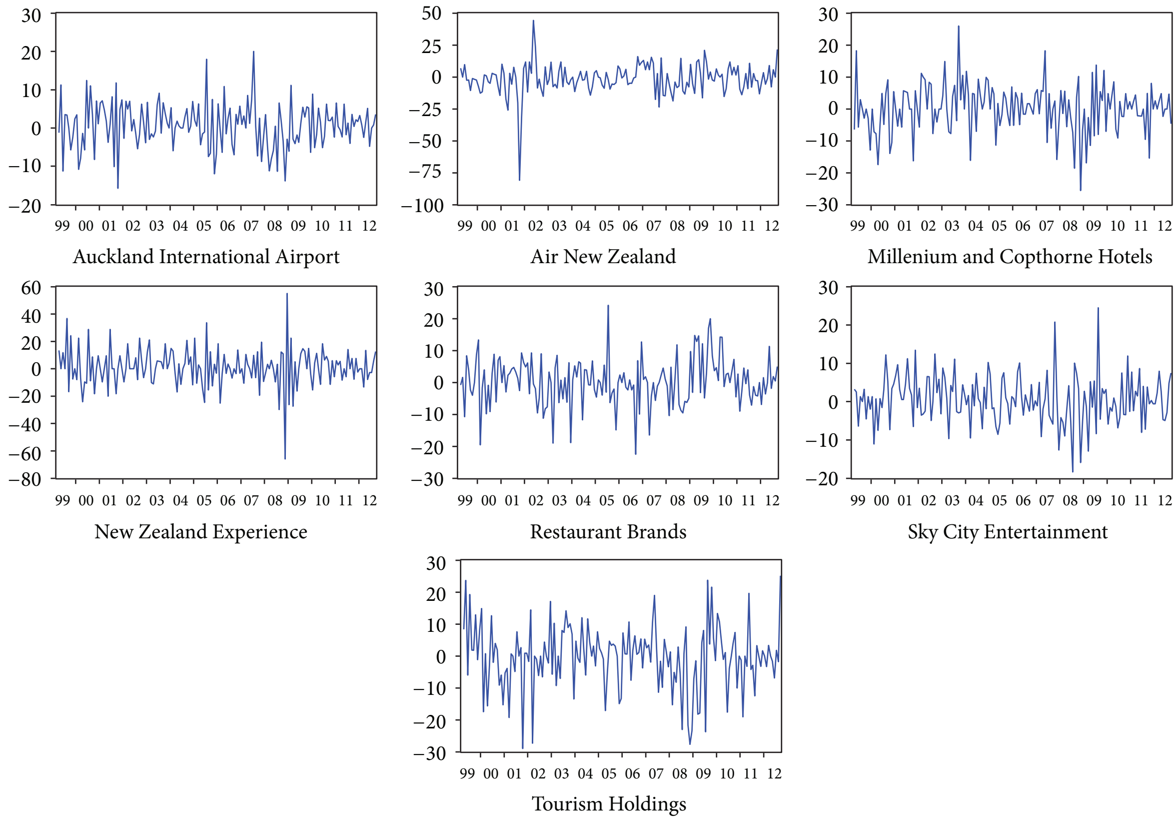

Figure 1: Monthly returns (%) for hospitality and tourism companies, 1999(3)–2012(9).

2012. Summary statistics for their rates of return are given in Table 1. During this period, the average monthly returns for all the stocks are less than 1% except for NZE, with negative returns for AIR and THL. The average monthly returns range from a high of 1.1% for NZE to a low of about −1.5% for AIR stock. Variance is a well-known measure of dispersion about the mean. The risk of return as measured by the standard deviation of return shows that NZE and AIA have the highest and the lowest risk, respectively. It is also worth mentioning that all the hospitality and tourism stocks have higher risks of return than the overall market's (given by NZX All Stock Index) standard deviation of 3.7 percent. A positive tradeoff between risk and return is only evident in NZE stock, whereas AIR stock displays relatively high risk and negative return. Using the Jarque-Bera test for normality, the null hypothesis of a normal distribution of return is not rejected for AIA, MCK, and RBD at the 5% significance level.

While Table 1 shows the risk of a stock as measured by the dispersion of its return distribution, another way to examine risk is to calculate the stock beta. According to the Capital Asset Pricing model (CAPM), the only factor that is important in influencing expected returns is the market return. Specifically, the expected return of a stock is determined by the risk-free rate of return (which is generally measured as the yield on Treasury bills), the stock beta, and the expected market return. The relationship can be written as follows:

$$\overline{R}_i = R_f + \beta_i \left(\overline{R}_m - R_f \right), \tag{1}$$

Table 2: Beta estimates for hospitality and tourism companies, 1999(3)–2012(9).

Company	Beta	t-stat	R^2
Auckland International Airport (AIA)	0.876	8.43	0.31
Air New Zealand (AIR)	1.250	5.32	0.15
Millenium & Copthorne Hotels (MCK)	0.561	3.60	0.08
New Zealand Experience (NZE)	0.142	0.48	0.001
Restaurant Brands (RBD)	0.645	4.29	0.10
Sky City Entertainment (SKC)	1.081	10.48	0.41
Tourism Holdings (THL)	1.573	8.93	0.33

where $\overline{R}_i$ = expected return of stock i; R_f = risk-free rate of return; $\overline{R}_m$ = expected return on market portfolio; β_i = beta or systematic risk of stock i to be estimated.

In other words, the expected return of stock i is the risk-free rate plus a risk premium given by $\beta_i(\overline{R}_m - R_f)$. The systematic risk as denoted by β is the coefficient of a stock which measures the responsiveness of its rate of return to that of the overall market. This is given by the covariance of stock i with the market portfolio as shown below:

$$\beta_i = \frac{\operatorname{cov}(R_i R_m)}{\sigma^2(R_m)}, \qquad (2)$$

where R_i = return of stock i; R_m = return of market portfolio; $\operatorname{cov}(R_i R_m)$ = covariance of stock i return with the market return; $\sigma^2(R_m)$ = variance of the market return.

The New Zealand benchmark NZX All Stock Index is the proxy for the market portfolio. Using the CAPM, the beta estimates for the seven companies are given in Table 2. All the stocks have positive and significant betas at the 5% level except for NZE. The estimated beta values range from 0.56 to 1.57 (excluding NZE). AIR and THL have higher market risk than AIA, MCK, and RBD, as shown by their respective betas. This is consistent with the risk of return findings in Table 1. Moreover, Table 2 shows that AIA, MCK, and RBD are less responsive to fluctuations in the market return (with beta values less than one). SKC, which has a relatively low risk of return, is however quite responsive to changes in the market return. What is also important is to examine the responsiveness of these stocks to other explanatory factors.

3. Literature Review

Following the pioneering work by Ross [19] and Chen [20], many studies which examine the macroeconomic determinants of stock returns applied the multifactor Arbitrage Pricing Theory model (see for instance [4, 21–24]). But very few similar studies have been undertaken in the past to analyse the effects of macroeconomic factors on tourism and hospitality stock returns [5, 25–31].

Barrows and Naka [25] examine the relationship between five selected macro variables and stock returns of hospitality (restaurant and lodging) companies in the US. The latter is taken from the restaurant and hotel/motel sectoral stock indexes in the Standard and Poor 500 (S&P 500) value-weighted Index. According to their study, inflation rates, money supply, and domestic consumption growth rates are significant explanatory factors of hospitality stock returns. Wong and Song [31] use the vector autoregressive modelling approach to investigate the relationship between hospitality (restaurant, lodging and casino) stock indices and a number of macroeconomic variables in the US. Their findings show that the interest rate variable is the major factor in explaining fluctuations in the stock indices. According to Chen [30], the discount rate and the federal funds rate of the US monetary policy have different impact on hospitality stock returns. There is no significant relationship between hospitality stock returns and changes in the discount rate. However, the study shows a significant link between restaurant stock returns and changes in the federal funds rate.

Chen et al. [26] and Chen [5, 27–29] analyse the stock returns of hospitality and tourism firms in Taiwan and China. In their study which documents the relationship between stock returns, macro, and nonmacro factors, Chen, et al. [26] find that changes in money supply and unemployment rate have significant impact on Taiwanese hotel stock returns. The latter is also affected by nonmacro factors, namely, domestic and international events. They include political events (the first and second democratic presidential elections in Taiwan, the September 2001 terrorist attacks in the US, and the Iraqi War in 2003), natural disasters (the 1999 earthquake and the 2003 SARS outbreak in Taiwan) and international events (the 1997 Asian financial crisis and several mega sports events). A similar study undertaken in Chen [28] for hotel stock returns in China also includes international tourism demand as an explanatory variable.

Chen [27] investigates the impact of macro factors under restrictive and expansive monetary environment on hotel stock investment in Taiwan. The author argues that investors tend to increase (decrease) their holdings of hotel stocks during expansive (restrictive) monetary periods. Chen [5] conducts cointegration and causality tests and finds support for a long-term relationship between business conditions and financial performance (as measured by stock returns) of tourism firms in China and Taiwan. Chen [29] examines the impact of economic and tourism factors on the corporate performance of Taiwanese hotels using panel regression techniques. Stock return is one of the measures of corporate performance used in the study. No significant relations are found for stock return performance, economic and tourism factors.

Other studies examine the relationship between nonmacro factors and stock returns such as the impact of acquisition activity [32], the influences of legislation actions [33], government intervention in tourism diversification [34], announcement/news on new hotel opening [35], SARS outbreak [36], business cycle, and firm-specific characteristics [37–39].

Unlike the aforementioned tourism studies, we use the two-step Arbitrage Pricing Theory approach to examine the risk premiums of hospitality-tourism stock portfolio in relation to market, macro, and tourism factors. Since our sample comprises small and large hospitality and tourism firms in New Zealand, this produces a spread of average returns and estimates for the variables under study. Moreover, we use an individual stock regression approach as this procedure helps avoid the error-in-variables problem [40].

4. Methodology

4.1. Model Specification. In contrast to the single-factor CAPM in which stock returns are explained solely by market returns, the Arbitrage Pricing Theory (APT) model by Ross [19] hypothesizes that stock returns are affected by a range of exogenous variables. According to APT, stock returns are influenced by systematic risks in the economy which affect all stocks to some degree. The linear relationship between stock returns and explanatory factors can be expressed as follows:

$$R_i = a_i + b_{i1}F_1 + b_{i2}F_2 + \cdots + b_{ik}F_k + \varepsilon_i, \tag{3}$$

where R_i is the return on stock i $(i = 1, \ldots, n)$; the intercept a_i is the expected return to stock i; $F_1, F_2, \ldots, F_k$ are the common explanatory factors affecting all stock returns; $b_{i1}, b_{i2}, \ldots, b_{ik}$ indicate the sensitivities of return on stock i (also called beta or factor loadings) to each unit of increase in the explanatory factors; and ε_{it} is a random independent and identically distributed error term. We assume the following:

(i) factors have zero mean: $E[F_k] = 0$;

(ii) factors are uncorrelated: $E[F_k F_m] = 0$ for all k and m;

(iii) disturbance term has a zero mean and constant variance: $E[\varepsilon_i] = 0, E[\varepsilon_i^2] = \sigma_i^2$, respectively;

(iv) disturbance term is uncorrelated across different stocks: $E[\varepsilon_i \varepsilon_j] = 0$ for all i and j, where $i \neq j$;

(v) disturbance term is uncorrelated with the explanatory factors: $E[\varepsilon_i F_k] = 0$ for all i and k;

(vi) number of explanatory factors cannot exceed the number of stocks under consideration ($k < n$).

Based on the above assumptions, (3) can be rewritten as

$$R_i = E[R_i] + b_{i1}F_1 + b_{i2}F_2 + \cdots + b_{ik}F_k + \varepsilon_i. \tag{4}$$

The model shows that stock return has three components:

(i) its expected return $E[R_i]$ which reflects the effects of the predicted values of factors;

(ii) its unexpected return due to new information about the factors;

(iii) an error term.

If $F_1, F_2, \ldots, F_k$ have a value of zero, then each n individual stock has return equal to its expected value $E[R_i]$ and the error term. The model shows how stock return can deviate from its expected value due to sensitivities to a number of explanatory factors and firm-specific events (captured by the error term). As the explanatory factors represent priced risk, investors require additional return for bearing systematic factor risk. These factors can be market and macroeconomic variables, while firm specific events (e.g., strike, defect product recall, etc.) generate unsystematic or idiosyncratic risk.

Investors are assumed to be homogeneous and they can form a well-diversified portfolio that eliminates stock-specific risk. To form an arbitrage portfolio, it is necessary that the portfolio weights (w) sum to zero: $\sum_{i=1}^{n} w_i = 0$. The return on portfolio is given by

$$\begin{aligned} R_p = \sum_{i=1}^{n} w_i R_i &= \sum_{i=1} w_i a_i + \sum_{i=1} w_i b_{i1} F_1 + \sum_{i=1} w_i b_{i2} F_2 + \cdots \\ &+ \sum_{i=1} w_i b_{ik} F_k. \end{aligned} \tag{5}$$

To obtain a risk-free portfolio, it must earn zero return (i.e., $\sum_{i=1} w_i b_{i1} = 0 \cdots \sum_{i=1} w_i b_{ik} = 0$) and (5) becomes:

$$R_p = \sum_{i=1}^{n} w_i E(R_i) = 0. \tag{6}$$

The equilibrium expected return of a stock is linearly related to the factor sensitivities of the portfolio:

$$E[R_i] = \lambda_0 + \lambda_1 b_{i1} + \lambda_2 b_{i2} + \cdots + \lambda_k b_{ik}. \tag{7}$$

The regression coefficients, $\lambda_1, \lambda_2, \ldots, \lambda_k$, are risk premiums which correspond to the factors $F_1, F_2, \ldots, F_k$. (Detailed discussion of the algebraic developments is given in [41].) If there is a risk-free stock, then λ_0 is the return on the risk-free stock which has no sensitivity to the factors. Hence, λ_0 is the risk-free rate ($\lambda_0 = R_f$) and (7) can be rewritten in the form of excess return:

$$E[R_i] - R_f = \lambda_1 b_{i1} + \lambda_2 b_{i2} + \cdots + \lambda_k b_{ik}. \tag{8}$$

Hence, the APT model is given by

$$E(R_i) = R_f + \sum_{k=1}^{K} b_{ik} \lambda_k. \tag{9}$$

Equation (8) shows that excess return is a linear combination of factor risk premiums. The factor premium can be interpreted as the expected return on a portfolio in excess of the risk-free rate for a portfolio with unit sensitivity to factor k and zero sensitivity to all others. It is worth noting that a factor risk premium can be negative [42].

We will use the APT approach to analyse the expected return on a portfolio of hospitality-tourism stocks in New Zealand, which is built upon estimates of the b_{ik}, the sensitivities of return on stock i (see (9)). The choice of explanatory variables that might affect returns is guided by economic theory and data availability. Unlike stock prices which are available on a daily basis, no higher frequencies than monthly data are available for tourism and some macroeconomic variables. (Data limitation has meant that several obvious choices such as GDP, industrial production, the CPI, and unemployment rate are not available at the monthly frequency in New Zealand.)

4.2. Data and Variables Used. The seminal work by Roll and Ross [43] and subsequent studies provide evidence of three to five factors used for the APT [40]. We hypothesize that the equilibrium expected returns of hospitality-tourism stocks are linearly related to the factor sensitivities of market, macro (namely, money supply and discount rate), and tourism demand variables. The factors chosen are broadly similar to those used in [4, 21, 23, 27, 30], among others.

While the inclusion of the market variable is a common practice in the economics and finance literature, this is not the case in past tourism studies which examine the influences of macroeconomic and tourism factors on stock returns. As investors tend to hold diversified portfolios (as measured by the market index) to reduce their risks, we expect movements in the hospitality and tourism stocks (like other common stocks) to be affected by market return. The NZX All Stock index is used as a proxy for the market variable. It is a market value-weighted portfolio of all existing stocks in the New Zealand Stock Exchange. Given the importance of tourism exports to the New Zealand economy, it is plausible that the risk and expected return of hospitality-tourism stocks are associated with inbound tourist flows to New Zealand. Hence, it is appropriate to include the international tourism demand variable in the model specification.

Stock returns are affected by monetary policy which is the deliberate attempt by the Reserve/Central Bank to influence money supply and interest rates in the economy. Expansionary (contractionary) monetary policy or increases (decreases) in the amount of money in circulation could stimulate (deflate) the economy and higher (lower) stock prices due to lower (higher) interest rates or costs of borrowing. The indirect link between monetary policy, economic activity, and stock returns has been discussed extensively by [44, 45]. We used M1 as a proxy for money supply. Money supply M1 includes notes and coin held by the public plus chequeable deposits, minus interinstitutional chequeable deposits and central government deposits.

Stock returns are also influenced by the discount rate which affects investors' perception of risk. Past studies have used changes in Treasury-bill yield (proxy for expected inflation) and changes in yield spread between Treasury-bonds and Treasury-bills [4, 21, 23]. These variables are related to the discount rate. We used the 90-day bank bill rate, the term structure of interest rates, and the official cash rate as proxies for the discount rate. The term structure of interest rates or term premium is defined as the difference between long- and short-term interest rates. The proxy variables used are the government 10-year and 1-year bond rates, respectively. The official cash rate (OCR) is the alternative proxy for the discount rate given that it is a more conventional monetary

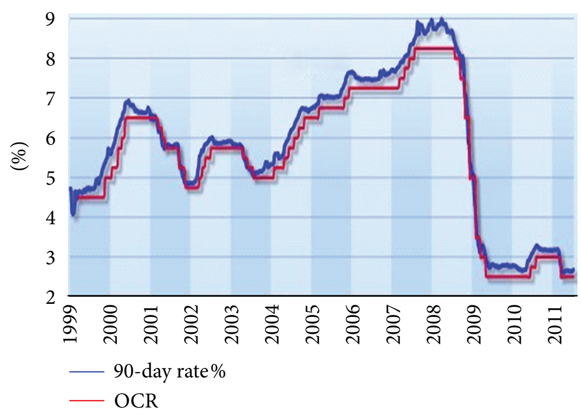

Figure 2: Official cash rate and 90-day bank bill rate weekly averages, 1999–2011/2011. source: [46].

tool used to influence the level of economic activity in New Zealand. Moreover, market interest rates are generally held around the Reserve Bank's OCR level [46]. The OCR was introduced in March 1999. Figure 2 shows the average weekly rates of the 90-day bank bill and OCR from 1993 to 2011.

The general linear regression model for stock return to be estimated is

$$R_t = \alpha + \beta_1 \text{mkt}_t + \beta_2 \Delta \text{ms}_t + \beta_3 \Delta \text{dr}_t + \beta_4 \Delta \text{ int\_tour}_t + \varepsilon_t, \tag{10}$$

where R_t = stock return at time t; mkt_t = return of market portfolio at time t; Δms_t = change in money supply at time t; Δdr_t = change in discount rate at time t; $\Delta \text{ int\_tour}_t$ = change in international tourism demand in New Zealand at time t; ε_t = independently distributed random error term, with zero mean and constant variance σ_u^2 at time t; $\alpha, \beta_1, \ldots, \beta_4$ = parameters to be estimated.

The return on each stock during period t does not include dividends which are only reported semiannually in New Zealand. We computed the monthly stock return by taking the change in logarithm of stock price (sp) as given by $R_t = \Delta \log \text{sp}_t = \log(\text{sp}_t) - \log(\text{sp}_{t-1})$. The monthly percentage changes in the NZX All Stock Index, M1 money supply and international tourist arrivals are proxies for market return, money supply, and international tourism demand, respectively [46–48]. Note that the variable of interest y_t is expressed as growth rate or rate of change by taking first difference of $\log y_t$ as follows:

$$\Delta \log (y_t) = \log \left(\frac{y_t}{y_{t-1}} \right) = \log \left(1 + \left(\frac{\Delta y_t}{y_{t-1}} \right) \right) \approx \frac{\Delta y_t}{y_{t-1}}. \tag{11}$$

However, the discount rate variable (proxied by bank bill rate, term premium, and cash rate) is expressed in levels. For instance, the change in the discount rate such as the 90-day bank bill rate (bbr) is defined as difference in levels: $\Delta\text{bbr}_t = \text{bbr}_t - \text{bbr}_{t-1}$.

Descriptive statistics for the explanatory factors are given in Table 3. According to the Jarque-Bera test, normality is not

Table 3: Descriptive statistics of explanatory factors, 1999(3)–2012(9).

Factor	Mean	Standard deviation	Normality
Return of market portfolio	0.0568	3.686	19.53
Change in M1 money supply	0.5665	2.881	577.42*
Change in 90-day bank bill	−0.0123	0.218	1052.4
Change in term premium	−0.0002	0.269	43.87
Change in official cash rate	−0.0123	0.210	3165.38
Change in tourist arrivals	0.1290	19.927	3.94*

Note: * indicates 5% significance level.

Table 4: Philip-Perron test statistics.

Variable	Philip-Perron	
	Without trend (critical value = −2.88)	With trend (critical value = −3.44)
Auckland International Airport	−14.26	−14.25
Air New Zealand	−9.59	−9.60
Millenium & Copthorne Hotels	−13.92	−13.89
New Zealand Experience	−20.75	−21.15
Restaurant Brands	−12.62	−12.62
Sky City Entertainment	−13.60	−13.65
Tourism Holdings	−11.76	−11.74
Change in market portfolio	−12.49	−12.46
Change in M1 money supply	−15.15	−15.08
Change in 90-day bank bill	−5.18	−5.29
Change in term premium	−8.71	−8.69
Change in official cash rate	−6.54	−6.68
Change in tourist arrivals	−11.22	−11.18

rejected at the 5% level for the M1 money supply and tourist arrival variables.

4.3. Unit Root Tests. The test for the stationarity of the returns and explanatory factors is the Philip-Perron test which is based on the following regression equation [49]:

$$\Delta y_t = \alpha + \beta t + \delta y_{t-1} + \varepsilon_t, \tag{12}$$

where Δy_t is the change in the variable of interest at time t, t is a deterministic time trend, and ε_t is a disturbance term which is independent and normally distributed with zero mean and constant variance. In order to test for unit roots, the hypotheses of interest are

$$H_0 : \delta = 0$$
$$H_1 : \delta < 0.$$

The null hypothesis of a unit root is based on the t-statistic (which has a nonstandard distribution) using simulated critical values. According to the Phillips-Perron (PP) unit root tests which are reported in Table 4, the PP statistics with and without trend for stock returns and explanatory factors are all less than the 5% critical value of −3.44 and −2.88, respectively. Hence, none of these series have unit roots.

5. Empirical Results

The two-step procedure [42] to estimate the influences of the explanatory factors on the hospitality-tourism stock returns is as follows. Initially, we regress time-series stock returns on these variables to estimate factor sensitivities for each stock using ordinary least squares over the period 1999(3) to 2012(9). Accordingly, twenty-one single equations are estimated and the time-series results are presented in Table 5.

In the second stage of the procedure, the estimated factor sensitivities are used as independent variables to explain expected returns (given by the estimated α—see (4) and (7)) by cross-section method over the seven stocks. The cross-sectional regression for the hospitality-tourism portfolio is run using three models to estimate the size and statistical significance of the factor premiums.

Model 1:

$$E(R_i) = \lambda_0 + \lambda_1 \widehat{\beta}_{\text{mkt}} + \lambda_2 \widehat{\beta}_{\text{ms}} + \lambda_3 \widehat{\beta}_{\text{bbr}} + \lambda_4 \widehat{\beta}_{\text{int\_tour}} \tag{13}$$

Model 2:

$$E(R_i) = \lambda_0 + \lambda_1 \widehat{\beta}_{\text{mkt}} + \lambda_2 \widehat{\beta}_{\text{ms}} + \lambda_3 \widehat{\beta}_{\text{tmp}} + \lambda_4 \widehat{\beta}_{\text{int\_tour}} \tag{14}$$

Model 3:

$$E(R_i) = \lambda_0 + \lambda_1 \widehat{\beta}_{\text{mkt}} + \lambda_2 \widehat{\beta}_{\text{ms}} + \lambda_3 \widehat{\beta}_{\text{ocr}} + \lambda_4 \widehat{\beta}_{\text{int\_tour}}, \tag{15}$$

Table 5: Time series estimates of factor sensitivity.

(a) Model 1: using 90-day bank bill rate as discount rate proxy ($n = 162$)

Firm	AIA	AIR	MCK	NZE	RBD	SKC	THL
Expected returns	0.684	−1.427	0.179	1.170	0.287	0.489	−0.283
dlog mkt	0.887	1.173	0.523	0.210	0.632	1.108	1.518
dlog ms	−0.088	−0.052	0.084	−0.045	0.052	−0.010	−0.211
Change in bbr	0.082	6.541	7.089	5.216	−0.748	−2.207	6.880
dlog Ta	0.017	−0.039	−0.001	0.109	−0.022	0.016	−0.004
Adjusted R^2	0.29	0.15	0.09	0.01	0.08	0.40	0.34

(b) Model 2: using term premium as discount rate proxy ($n = 162$)

Firm	AIA	AIR	MCK	NZE	RBD	SKC	THL
Expected returns	0.686	−1.507	0.080	1.048	0.309	0.531	−0.366
dlog mkt	0.885	1.217	0.577	0.275	0.620	1.086	1.564
dlog ms	−0.092	−0.063	0.088	0.023	0.036	−0.026	−0.223
Change in tmp	0.349	−1.488	−3.053	−7.974	1.687	2.183	−1.453
dlog Ta	0.017	−0.039	−0.003	0.103	−0.021	0.018	−0.004
Adjusted R^2	0.29	0.14	0.06	0.02	0.09	0.40	0.32

(c) Model 3: using official cash rate as discount rate proxy ($n = 162$)

Firm	AIA	AIR	MCK	NZE	RBD	SKC	THL
Expected returns	0.676	−1.432	0.142	1.070	0.283	0.505	−0.305
dlog mkt	0.891	1.171	0.541	0.270	0.635	1.100	1.527
dlog ms	−0.096	−0.006	0.097	−0.124	0.042	−0.009	−0.182
Change in ocr	−0.835	8.278	4.877	−6.262	−1.509	−0.935	6.469
dlog Ta	0.017	−0.035	0.002	0.107	−0.023	0.016	−0.0002
Adjusted R^2	0.29	0.16	0.07	0.01	0.09	0.40	0.34

where bbr, tmp, and ocr are the 90-day bank bill rate, term premium, and official cash rate, respectively. Using White's [50] covariance estimator, the cross-sectional regressions for the equilibrium expected returns on the hospitality-tourism stock portfolio are (parentheses denote White corrected t-statistics).

Model 1:

$$E(R_i) = \underset{(2.15)}{0.88} - \underset{(1.33)}{0.65}\widehat{\beta}_{\text{mkt}} - \underset{(0.27)}{0.96}\widehat{\beta}_{\text{ms}} - \underset{(1.48)}{0.09}\widehat{\beta}_{\text{bbr}} + \underset{(2.08)}{9.95}\widehat{\beta}_{\text{int\_tour}}$$

$$\text{Adjusted } R^2 = 0.52. \tag{16}$$

Model 2:

$$E(R_i) = \underset{(4.33)}{1.35} - \underset{(2.61)}{1.40}\widehat{\beta}_{\text{mkt}} - \underset{(0.87)}{2.53}\widehat{\beta}_{\text{ms}} + \underset{(2.60)}{0.18}\widehat{\beta}_{\text{tmp}} + \underset{(3.53)}{16.52}\widehat{\beta}_{\text{int\_tour}}$$

$$\text{Adjusted } R^2 = 0.75. \tag{17}$$

Model 3:

$$E(R_i) = \underset{(0.06)}{0.03} + \underset{(0.59)}{0.30}\widehat{\beta}_{\text{mkt}} + \underset{(0.44)}{1.32}\widehat{\beta}_{\text{ms}} - \underset{(1.56)}{0.12}\widehat{\beta}_{\text{ocr}} + \underset{(0.81)}{5.69}\widehat{\beta}_{\text{int\_tour}}$$

$$\text{Adjusted } R^2 = 0.44. \tag{18}$$

International tourism plays a significant role in explaining the cross-sectional variation of estimated expected returns on the hospitality-tourism portfolio in New Zealand. Note that the tourism sensitivity variable has a significant positive coefficient in models 1 and 2. The estimated risk premium (λ_4) ranges between 9.95% and 16.52%. Furthermore, the tourism demand risk suggests that the expected excess return (return above the risk-free rate) tends to increase with a positive tourism arrival surprise. A one-unit increase in tourist arrival sensitivity would result in expected return increase of about 10 to 17 percentage point. The tourism variable has the highest risk premium among all the factors investigated.

The market sensitivity variable is statistically significant at the 5% level in model 2. We expect stock returns to increase with a positive market return risk premium but it appears that the premium associated with market risk is negative. The discount rate sensitivity also helps explain the cross-sectional variation of expected returns on New Zealand's hospitality-tourism stocks. The risk premium is statistically significant at the 5% level in model 2 in which the term premium is used as a proxy. This implies that a higher discount rate term premium results in higher future cash flows and higher expected stock returns. The expected return of the hospitality-tourism portfolio tends to increase by about 0.2% with a one-unit increase in the sensitivity to term premium as shown in model 2.

Using the intercept (λ_0) as an estimate of the risk-free rate, the estimated values are significantly different from zero at the 5% level in models 1 and 2. The implied values of the expected returns to the unit-sensitivity portfolio are 0.88% and 1.35%, respectively. The adjusted R-squared values for the three models vary from 0.44 to 0.75, indicating that 44% to 75% of the cross-sectional variation in the expected return of hospitality-tourism portfolio is accounted for by these variables.

6. Conclusion

This paper presents the empirical results of stock return performance of several hospitality and tourism-related companies in New Zealand. Detailed analysis of the stocks' risk/return characteristics is discussed using mean, standard deviation, and beta estimates. The descriptive statistics of the sample provided some useful insights into the diverse financial performance of these companies. Furthermore, the beta findings based on the CAPM provided evidence that some stocks are more responsive than others to fluctuations in the market return.

We used the Arbitrage Pricing Theory approach to examine the cross-sectional returns of these stocks over time. Our choice of market, macro, and tourism factors is similar to those used in previous APT studies and Chen [27, 30]. The time series regressions used natural logs of the variables except for discount rates which are in levels. Although the expected portfolio returns of the hospitality and tourism stocks are not exclusively due to the market, macro, and tourism variables, our findings of the cross-sectional regression models have very good explanatory power.

The research findings offer useful information and some implications for tourism management. First, this study provides valuable insights to investors in understanding the different sources of risk for the expected return on hospitality-tourism stock portfolio. Second, the cross-sectional portfolio evaluation shows that there is a significant relationship between expected returns, market, macro and tourism factors. It is not surprising that these stocks have a high sensitivity to international tourism demand risk. In fact, an increase in tourism demand sensitivity makes the largest contribution to expected return, among the factors under study.

Third, given the high tourism demand priced risk, it is imperative for firms and policymakers to promote inbound tourism through effective marketing and management. This in turn can provide higher expected returns and create shareholder value for investors. Additionally, it is prudent for hospitality and tourism firms to attract more investors to raise capital for future expansion. This is fundamentally important as more companies are turning to capital raising worldwide due to costly borrowing from the international money markets, related to the ongoing concerns about US and Europe's debt problems.

Finally, the study makes a contribution to the hospitality-finance literature, identifying research gaps and advancing the understanding of hospitality-tourism expected returns based on market, macro, and tourism factor risk premiums. However, the study has limitations which include the relatively small sample of hospitality and tourism companies used. This is because there are very few such companies listed on the New Zealand stock exchange. Future research using data from different countries can advance our understanding of hospitality-tourism expected returns and factor risk premium as market situations vary from country to country.

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2

Tour Route Multiobjective Optimization Design Based on the Tourist Satisfaction

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The question prompted is how to design the tour route to make the tourists get the maximum satisfactions considering the tourists' demand. The influence factors of the tour route choices of tourists were analyzed and tourists' behavior characteristics and psychological preferences were regarded as the important influence factors based on the tourist behavioral theories. A questionnaire of tourists' tour route information and satisfaction degree was carried out. Some information about the scene spot and tourists demand and tour behaviors characteristic such as visit frequency, number of attractions visited was obtained and analyzed. Based on the convey datum, tour routes multiobjective optimization functions were prompted for the tour route design regarding the maximum satisfaction and the minimum tour distance as the optimal objective. The available routes are listed and categorized. Based on the particle swarm optimization model, the priorities of the tour route are calculated and finally the suggestion depth tour route and quick route tour routes are given considering the different tour demands of tourists. The results can offer constructive suggestions on how to design tour routes on the part of tourism enterprises and how to choose a proper tour route on the part of tourists.

1. Introduction

With the development of economics, more and more people have leisure time to travel. During the travel, it is necessary for the tourist to determine the travel destination and traffic mode and visit more scenic spots and historical sites in the limited time budget and get the maximum satisfactions. For some tourists, it will take them some time to determine the tour route before or during the travel [1], especially for those tourists who visit the scenic spot for the first time. So for tourism enterprises the most important thing is to provide reasonable tour route and different scenic spots to attract more tourists and enhance the attractions charm and popularity. More and more tour route products are analyzed and provided so as to meet the different demands of tourists. And the problem prompted for the tourism enterprises is how to design and provide the tour route system to make the tourists get the maximum satisfactions according to the tourists' demand, what the tourists' demand is, and how to obtain the tourists' demand. The tour route system refers to the continuous space chain connected with each landscape feature point of a tourist area with the concepts of time and space. It has three different levels: one is accessibility tourism routes connected by several tourist center cities; the second is the main tourist routes in which the tourist center of the city is defined as a "home base" and various tourist scenic spots are links to the tourist center of the city; the third is tour route within the scenic which is discussed in this paper [2].

The design of tour route is associated with the development of Chinese tourism academic research and is divided into three categories. One is from space research, mainly focused on the characteristics and evolution of the spatial structure of the tourist destination. The second is from an economic point of view to solve tourists' destination choice decision problem among multiple destinations with microeconomic method to obtain the greatest satisfaction during the tour. The third is studied on operational research; for example, Tang Li-fan proposed the optimal tourist trails system design method based on graph theory. Domestic and foreign scholars have found that the trails system organizations play an important role in the whole travel process and begin to explore the best mode such as Campbell mode [3], Stewart-Vogt multidestination travel mode [4], Lundgren mode [5], and Jigang and Yifang mode [2]. It can be concluded that the recent route research mainly focuses on regional scale instead of microscale study such as scenic internal travel route design. Some route designs still stay at the conceptual level and lack maneuverability. As personalized trend is increasingly evident, every tourist has its own psychological preferences and demand so that the same travel route design cannot meet all tourists' demand. So the tour route design should be given to make the tourists get the maximum satisfactions considering psychological preferences of tourists. It is very necessary for us to obtain the tourists' satisfaction degree and analyze the relationship between the tourists' satisfaction degree and travel route choice behavior to enhance the travel behavior models.

To get the reasonable tourism organization mode, the tour routes organization model of the domestic and foreign is summarized and evaluated. Considering the influence of tourists' behavior characteristics and psychological preferences, tourist routes optimal model based on multiobjective optimization function is prompted.

2. Behavioral Theories

This section discusses behavioral theories that may explain the dynamics in satisfaction. How do people evaluate their satisfaction? Judgments of satisfaction are influenced by the available information and by the heuristics people use at the time of making these judgments [6–10]. They present a model showing the influence of mood and comparison processes on satisfaction evaluations. Three types of comparison processes have been discussed in the literature: comparison to self, comparison to others, and counterfactuals [11].

Comparison to self involves comparing one's present situation with one's previous situation or predicted future situation. Tourists feel different ratings of satisfaction for each attraction which involves comparing one attraction with another attraction or comparing satisfaction of this tour with that of one's previous tour experience. Perceived improvements in one's situation (e.g., better health, etc.) will lead to the increases in ratings of satisfaction, but it is limited by changing aspiration levels and adaptation effects. Comparison to others (or social comparison) is the most popular type of comparison discussed and involves comparing one's own situation to that of a comparison group. People make judgments about satisfaction degree based on whether one is better (downward comparison) or worse (upward comparison) than others. Finally, counterfactuals refer to comparisons of one's current situation with hypothetical situations that did not happen but could have happened and making judgments accordingly.

Thus, comparison processes involve reference points which are used as the basis of judgment. In prospect theory, reference points are used as the basis of evaluation of outcomes; outcomes that are better than the reference point (e.g., larger monetary value) are perceived as gains and those that are worse are perceived as losses [12]. A number of studies in the transportation field have attempted to explain route choice or mode choice using prospect theory and reference points. The effects of critical incidents on car users' predicted satisfaction with public transport were analyzed [13, 14]. Also the influence of mood on satisfaction evaluations should be discussed. The congestion level of the attraction will affect the tourists' feeling and the attitude of the attraction. The more crowded the attraction is, the less satisfied the tourist feels.

In summary, in the context of the tour route experiment described in this paper, it may be postulated that when tourists are asked about their satisfaction with the total tour and each attraction, the information they used and the processes are different from those in operation after they have been "forced" to think about their options. After experimenting with suggested tour route applied by the tourism enterprises, they would gain new information and adjust any prior misperceptions about the tour. Therefore the tourists would be more aware of the options they have. Consequently, the measure of tour satisfaction is expected to be important.

3. Influence Factors of Tour Route Design

Tour space is divided into large, medium, and small scales. This paper puts forward basic principles of tour route design within small scale related to the tourists diversity of spatial behavior, whose route design is within the scenic area.

3.1. Tourists Demand Diversification. The diversification of tourists demand can be divided into two levels.

On the microlevel, tourists with different psychological characteristics have different travel motivations which can lead to different travel behavior. The behaviors of tourists are limited by the subjective conditions such as gender, age, national, psychological interest, ability, occupation, income, education level, social status, family structure, and residence conditions which may have different influences upon the spatial behavior of tourists [15, 16]. Different tourists have different attitudes or perceptions of the same attractions. The tourists flow volume and direction in the different attractions are closely related to the level and visibility of the destination. Positive correlation exists between the attractions visibility and tourist accommodation, which lead to the tour route utilization being extremely uneven and the Gini coefficient being as high as 0.38. So the satisfaction degree of the attractions is defined and asked about in the tourists' questionnaire.

The number and the tour order of the attractions are usually different for each tourist because of the diversification of tourists demand. And to evaluate the diversification of tourists demand, Tour Route Diversification Index is defined. The lager the Tour Route Diversification Index is, the bigger the diversification of tourists demand is.

On the macrolevel, the spatial behavior exhibited some regularity which depends on the travel destination features and traffic conditions.

3.2. Constraints Condition of Tour Route Design. The choices of the tour route are not only affected by the tourists' subjective view but also by the tour constraints condition such as economic constraints, physical constraints, and time constraints [16]. Economic constraints make tourist save the transport costs or the tickets cost during the choice of tour routes. Physical constraint makes tourist walk less and the number of the attractions visited during the tour is limited. Time constraints mean each tourist has a tour time budget and hopes to visit more attractions within the time budget and get the greatest satisfaction. At the same time, for each tourist, in order to complete the experience of the attractions, there should be a basic time guarantee in each attraction. The effective residence time for each attraction of the tour route is defined and investigated. The differences of the effective residence time at different attractions are caused by the characteristics of different tourists which lead to the diversification of tour route.

From the above, it can be concluded that, except for the diversification of tourist's demand, transport and tickets cost, physical constraint, tour time budget, number of attractions, and effective residence time are the important factors which will affect tourists' tour routes choice and must be considered during the tour route design.

4. Tour Route Investigation and Analysis

4.1. Survey Design and Implementation. The survey consisted of three parts: socioeconomic and demographic characteristics, travel behavior of tour route, and the demand and tour behavior characteristic of tourists.

In the first part, socioeconomic and demographic characteristics of tourists were interviewed such as gender, age, national, psychological interest, ability, occupation, income, education level, social status, family structure, and residence conditions which may have different influence upon the spatial behavior of tourists.

The subject of travel behavior of tour route was to get some information about the scene spot such as scenic type, expenditure, tour time, total number and spatial distribution of the attractions in scenic spots, number of attractions and effective residence time, visited order of the attraction, and so forth which can support datum sustain for tour route design.

The demand and tour behavior characteristic of tourists such as tour motivations and goals and tour time budget are collected. Finally the perception and experience of the tour such as the congestion level and satisfaction degree of the attractions and the revisit preference of the tourist are investigated.

The survey takes the mode of quiz face to face in the Dajue Temple in Beijing. The survey was conducted from April 15 2012 to May 20. A total of 60 respondents were obtained.

4.2. Analysis on Survey Results. This section presents descriptive findings from the experiment related to tourists' characteristics, tour route choice, perceptions and attitudes, and tour satisfaction.

Socioeconomic and demographic characteristics were summarized and analyzed. About half of the participants were male. The majority of participants were between 20 and 40 years old, with an average age of 43 years. The average size of the tourist was 3.1 and most of them are between 3 and 4. Moreover, the majority of participants had high income.

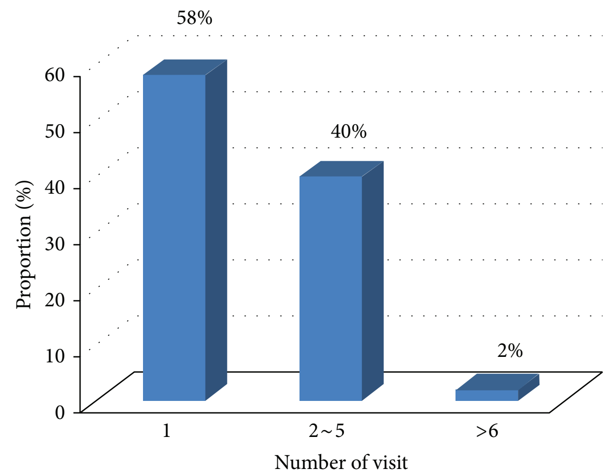

Figure 1: Number visit distribution.

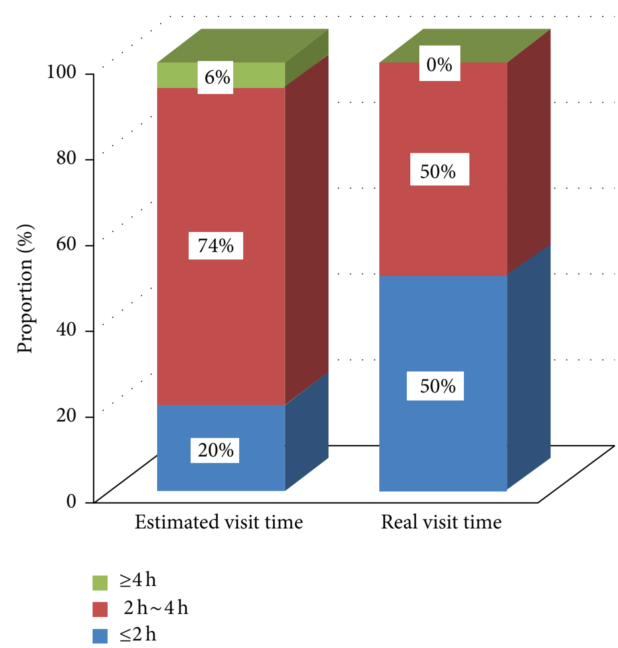

Figure 2: Comparison between tour budget time and real visit time.

25 percent of the participants had annual income greater than ¥100000, and 10 percent of the participants did not report their income.

As shown in **Figure 1**, for 58 percent of the tourists it is the first time to visit Dajue Temple and about 40 percent of the tourists revisit Dajue Temple. Trip mode is interviewed and most of the tourists came to the Dajue Temple with private car and public transit.

Each tourist has his (her) own tour time budget. It is about 74 percent of the tourists whose estimated visit time is between 2 and 4 hours as shown in **Figure 2**. 50 percent of the tourists finished visiting Dajue Temple within 2 hours. Comparing the tour budget time with real visiting time, it can be concluded that for about 30 percent of the tourists their real visiting time is less than their tour budget time.

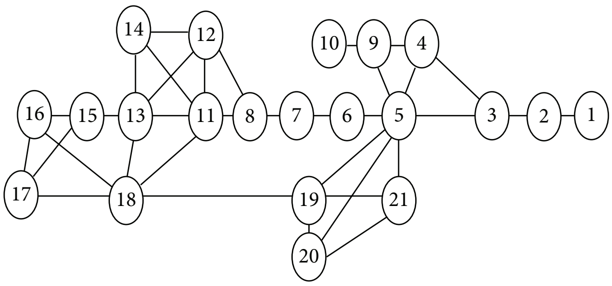

Figure 3: Distribution of the attractions of Dajue Temple.

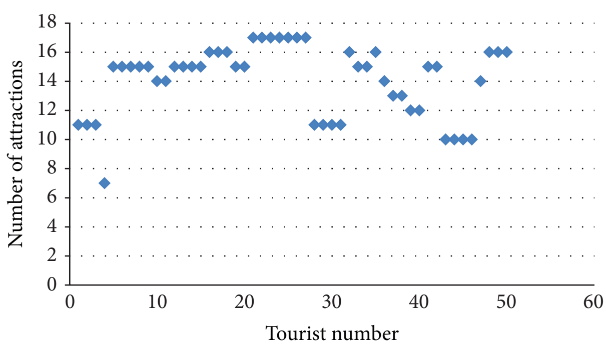

Figure 4: Number of attractions in tour route.

There are 21 attractions in Dajue Temple which is a famous temple and lies in the west of Beijing. The distribution of the attractions of Dajue Temple is listed in Figure 3. The total number of attractions which the tourists visited in their tour route is between 7 and 17 as shown in Figure 4. The total numbers of visited attractions by revisit tourist are less than the tourist for the first time. They will gain more satisfactions during the tour. Hence, during the tour route design, the tourist type should be considered. Numbers 6 and 3 as listed in Figure 3 are the famous attractions and all the tourists like to visit them. For some reasons such as the out-of-the-way of the attraction of the lack of traffic guilds some attractions are less visited.

Effective residence times of each attraction are gained. It can be given that most of the effective residence is between 5 and 20 minutes except 2 attractions and the average effective residence time is about 15 minutes as shown in Figure 5.

The main motivations of the tourists to Dajue Temple interviewed are as shown in Figure 6: "accompany the family, and friends" and "enjoy the scenery," accounted for 32% and 30%, respectively; the purpose of physical exercise and relaxation accounted for 13% and 12%, respectively; religious beliefs purposes accounted for only 8%.

Measures of satisfaction with the attractions were obtained. Prior to the survey, participants rated their satisfaction on a 5-point scale anchored by "very dissatisfied" to "very satisfied," as a response to the following question: "taking all things together, how satisfied are you with the attraction?" The satisfaction degree of the attraction is defined to be between 1 and 5. The higher the satisfaction degree of the attraction is, the better the tourists feel.

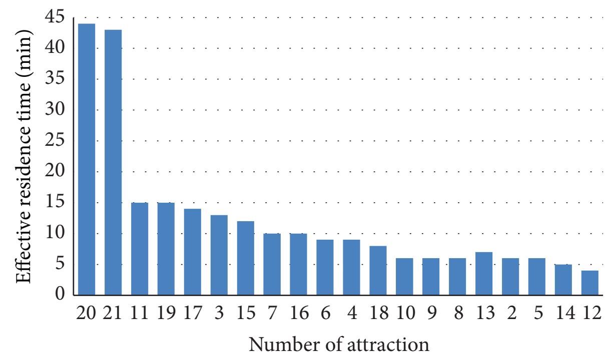

Figure 5: Effective residence time.

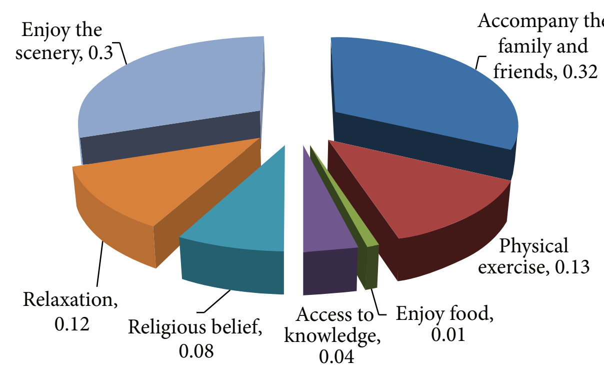

Figure 6: Motivation of the tourists.

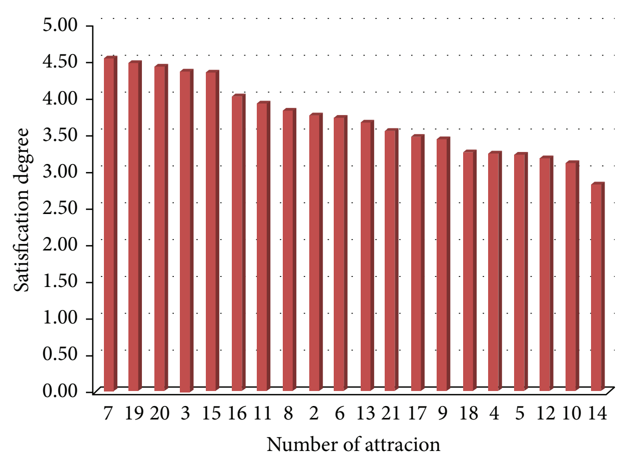

Figure 7: Satisfaction degree of attractions.

It can be concluded that the highest satisfaction degree of the attraction is Number 7 attraction which is 4.54 as shown in Figure 7. The average satisfaction degree of the attraction is between 3 and 5.

The relationship between the visit frequency of attraction and satisfaction degree and effective residence time and satisfaction degree are studied and listed in Figures 8 and 9. The results show that visit frequency and effective residence time and tourists attractions satisfaction are positively correlated with satisfaction degree of the attraction. The higher

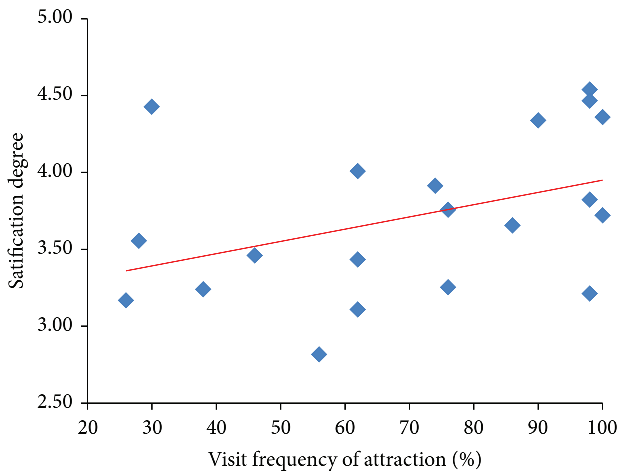

FIGURE 8: Visit frequency of attraction and satisfaction degree.

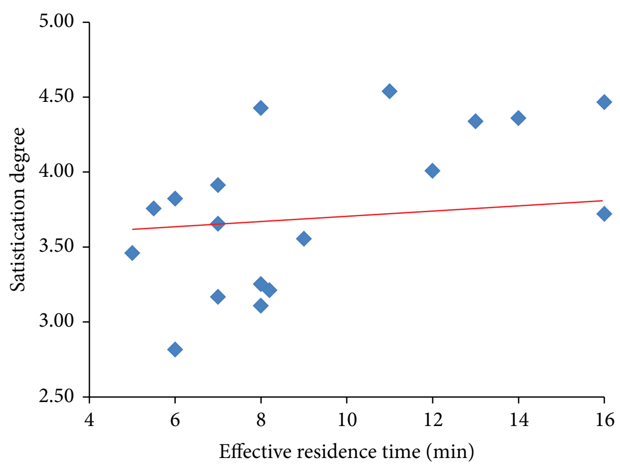

FIGURE 9: Effective residence time and satisfaction degree.

the satisfaction degree is, the more effective residence time is, and the higher the visited frequency of the attraction is.

5. Tour Route Design Based on Multiobjective Optimization Model

5.1. Multiobjective Optimization Model. During the tour, each tourist has a tour time budget and the tourists hope to visit more attractions within the time budget and get the greatest satisfaction. It can be concluded that optimal design of tour route is a multiobjective optimization procedure. The multiobjective optimization model is carried out for the tour route design.

Multiobjective optimization problem is listed as follows [17]:

$$\begin{gathered}\min \ y = f(x) = \{f_1(x), f_2(x), \ldots, f_n(x)\}, \\ n = 1, 2, \ldots, N, \\ \text{s.t } g_i(x) \leq 0, \quad i = 1, 2 \ldots, m, \\ h_j(x) = 0, \quad j = 1, 2, \ldots, k, \\ x = \{x_1, x_2, \ldots, x_D\},\end{gathered} \tag{1}$$

where x is the decision vector of D, y is objective vector, $g_i(x)$ is the ith inequality constraints, $h_j(x)$ is the jth equality constraints, and $f_n(x)$ is objective function.

Two indicators are considered during the optimal design of the tourist routes. Optimized objective functions are described as follows:

$$\begin{gathered}\text{Min} \sum_n I_E^i \cdot x_i, \\ \text{Max} \sum_n I_T^i \cdot x_i,\end{gathered} \tag{2}$$

where $x_i = 1$ which means the ith attraction is on the tour route and $x_i = 1$ which means the ith attraction is not on the tour. I_E^i is the distance between $i-1$th and ith attraction; I_T^i is the satisfaction degree of the ith attraction.

Because the tourists are more concerned with the satisfaction degree of the attraction during the optimal design of the tourist routes than the distance, the maximum satisfaction degree of the attraction is set as the first optimization objective and the minimum distance is set as the second optimization objective. The multiobjective optimization model is expressed as shown in

$$\min z = P_1 (d_1^-) + P_2 (d_2^+), \tag{3}$$

$$\text{s.t} \sum_i I_T^i \cdot x_i + d_1^- + d_1^+ = E_{\max}, \tag{4}$$

$$\sum_i I_E^i \cdot x_i + d_2^- + d_2^+ = E_{\min}. \tag{5}$$

In addition, according to the tourists demand, the constraint of the tour time and number of the visited attractions are listed as follows:

$$\begin{gathered}0 < T \leq T_{\max}, \\ i_{\min} \leq i \leq i_{\max},\end{gathered} \tag{6}$$

where P_1 and P_2 are priority factors, P_1 is first priority factor, P_2 is second priority factor, $E_{\max}$ is the maximum satisfaction degree, d_1^- is the negative deviation value degree, d_1^+ is the positive deviation value, $E_{\min}$ is the minimum length of tour route, d_2^- is the negative deviation value, and d_2^+ is the positive deviation value.

5.2. Calculation of the Multiobjective Optimization Model. The level algorithm is carried out to calculate the multiobjective optimization model.

Step 1: optimizing the P_1 level in objective function

$$\max z_1 = d_1^-. \tag{7}$$

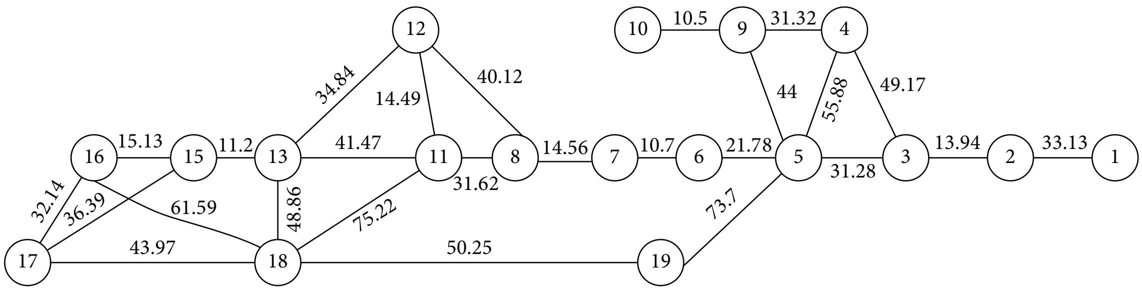

Figure 10: Distance.

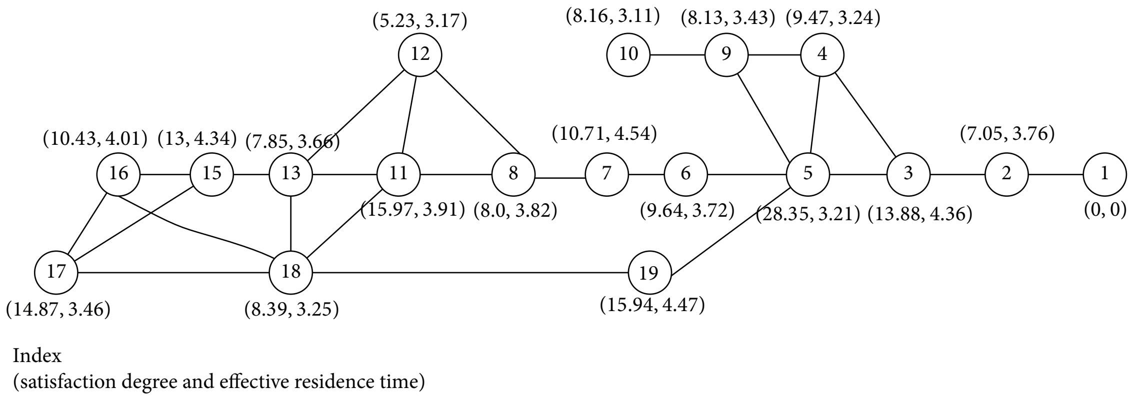

Figure 11: Effective residence time and satisfaction degree.

Table 1: Tour time.

Tour time	Proportion (%)
≤3	45
>3	55
Total	6

Step 2: optimizing the P_2 level in objective function

$$\min z_2 = d_2^+. \tag{8}$$

Step 3: Analysis of deviation: deviation index of satisfaction degree (σ_s) and tour route distance (σ_d) are defined and calculated.

Step 4: Based on the particle swarm optimization model, the priorities of the tour routes are calculated [17–19].

5.3. Sample. The distance and effective residence time are listed in Figures 10 and 11.

According to the questionnaire about tour route tourist, the number of visited attractions is between 7 and 17. The available routes are listed and categorized by the tour time as listed in Table 1.

It can be seen that 45 percent of the tourists' tour time is less than 3 times and 55% is larger than 3 hours. So the route which tour time is less than 3 hours is defined as quick tour and the route which tour time is larger than 3 hours is defined as depth tour.

The deviations of two routes are calculated, respectively, and listed in Table 2 and Table 3.

Deviation index of satisfaction degree (σ_s) and tour route distance (σ_d) are calculated. Deviation index of satisfaction degree is listed in Table 3. For the depth tour route, only when σ_s is between 1 and 0.18 and σ_d is between 0 and 0.104, the route is the acceptable result. For the quick tour route, only when σ_s is between 0 and 0.053 and σ_d is between 0 and 0.172, the route is the acceptable result.

The priory of the tour route is calculated and the suggested depth tour route and quick route are given, respectively, as shown in Figure 12.

Comparing the depth tour route with quick route, there are some differences among total number of the attraction, tour order, effective residence time, and so forth. For the suggested depth route, the total number is less than the quick tour route. Some attractions which are less famous are introduced so that the revisited tourists can experience and enjoy the tour route.

6. Conclusion

Conclusions can be given as follows.

A questionnaire about tourists' tour route and satisfaction was carried out and some information about the scene spot and tourists demand and tour behavior characteristic is concluded and analyzed. Visit frequency and effective residence time are positively correlated with satisfaction degree of the attraction. Comparing the tour budget time with real visiting

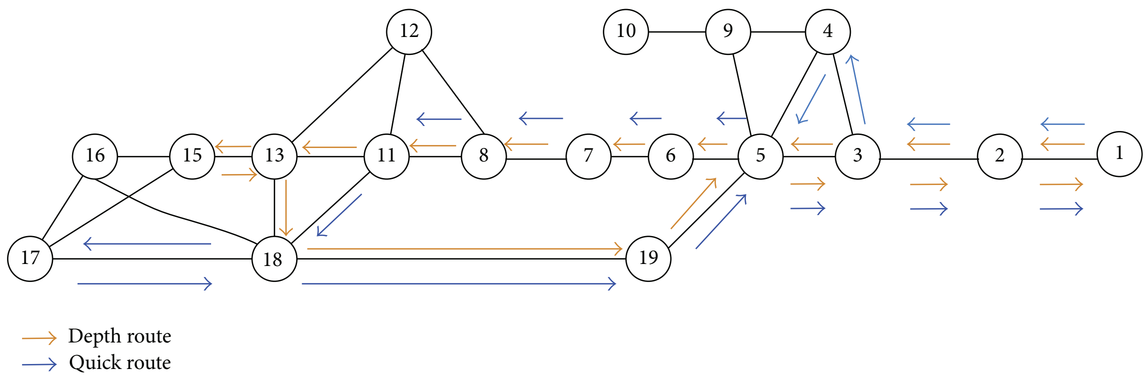

FIGURE 12: Suggested depth tour route and quick route.

TABLE 2: Parameter of depth tour and quick tour.

	Satisfaction degree		Distance		Tour time	
	Depth tour	Quick tour	Depth tour	Quick tour	Depth tour	Quick tour
Max.	3.40	3.44	672.73	670.68	3.61	2.99
Min.	2.99	2.69	488.70	388.99	3.01	1.72

TABLE 3: Deviation index of satisfaction degree.

	σ_s		σ_d	
	Depth tour	Quick tour	Depth tour	Quick tour
η	0.018	0.053	0.104	0.172

time, it can be concluded that for about 30 percent of the tourists their real tour visiting time is less than their tour budget time.

Based on the convey datum, tour routes multiobjective optimization functions are prompted considering the tourists' behavior characteristics and psychological preferences. According to the distribution of the route time, the route which tour time is less than 3 hours is defined as quick tour and the route which tour time is larger than 3 hours is defined as depth tour. The priorities of the tour routes are calculated and the suggested depth tour route and quick route are given, respectively. The results show that visit frequency and effective residence time and tourists attractions satisfaction are positively correlated with satisfaction degree of the attraction.

Furthermore, during the tour route convey, it can be found that the congestion level of the attractions will affect the tourists' satisfaction degree. The more crowded the attraction is, the less satisfied the tourist feels. Also tourists will reduce the effective residence time in the crowded attractions and change their tour route under the information provided and distributed by the tourism enterprises. So the mechanism and influence of the congestion level on the tour route should be studied in the future.

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3

Internet Tourism Resource Retrieval Using PageRank Search Ranking Algorithm

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At present, there is a wide variety of tourism resources on the Internet. Tourism management departments must monitor these resources. At the same time, tourists must also retrieve personalized information that they are interested in. This requires a lot of time and energy. This essay studies and implements the tourism network resource monitoring system. The main work completed in the thesis proposes and constructs a topic collection algorithm and establishes a starting point, topic keywords, and a prediction mechanism. The algorithm includes three stages: the first climbing stage, the learning stage, and the continuous climbing stage. Open category directory search is used for similarity judgment and result evaluation. The experimental results show that with the continuous execution of the crawling process, the collection speed of related pages is getting faster and faster. We propose an algorithm for the extraction of wood based on the density of Internet tourism resources. The algorithm calculates the ratio of Internet tourism resource labels by row and uses a threshold extraction algorithm to distinguish area from private non-Internet tourism resource area. Experimental results show that the algorithm can successfully extract the main content of the article from a wide variety of web pages. This thesis takes the monitoring of tourism network resources as the research object and establishes a tourism network resource monitoring system, which can provide users with customizable, all-round, and real-time tourism network resource collection, extraction, and retrieval services so as to monitor tourism resources. The research results of this article can promote the construction of tourism informatization and can help users grasp the latest tourism information, thereby bringing great convenience to tourism. The system only downloads travel-related information through the use of topic collection technology, reducing the interference of irrelevant redundant web pages.

1. Introduction

Internet applications have penetrated into my country's cultural, economic, political, and social life and other fields, and China's tourism information industry has also developed rapidly [1]. The network has gradually evolved from a convenient communication tool and efficient new media to a huge virtual society [2]. The rapid development of the tourism economy and information technology has caused tremendous changes in the information-intensive industry of tourism [3]. As an important channel to provide tourism information resources, tourism websites have gradually become the main source of reference for most potential tourists to obtain information before they travel, and they have played an increasingly significant role in the travel decision-making of tourists [4]. In all subjects, travel websites have a huge amount of travel information about scenic spots, user comments, scenic spots introduction, and other related information. It takes a lot of time for tourists to extract tourist information that they are interested in from these websites [5]. Due to the business cooperation relationship, travel websites will only provide travel information that has a cooperative relationship with them, and it is difficult to provide tourists with all-round, massive, high-quality, and low-cost services [6].

In the past ten years, the technology of extracting Internet travel resources from web pages has been extensively studied, and many methods have emerged. Patel et al. [7] proposed a mechanism using artificial intelligence to identify noisy data such as border advertisements and redundant irrelevant links. However, this technology is not suitable for practical use because it requires a huge artificially defined training set and requires knowledge of related fields to establish classification rules. Gayar et al. [8] proposed another extraction technology based on vision. Based on the algorithm, Marine [9] used the method of machine learning to sort the blocks in the web page by importance, and the sorting is mainly based on the location and size of the space attribute, the number of content attributes, pictures, and links. Gleich and Rossi [10] proposed a technique for extracting templates from custom controls contained in web pages. Chung et al. [11] proposed the structure of the website type tree, which treats similar types in the tree as meaningless. Elbarougy et al. [12] proposed an extraction algorithm to improve the accuracy of the content classification of the digital library. In order to solve the defect that the algorithm can only identify a single Internet tourism resource segment, the Internet tourism resource slope is proposed. Granka [13] proposed a link threshold filtering algorithm, which removes advertising links and navigation elements by calculating the ratio of text in hyperlinks. This technology mainly relies on the block technology of web page; the segmentation of web pages is mainly based on the location of Internet tourism resources, pictures, and scripts [14]. Then, different extraction algorithms were mixed for Internet tourism resource extraction, and the results proved that the specially selected hybrid extraction algorithm is better than the extraction algorithm alone [15]. If the starting point cannot well guide the search ranking to the relevant pages, then the number of relevant pages found by the search ranking will be very small [16]. For proposing the search and sorting system, which is developed, the system does not need to start in advance, but it can still find pages related to the topic [17]. One is proposed by and to provide a search sorting keyword describing the user's interest. Crawlers use these keywords to find candidates through search engines and start with those found. The advantage of using this technology is that users do not need relevant professional background knowledge [18]. However, if there is no relevant interest classification in the public network catalog, then the algorithm will lose its effectiveness. The topic-related crawler simply chooses a direction to visit the Internet [19]. At present, there are many sorting technologies, which can be divided into two types: link-based sorting and content-based sorting. Backlinks indicate the number of links that point to the same link. The higher the value is, the greater the importance is [20]. Forward links indicate the number of links sent from one. The page rank is the ratio of the sentences of backward links and forward links. Experiments show that web page rank is the best evaluation parameter in the ranking [21]. If the information does not exist, then the page level cannot be calculated. The concept of "hub value" is proposed in the adjacent ordering. A good hub is most suitable as a starting point because it will point to more topic-related pages [22]. Similar to the calculation process of web page rank, the pivot value also needs the link information between web pages to be calculated, then a point of view is put forward, and most of the topic-related pages are in the same parent directory. A similar view was also put forward. Pages under the same web directory are more relevant to the same topic [23] and put forward an algorithm, which can let the search sorting learn, store, and point to the path of the relevant page. For the content-based sorting algorithm, this algorithm uses the topic similarity space vector for ranking operation. The algorithm first calculates the similarity between topic keywords and web page text content [24, 25]. If the collected pages have a high degree of similarity, then this page and the pages in this page will be considered related to the topic [26–29]. Similarity includes two aspects: the similarity of content Internet tourism resources and the similarity of anchor Internet tourism resources [30, 31]. The content text similarity indicates the similarity between the content and the topic, and the anchor text similarity indicates the similarity between the web page and a certain topic [32–34].

At the same time, due to the concealment and freedom of the Internet, the Internet also contains a lot of false travel information, causing many tourists to suffer a certain degree of economic loss. Information retrieval services have penetrated into social life and brought great convenience to people's lives [35]. However, the search service dedicated to tourism is still in the exploratory stage. This article takes the tourism industry as the main object and adopts information retrieval-related knowledge to establish a tourism network resource monitoring system to provide users with customizable, omnidirectional, and real-time information delivery [36]. An improved algorithm is proposed to calculate the personal characteristic matrix, and the improved algorithm is compared with the existing algorithm. A search ranking algorithm based on scoring is used for ranking.

2. Construction of Internet Tourism Resources Retrieval Model Based on PageRank Search Ranking Algorithm

2.1. Hierarchical Distribution of Tourism Resources Retrieval. Feature matrix M is constructed according to the user's travel information retrieval history, and the category matching is performed through the user's travel information retrieval words. This article introduces the Rocchio batch learning algorithm and aims at the algorithm when there are too many retrieval records. For problems such as the low operating efficiency of the algorithm, an adaptive search strategy is used to optimize its operating efficiency. When the user enters a different search keyword, the user's search characteristics will be adaptively modified accordingly. The improved adaptive PageRank algorithm proposed in this article is shown in

$$p(x) = \sum \mathrm{sim}(x, x-i) \times y(x, x-i). \tag{1}$$

Among them, M represents the personal characteristic matrix obtained at t time, and i represents the data obtained from the 0 time to the t time and related to the retrieval category, which represents the weight of the j word in the data related to the retrieval category i obtained between the $t-1$ and t times with the following:

$$\mathrm{sim}(x, y) = \frac{\sum w(i, j)}{\sqrt{w(i) \times w(j)}}. \tag{2}$$

In order to further improve the matching efficiency, this article proposes a hybrid feature threshold extraction matching method. The hybrid feature uses user retrieval features and general retrieval features. Among them, C represents the user search feature category, and C-g represents the general search feature category. The matching algorithm for each category is as follows:

$$f(x) = \frac{n(i,j)}{\sum n(i) \times x(i,j)}. \quad (3)$$

After the user enters a search term, it is matched with the characteristics of different categories, and the three search results with the highest similarity are returned to the user. Define the searched Internet tourism resource that has not been classified by the search feature as *N*, and the total number of data is *M*. Define the data that have been archived by category and are consistent with the user search category *i* as *N*, and the total number of corresponding data is *M-i*; then, the results obtained from *N* and *N* retrieval will be sorted in a mixed manner.

$$m(i,j) = \frac{1}{n \times \left(\sum f(k,j) \times y(k,i)\right)}. \quad (4)$$

For each search of the user, the algorithm will feed back 3 categories with high relevance to the search term to the user and use the formula to score the relevance of the search category and the search keyword. Vector space model is a statistical model used to calculate the relevance of web pages. In this statistical model, a set of linearly independent basic vectors are used to represent web pages in the WWW. In the vector space model, in order to facilitate understanding, we use the following way: (*W*1, *W*2, ..., *Wn*) represents a group of web pages; (*T*1, *T*2, ..., *Tn*) represents the number of web pages. The feature item *Wi* = (*wi*l, *Wi*2, ..., *Win*) represents the weight of the feature item in the web page; for example, the weight of the feature item *T-j* in the Internet tourism resource *W-i* is *W-j*. The correlation between web pages is *W-i*.

According to the Rel (*W-i*, *w-j*), it can be seen from Figure 1 that the VSM model uses the cosine of the angle between vectors *W-i* and *W-j* to calculate the correlation; that is, the larger the angle between vectors *W-i* and *W-j*, the less relevant of the corresponding w curve pages. Assuming that a piece of data appears more frequently in different retrieval result lists, the score of the data can be expressed as the sum of the score values of each retrieval queue.

$$s(i,j) = \frac{s(i, j \times m) + s(i \times n, j) + s(i \times j, n)}{3}, \quad (5)$$

where *n* represents the number of all search categories related to the search keywords, and sc ore-*c* represents the scores of the top three search categories *c* in terms of relevance. Rankci represents the ranking of the retrieval category *c*, and ideal_rank represents the highest possible ranking of the retrieval category *c*. Among them, *M* is the topic degree of the word adjoining in web page, *T* is the total number of words in eeb page *j*, and level (*M*) is the word frequency of the word in web page *j*. The topic degree of a word determines the importance of the word in the web page, and the topic degree can reflect the topic content of the web page. In fact, the idea of keyword thematic degree and the deterioration of word frequency are conceivable to a certain extent, and they are all developed on the basis of word frequency.

$$u(i,j) = \max\left(s(i \times n, j), s(i, j \times m)\right). \quad (6)$$

U represents the set of web pages that needs to be judged, and the vector *m* and the vector *n* represent the pivot value and core value of the page. First, the the vector *m* and the vector *n* are initialized, and the range of the core value and the pivot value is one. It indicates the core weight of the page and the pivot weight of the page. If there are links on the page of the first host, these links point to a certain page of the second host, then each link is assigned a value, and this value is used to calculate the core value of the page in the second host. In the same situation, if a web page in the first host is pointed to by a page in the second host, then each linked page is assigned a value of certainty. The core value and pivot value are used to solve mutually reinforcing problems.

2.1.1. PageRank Search Ranking Algorithm. Assuming that the length of all search result lists is *N*, the score of the *i* data in the list is $(N - i + 1)$, so the highest score of the first data in the search result list is *N*, and the last data have the lowest score. Assuming that a piece of data appears more frequently in different search result lists, the score of the data can be expressed as the sum of the score values of each search queue. Then, the data that appear in multiple search result lists have a higher score than the data that appear alone. First, score each retrieval result data to get the total score, and then aggregate the data appearing in the different retrieval result queues into a list and sort them in ascending order of weight. The scoring base *W-j* of the retrieval queue is shown in

$$v = \frac{1}{1 + t(i,j) - s(i,j) \times t(i \times a, j \times b)}. \quad (7)$$

Among them, *a* represents a set of keywords related to the topic and *b* represents a web page for comparison. Claw and carve separately indicate the number of words in the collection and the number of words in the web page. It can be seen that the similarity result is between 0 and 1. The higher the result value, the higher the similarity. This algorithm is a clustering algorithm for Internet tourism resources that has nothing to do with the content of web pages. First, we need to construct a two-way graph of hyperlinks between keywords and pages. The construction principle is as follows: all keywords are represented by circular nodes, and all hyperlinks are used. The square node indicates that if the user enters keyword A in the query interface for the query process, hyperlink B appears in the returned result page and is effectively clicked by the user; then, a two-way edge is established between keyword A and hyperlink B, represented by a solid double-headed arrow. If the hyperlink in the return result page is clicked by the user by mistake, it is represented by a dashed double-headed arrow. The result is a two-way graph of hyperlinks between keywords and pages.

Among them, assuming that search category C has the best similarity to the search keywords, rankC is 1. RankC is 0.5 if it ranks second, and rankC is 0.25 if it ranks third. SimC is Sim (q, c), and numC is the number of data in the search list. If a search result list has not been processed by search category aggregation, rankC is 0.5 and simC is 0.1. Assume that the search category with the highest relevance to the search keyword has a relevance greater than 0.1. In addition, if the lengths of all lists obtained from the search are the same, the score base of NC1 is greater than the score base of NC. This will cause the data score in NC1 to be higher than the data score in NC. In view of the flaws of the standard Rocchio algorithm from Figure 2, it is assumed that the user input search keyword is new, but there is no such search keyword in the personal search feature matrix and the general search feature matrix. Then, the data that appear in multiple search result lists are higher than the score that appears alone. Firstly, each retrieval result data is scored to obtain the total score, and then the data appearing in the different retrieval result queues are summarized into a list and sorted according to the weight from the largest to the smallest.

Then, the relevance of the search keywords and all search categories is 0; that is, the scoring base $W\text{-}j$ of the search list is 0. At this time, the system will only return the data list in the NC. Using the search category with higher relevance for keyword search, the returned data score is recorded as x, and the search category with lower relevance is used for keyword search, and the obtained data score is recorded as y; then, $x > y$ must be (the parameters rankC and simC in $W\text{-}j$ are used to guarantee this rule). If a search keyword is grouped into the wrong search category, the result data of the search will be very small. When all the data scores are calculated, they are sent to the user in descending order of the scores, and the number of feedback data is recorded as M. Then, in multiple search result lists, there are several data with consistent scores; then, the higher the score base $W\text{-}j$ of the column where the data is located, the higher the ranking of the data.

2.1.2. Retrieval Model Parameter Optimization Processing. Figure 3 shows the structure of the acquisition system, which is mainly composed of the following parts. The acquisition control module is mainly responsible for parsing the system configuration file and controlling the operation of the entire system according to the relevant attributes in the configuration file. The control module is also responsible for the management and data communication between multiple acquisition subthreads in the parallel system. The collection module is responsible for managing multilevel queues and accessing the corresponding web pages according to them. The link extraction module is mainly responsible for analyzing hyperlinks from the source code of web pages, analyzing the format of the hyperlinks, and analyzing the hostname and requested file name and has the function of judging the weight. Implementation of the protocol analysis module is responsible for requesting files from the corresponding host, determining the inaccessible website directories according to the contents of the files, and feeding the directories back to the collection module.

The nonrepetitive parsing by the link extraction module will be stored in the buffer area. The buffer area is composed of a queue to be captured, a queue for successful capture, and a queue for failed capture. Among them, the queues to be fetched are divided into multilevel queues according to the order of priority. This module is mainly responsible for converting the domain name of the web server into. This module requires multithreaded security features and guarantees the high speed of message communication. The buffer module stores the visited counterparts in the buffer according to a certain strategy to minimize the number of requests. According to a certain strategy, the web page library extracts themes, contents, and information from the downloaded web pages and saves them in the file system. Internet tourism resources are preserved in a uniform format to ensure the efficiency of visits. The web page download module uses the protocol to send and receive the data returned by the server through asynchronous technology. The theme collection module uses the theme collection algorithm to establish a related database and collects the pages related to the theme based on the collection database. The early research of the PageRank algorithm was mainly used in Figure 4 for the sorting problem of search result page sets, and it has been successfully applied to the topic relevance prediction module of search URLs to be sorted. It can be seen that the research on the PageRank algorithm can better determine the topic relevance of web pages to improve the accuracy of the subject-oriented sorting search strategy.

The current mainstream search engine Google in the Internet industry uses the PageRank algorithm. If a search keyword is grouped into the wrong search category, the result data of the search will be very small. When all the data scores are calculated, they are sent to the user in descending order of the scores, and the number of feedback data is recorded. The basic idea of the algorithm is that it calculates the PR value of each web page in the result page set and determines the topic relevance according to the PR value, and thus determines the web page's relevance. If a web page is linked more often, its importance is higher. In this directed graph, the PR value of node q is t.

3. Application and Analysis of the Internet Tourism Resource Retrieval Model Based on PageRank Search Ranking Algorithm

3.1. Retrieval Model Feature Matching. In order to verify that the search performance of the topic ranking search model based on semantic understanding and dynamic web pages proposed in this paper is better than general web search ranking, the following three aspects are tested: (1) Compare the query performance of the keyword query interface and the query interface based on keyword semantic expansion. Select a set of words as the user query keywords, obtain the

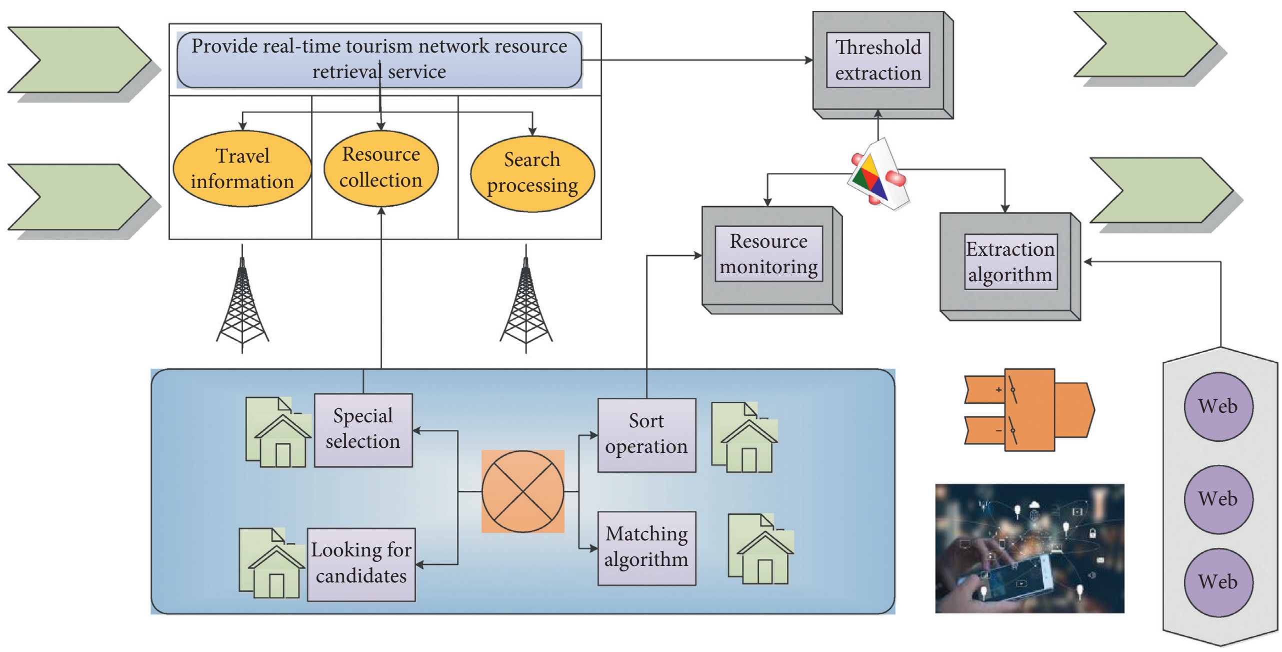

Figure 1: Hierarchical distribution of tourism resources retrieval.

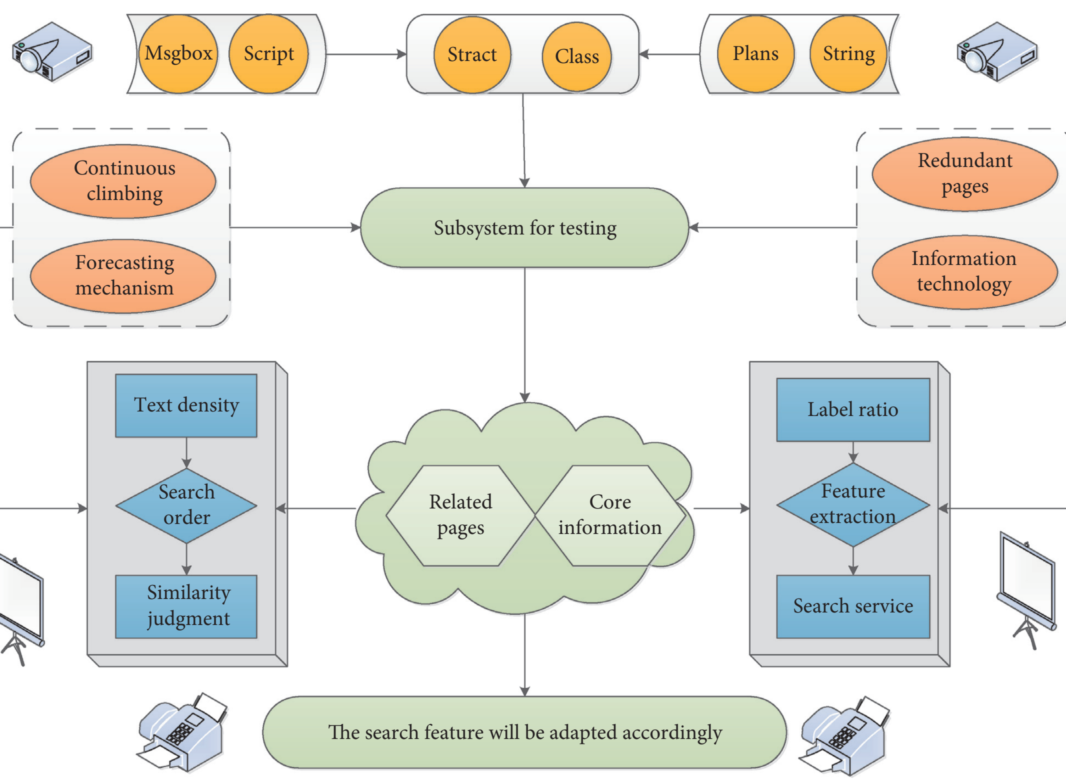

Figure 2: PageRank search ranking algorithm process.

user extended keywords through semantic expansion, and then use Nutch's network search for sorting from the test site. Randomly crawl 5000 web pages, use keywords and extend keywords as user query keywords to call Nutch's full-text search to obtain query results, and compare the query efficiency by comparing the returned result pages. (2) Compare the ranking search performance of static web search ranking and dynamic web search ranking. Select a dynamic website with a travel theme as the test site, and run Nutch web search ranking and dynamic web search ranking

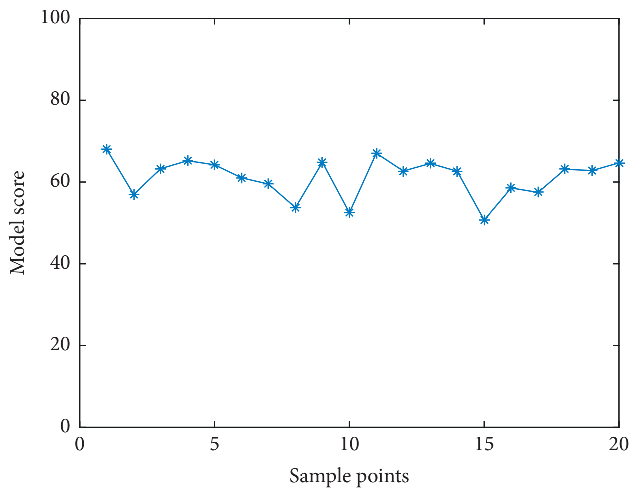

Figure 3: Retrieval model score line chart.

three times under the same software and hardware environment, which lasted 10 h, 15 h, and 20 h. After the search, sorting, and crawling work is finished, all the web pages that it crawls are indexed and the size of the web index file is recorded.

The final result should not include the above three parts, as shown in Figure 5. The Internet tourism resource density algorithm first reads Internet tourism resources by row, counts the number of nonlabel characters in each row and records it as a sample, records the number of characters belonging to the label in each row, and calculates the ratio of the two. What it needs is special attention. The literature algorithm and the algorithm proposed in this paper are used to calculate the user retrieval feature matrix M, and then the user retrieval feature matching algorithm is used for category matching, and the matching accuracy is calculated. The calculated rows are stored in a one-dimensional array in the memory, and then the first-class clustering algorithm is used for clustering so as to extract the content of Internet tourism resources. Before clustering the data in the one-dimensional array, the data need to be smoothed. If data smoothing is not performed, some important data may be lost, such as news headlines. Because these Internet travel resources read by line may be too short, below the threshold of the clustering algorithm, they are discarded by the clustering algorithm.

By giving a specified radius length, calculate the smoothing value of each element in the one-dimensional array. Throughout the experiment, the total number of rows is used for calculation. In order to test the correctness of the algorithm and the results of the clustering algorithm, the experimental results must be compared with the results of manual analysis. For the scientificity and correctness of the test, two test standards are used for the test. The first test method uses the longest common subsequence to calculate the longest common subsequence between manual extraction and extraction. Before calculating, you need to remove special tags, blank lines, and extra spaces. Therefore, it is necessary to provide a relevant start at the beginning, and it is necessary to provide a method for judging the relevance of the page. Topic similarity indicates the similarity between the page and the topic. The pivot calculation is used to judge whether a page is a pivot page and whether it is suitable as the initial similarity in Figure 6. It is used to judge whether the web pages collected by the system are related to a specific topic.

Since the PR value of all web pages is calculated offline, the algorithm has a short response time in practical applications and has good search performance. However, the algorithm does not consider the theme characteristics of the web page. It can be seen from the results in the figure that the average retrieval accuracy of the algorithm proposed in this article is higher than that of the standard algorithm. It does not mean that the page is related to the topic, which will cause the topic of the search result page set to be irrelevant, that is, the phenomenon of topic drift, which not only consumes network resources but also wastes user time. Therefore, the PageRank algorithm for topic search T-PageRank is proposed, which combines the topic relevance of a web page with its PR value to calculate the topic relevance of a given web page. Since the PR value is the probability of a web page being accessed in the physical sense, the initial value can be assumed to be $1/N$, where N is the total number of web pages. In general, the sum of the PR values of all web pages is 1. In addition to linking A to D, A also links C and B, so when the user visits A, there is a possibility of jumping to B, C, or D, and the jumping probability is 1/3.

3.2. Function Realization of Search Sorting Algorithm. In order to verify the effectiveness of the algorithm proposed in this article, a cross-simulation test is performed on it. Divide the user's travel search records into 10 subsets, each with the same number of travel search records. Run the retrieval algorithm 10 times for each different data subset, and use 9 of them as the training set. If the average value is greater than the standard deviation of all data, then the cluster is likely to be a web page body segment.

The experiment selects (scenery, destination, hotel, ticket, and food) as user query keywords and user expansion keywords obtained through semantic expansion. Then, use the original query keywords and the expanded query keywords as the user query terms, and use Nutch's full-text search to query to obtain the query results. From Figure 7, we can see that in the 30,000 web pages randomly crawled by Nutch's network search ranking, the user query keywords are semantically expanded and compared with the original user query keywords and the accuracy has been improved. It can be seen from the results that the accuracy of the three hybrid feature threshold extraction matching algorithms is not much different, but they are all more accurate than the user retrieval feature matching general retrieval feature matching, so the hybrid feature threshold extraction matching algorithm is better than other algorithms. 2. Compare the ranking search performance of static web page search ranking and dynamic web page search ranking. As a test site, run Nutch network search ranking and dynamic web search ranking 5 h, 8 h, and 10 h under the same software and hardware environment, and get the number of web pages searched by ranking.

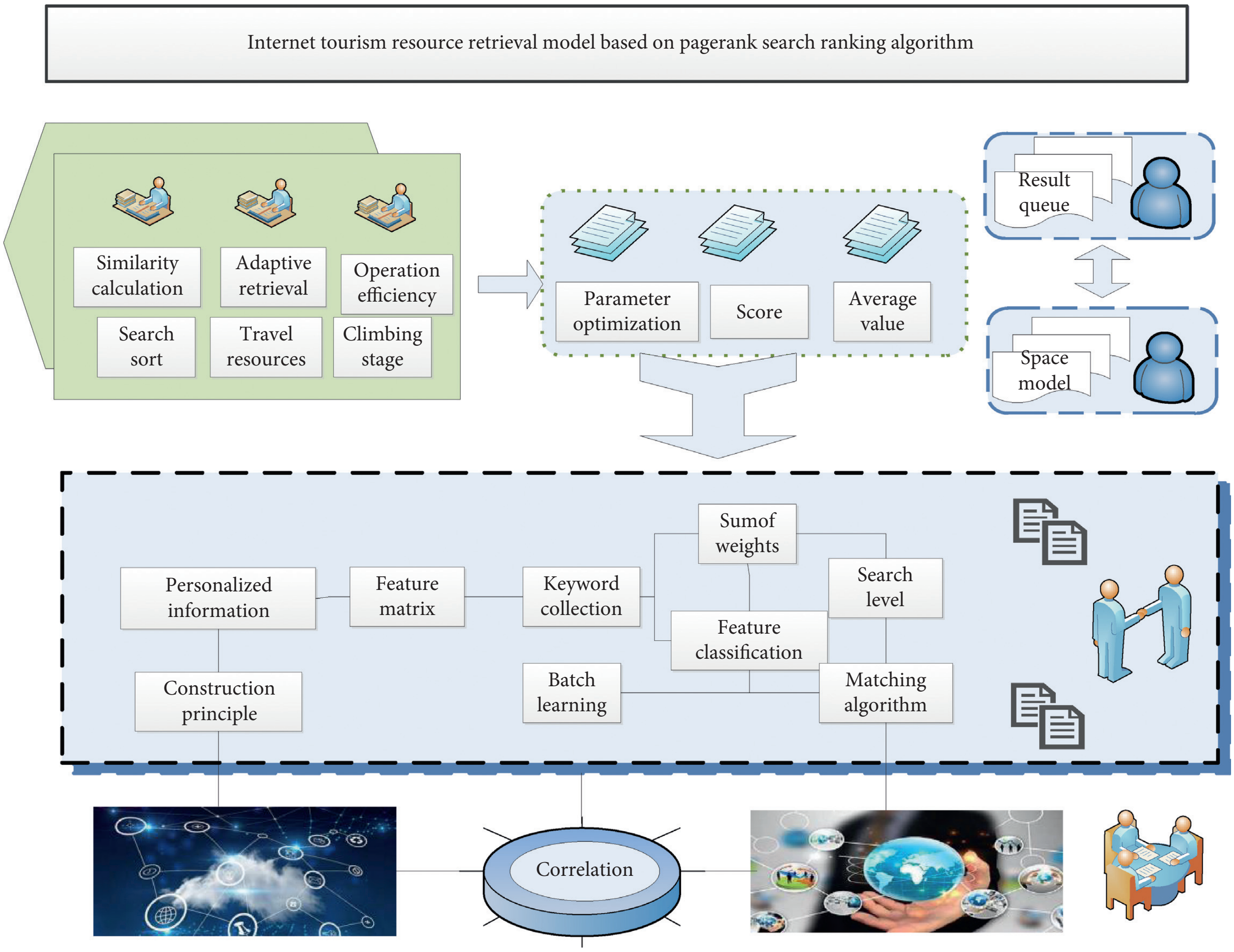

Figure 4: Internet tourism resource retrieval framework using PageRank search ranking algorithm.

Use the Rocchio algorithm proposed in this article to calculate the user retrieval feature matrix M and then use the user retrieval feature matching algorithm for category matching and calculate the matching accuracy. In order to further verify the performance of the algorithm, consider using the mixed feature threshold extraction matching algorithm and gradually increase the training set. The specific accuracy comparison of the three matching algorithms is shown in Figure 8. The above experiment shows that when the data training set is small, the accuracy of the user search feature matching algorithm is lower than that of the general search matching algorithm. Even if the training set is small, the hybrid feature threshold extraction matching algorithm can still obtain better results. When the training set gradually increases, the accuracy of the user retrieval feature matching strategy and the hybrid feature threshold extraction matching strategy will increase.

3.3. Example Results and Analysis. The experimental environment is as follows: hardware environment, 4 GHZ memory, 230 G hard disk, CPU 4-core Intel (R) Xeon (R); operating system: MicrosoR Windows XP Professional SP3; software environment: Nutch. 1.4, Eclipse. 3.5.0. This experiment uses the Nutch web search ranking as the general web search ranking and then considers the search strategy of the model proposed in this article from the three aspects of semantic expansion, dynamic web pages, and topic filtering. The search index of the search strategy is compared with the search performance of the topic search ranking based on semantic understanding and dynamic web pages proposed in this article and the general web search ranking. Nutch is an open-source web search engine based on the Java language. It is mainly divided into two functional blocks: network search sorting and full-text search. The main function of the network search sorting function block is to grab web pages from the web and then provide these web pages. The main function of the full-text search function block is to retrieve relevant web pages from the web pages crawled by the network search sort according to the query keywords and return them as results.

After smoothing, it is found that the cohesion within the paragraphs of the article increases, and the difference between the paragraphs increases. The square difference of the entire one-dimensional array is smaller than that before processing, indicating that smoothing has obtained good results. The standard deviation between the data before smoothing is larger, and the standard deviation after data

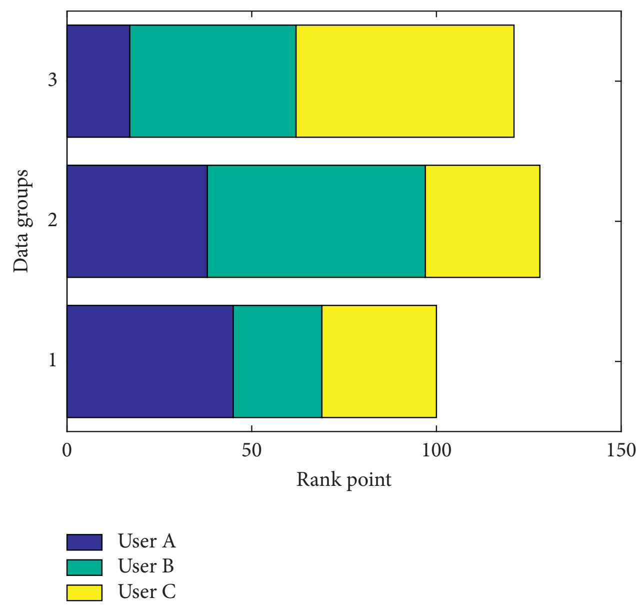

Figure 5: Sorted search stacked histogram distribution map.

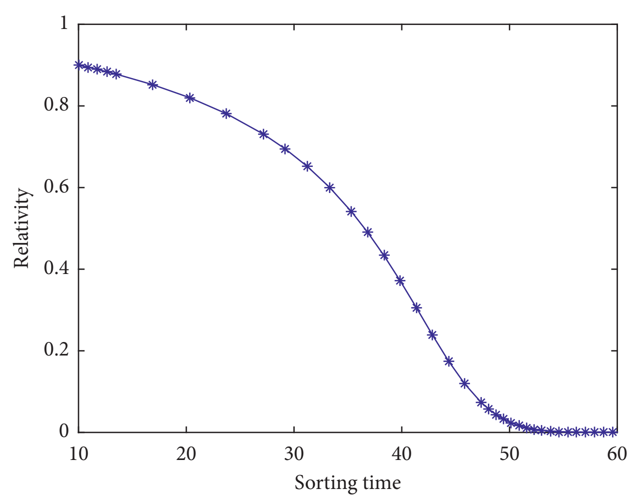

Figure 6: The dependence curve of tourism resource retrieval with the number of searches.

smoothing is reduced. From the perspective of the change in standard deviation in Figure 9, the difference between the data has been further reduced. The above experiment shows that when the data training set is small, the accuracy of the user retrieval feature matching algorithm is lower than that of the general retrieval matching algorithm. In order to verify the effect of data smoothing, two sets of comparative experiments were carried out. In the first group, the clustering operation is performed directly on the group without smoothing processing. The sum of the left and right sides is averaged as the smoothing result. The threshold extraction process calculates the standard deviation of the smoothed array, traverses the array, extracts the rows whose value is greater than the standard deviation, and stores the above-mentioned text rows in the result file.

The above experiments show that when the training set of data is relatively small, the accuracy of the personal feature matching algorithm is lower than that of the general matching algorithm. Even if the training set is small, the hybrid feature matching algorithm can still obtain better results. When the training set gradually increases, the accuracy of the personal feature matching strategy and the hybrid matching strategy will increase. This module mainly includes two processes: the first process is smoothing and the second process is threshold extraction. The highest recall rate can be achieved in this mode, which means that the retrieval effect is the best in this mode. The results of the three strategies are not much different, but all have a certain degree of improvement over the strategy. From the experimental results, the strategy is relatively good. It can be seen

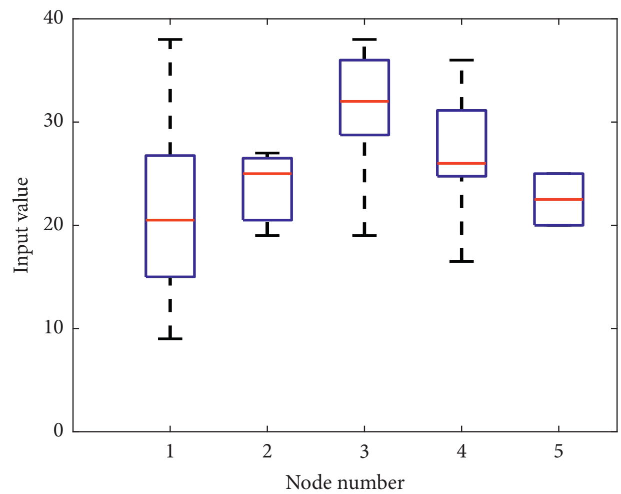

Figure 7: The box plot of the algorithm value changing with the number of nodes.

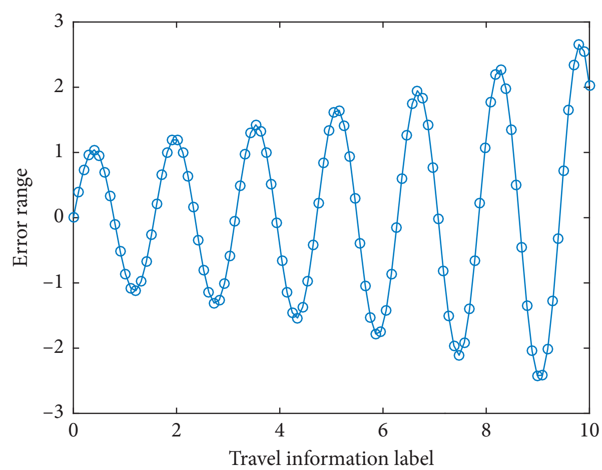

Figure 8: Error curves of different tourism resource levels.

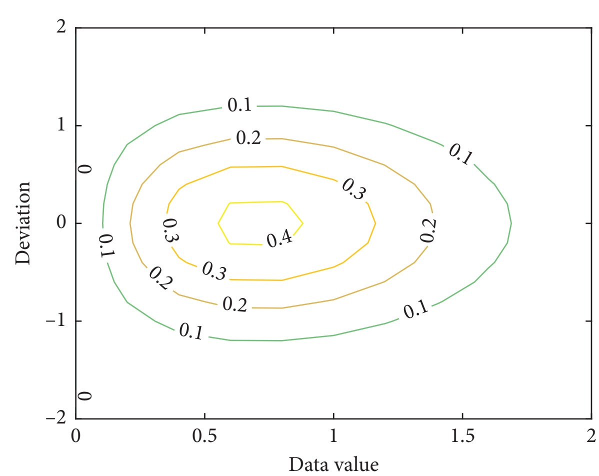

Figure 9: Retrieving model data value deviation contour distribution.

from Figure 10 that the topic ranking search strategy based on the domain topic has a higher precision rate. Through the above tests, we can see that semantic expansion of user query keywords can improve the accuracy of user queries; compared with static web search rankings, dynamic web search rankings are slower to search on designated test sites but

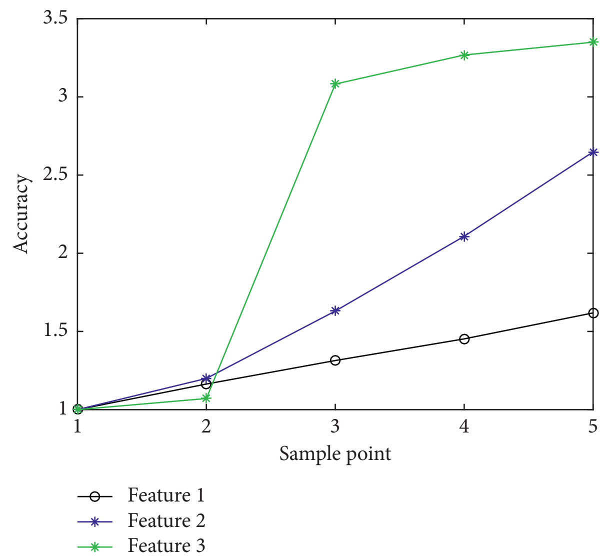

Figure 10: Accuracy line graph of algorithm sample points.

have higher search results. After the construction of the personal search feature matrix M is completed, the correlation between the search categories in the matrix and the search keywords can be obtained, and the correlation score can be performed. The statistical results show its superiority. The topic ranking search model based on semantic understanding and dynamic web pages comprehensively considers the semantic expansion of user query keywords, dynamic web search ranking, and topic filtering strategies and is superior to general web search ranking in terms of recall and accuracy.

4. Conclusion

This article studies and implements the tourism network resource monitoring system and expounds related algorithms and related technologies used in the development of the system. The main work of the thesis is to give the relevant requirements of the theme collection subsystem of travel network resources and then describe the key technologies involved in the theme collection of travel topics such as topic similarity, pivot value calculation, and similarity judgment. The subject collection process is divided into the first sorting search phase, the learning phase, and the continuous sorting search phase. We give an experimental evaluation method and study it through the tourism network resource monitoring system. The experiment verified the performance of the topic capture. An Internet tourism resource extraction algorithm based on Internet tourism resource density is given, and an improved method of data smoothing is proposed. The smoothed data are clustered to extract the main Internet tourism resource content of the web page, give the final experimental results to realize the personalized retrieval subsystem, and use the feature matrix to express the user's interest characteristics and its improved algorithm. Three mixed feature matching strategies are proposed, and the matching effects are compared. An improved score-based web ranking algorithm is used, and a comparison of experimental results is given to realize the tourism network resource monitoring system, introduce the module functions according to the system modules, and give the system screenshots to show the operating effects of the system. The system uses the Internet tourism resource extraction algorithm based on the Internet tourism resource density to remove the noise data from the web pages and improve the response time of the system. Internet tourism resource extraction technology also brings great convenience to data processing.

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A New Hybrid Fuzzy Model: Satisfaction of Residents in Touristic Areas toward Tourism Development

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This research brings a practical approach to the issue of the level of satisfaction from residents in tourist destinations by using three attractive methods together. After reviewing the theoretical foundations and the meta-synthesis method in identifying indicators, fuzzy Delphi was used for screening, fuzzy SWARA (stepwise weight assessment ratio analysis) for weighting, and fuzzy EDAS (evaluation based on distance from average solution) for 16 very important tourism areas in Iran. Six important factors (economic, cultural, environmental, perceptual, social, and health) along with 42 important criteria were identified in the meta-combination method, while also obtaining the total weight of the indicators. Finally, the sensitivity analysis of the model is performed and practical suggestions presented.

1. Introduction

Tourism in today's world is considered an industry and the third most dynamic, prosperous, and developing economic phenomenon that has overtaken other global industries after the oil and automotive industries [1]. Tourism is a service activity where satisfaction has a tremendous impact on the interests of its stakeholders [2]. The importance of this issue, especially by governments and their interest in meeting the local needs of the tourism region, provides better public and private services [3] (114, [4, 5]). One of the most effective trends in tourism development is to pay attention to the host community and their level of satisfaction with the presence of tourists in the tourism target areas [6]. Experts believe that there is a direct relationship between tourism and quality of life because tourism increases the quality of life by reducing poverty, increasing per capita income, and it also may increase environmental pollution crimes ([7]; 879). If tourism is understood as a tool for economic development for the local community by providing factors such as employment and investment opportunities, tax revenues, restaurants, accommodation services, natural and cultural attractions, festivals, and recreational opportunities, the quality of life for residents improves and promotes the development of the region ([8]; 4).

Vosughi et al. [9] believe that recognizing the factors affecting the satisfaction of the host community should be considered in the success of sustainable tourism development. Reducing costs, maximizing environmental, economic, and social benefits to attract stakeholders [10] are on the one hand, while maintaining cultural integrity, biodiversity, and support systems, building local community capacity, and monitoring them are on the other [11]. Brokaj [12] believes that giving support to the local community in managing the tourist destination and achieving a codified plan so that the host community is fully satisfied is crucial.

Zhang et al. [13] have focused on the issue of resident commitment to respecting tourists and tourism-related activities and actions based on the specific conditions and characteristics of the area in various aspects to other activities. Jaafar et al. [14] also believe that tourism is a social-cultural attraction itself before it is considered an economic phenomenon. Researchers have linked perceived tourism influences to resident satisfaction with tourism development (STD) or analyzed the relationship between tourism influences and resident support for tourism development [15–17].

Academics and stakeholders [18–22] have increasingly accepted the issue of resident satisfaction with the purpose of tourism and attention to tourism development features. They believe that a successful tourism development program can provide economic benefits to rural communities by strengthening employment and business opportunities. The results of structural equation modeling show that the perceived effects from residents are not significantly related to their support for future tourism development. In contrast, resident satisfaction was clearly associated with their support for such progress, indicating that local resident satisfaction with existing tourism development could be an important predictor for their further support for such development.

Foroni et al. [23] analyzed a questionnaire developed by the European Commission for Local Residents by the European Tourism Index (ETIS). In this study, they present real results and suggest the relationship between tourism and host communities. Mohammad Alrwajfah et al. [23] showed that the social demographics of respondents and society's dependence on their understanding of tourism influence tourism development. Gender and distance from tourist sites are also seen as very important factors in influencing the perceptions of local residents. In addition, the perceived economic impact is the most important aspect for these respondents and the perceived negative effects that significantly satisfy them do not affect them. The tourism industry is also important in terms of its role in GDP and creates many job opportunities in many countries ([25]; 135). According to the World Travel and Tourism Council, the share of travel and tourism in the world's GDP in 2012 grew by 3%. This growth rate has been faster than the growth of the global economy (2.3%) and also faster than the growth of a number of large industries, including manufacturing, services, business, and retail. The tourism industry's direct share of the world's gross domestic product was US$ 2.1 trillion, and the industry directly supports 101 million jobs ([26]; 134). Also, according to the World Tourism Organization, tourism has become one of the three factors affecting economic development in more than 50% of the world's poorest countries, while reaching 10% of GDP in Western countries and 40% of the GDP in poor countries ([26]; 517).

As can be seen, the concept of resident satisfaction toward tourism and its impact on the development of tourism has been written from different aspects and with different models and methods. However, less attention has been paid to evaluating and ranking satisfaction indicators using multicriteria decision models. Understanding the needs and problems of the tourist target in tourism-related issues is one of the necessities of planning and management in all dimensions. In addition, the importance of the role of local residents in supporting and deciding on tourism development, and its effects on tourism are important needs that have received less attention in Iran. The important point is that, although the principles of tourism are benevolent and ensure the interests of host communities and tourists in the long run, their implementation is difficult given the political, economic, social, cultural, and health conditions prevailing in developing countries. Therefore, this research departs from previous papers by using a hybrid approach where results obtained from multicriteria decision-making models as regards to weights and priorities are conceptually cross-checked with qualitative descriptions of each alternative touristic area.

Iran is a country that has significant capabilities in the field of tourism that are related not only to its historical attractions but also to its cultural and climatic diversity. Iran is a country with four seasons of climatic and animal diversity including high mountains, vast deserts, and dense forests. Iran is a country with a history of governing for 2,500 years and has one of the largest and oldest collections of historical monuments in the world. The people of this country are also very warm-hearted, kind, and hospitable. Anyone who considers these features will make Iran one of their top tourist destinations in the world. But despite all of Iran's attractions, its share in the world tourism market is not very significant. However, this share has improved and reached a more acceptable level, especially in recent years due to the openings that have taken place in the international arena. Iran is the 89th most competitive country in the world in terms of tourism and travel and is ranked 11th among 15 countries in the Mena region [28]. One of the indicators examined in travel and tourism policies is the price competitiveness index. Changes in the exchange rate in Iran rank first in the world in this index. Due to low airport tolls, cheap fuel, and high purchasing power of foreign tourists in Iran, this country is ranked first in terms of price competitiveness with its natural and cultural resources being a strength in attracting foreign tourists to Iran.

In this article, the regular structure first identifies the satisfaction indicators of tourism target region residents with the Fuzzy Delphi approach and the opinions of tourism industry experts in Iran. Then, the weight of the indicators was measured using the Fuzzy SWARA (stepwise weight assessment ratio analysis) approach, and the Fuzzy EDAS (evaluation based on distance from average solution) approach was used for ranking the indicators. Finally, sensitivity analysis was performed with Fuzzy COPRAS (COmplex PRoportional ASsessment), Fuzzy MABAK, and Fuzzy TOPSIS (technique for order of preference by similarity to ideal solution) approaches. Figure 1 illustrates the research structure well.

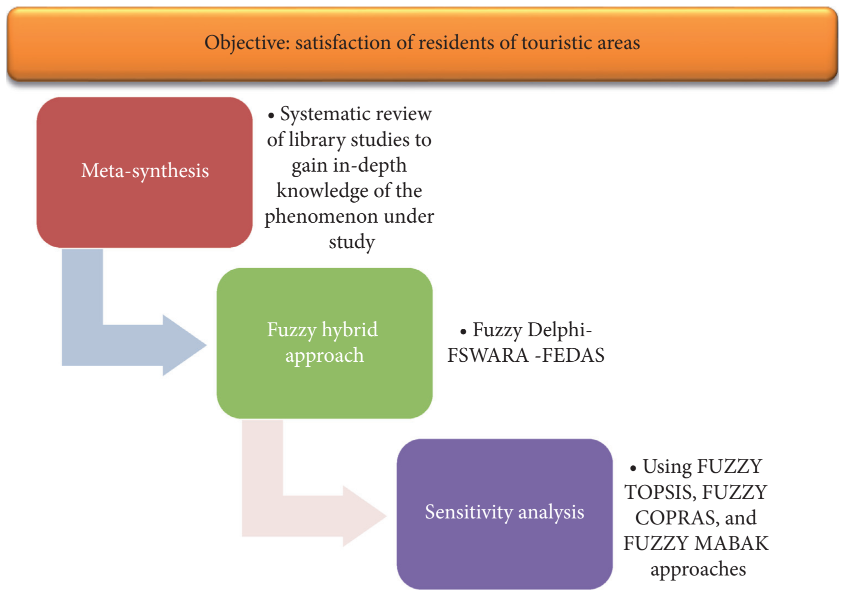

Figure 1: Research structure.

1.1. Research Gap. Tourism is one of the strongest industries in global economic development and has many positive and negative effects. One of the key factors in tourism development is the satisfaction of the locals [1]. For growth in the tourism industry, applying development principles is increasingly important for stakeholders, tourists, and host communities [10] along with maintaining cultural integrity, essential environmental processes, biodiversity, and life support systems for sustainable tourism as defined by the World Trade Organization that requires close monitoring of tourism satisfaction, capacity building of the local community, and continuous monitoring of their reactions to tourism activities [11]. Tourism development is one of the methods of reconstruction and socioeconomic development for increasing the welfare of destination residents, and in addition to tourists, it should be useful for residents and other stakeholders. The effects of tourism may cause discomfort and dissatisfaction in the host community, which in turn may cause problems in the long-term sustainability of the tourism industry and its economic benefits [29]. If the host community believes that tourism development is destroying their social and physical environment and that tourists are the cause, the quality of interactions between residents and tourists may decline [30], though revenue from tourism activities can become a real economic bridge with psychological and social effects [31]: 1807). Basically, the judgment of the host community towards tourism with the increase in the number of visitors in the destination community includes a range of satisfaction, indifference, resentment, and hostility [32]. The study of the approach to potential effects of tourism from two dimensions of costs and benefits (positive or negative effects) generally shows a negative relationship between costs and support for the development of the tourism industry and a positive relationship between benefits and support of local communities [33]. The image of local residents is a mental structure based on several selective perceptions of information about a place [34]. There are several theoretical frameworks for understanding people's reactions to tourism. The Social Exchange Theory (SET) is an underlying framework for all methods and approaches based on the host community's assessment of the costs and benefits expected from tourism. In fact, how local residents assess the set of costs and benefits of tourism will affect their attitudes ([35]:759–760). In the Life Cycle Theory (LCT), evaluating the development of destination tourism over time is important. Thus, the attitude of the host is influenced by the process of change and development in tourism ([36]; 39). Factors that influence the host community's views on tourism are often described as social, economic, and environmental effects with positive effects being benefits and the negative effects being costs. In general, theorists and researchers have stated that there is an inverse relationship between the level of tourism development and the objective and subjective criteria of social and environmental effects on the host ([37]; 83). Therefore, examining and evaluating the mental image of the host community towards tourism is a complex matter. The mental image of local residents is one of the key factors in understanding support for the development of the tourism industry, which emphasizes the unique characteristics of the place rather than the individual's psychological involvement in the place. Stable dependence, on the other hand, is a dynamic structure and is less subject to change [38]. Experts believe that there is a direct relationship between tourism and quality of life because tourism reduces poverty, increases per capita income, but may also increase the crime rate of environmental pollution, causing changes in the quality of life ([7]; 879). If tourism becomes a tool of economic development for local communities, it may be possible to provide quality services, tax revenue, restaurants, accommodation services, natural and cultural attractions, festivals, and entertainment ([8]: 4). In addition to the economic aspects, this industry brings about cultural and social changes to the tourist destinations [1].

One of the types of tourism is rural tourism. Today, the share of this type of tourism is between 10– 25%. The expansion and development of tourism in rural areas is one of the main elements that assist rural populations suffering from poverty, low wages, and economic and socialization problems. Resident understanding of the policy of minimizing the negative effects of tourism development makes it easier to minimize its waste, which leads to the development of the community and more support for tourism. Therefore, in summary, in the case of understanding the positive effects of tourism, this industry could be transformed into a tool for economic, social, and environmental development in terms of standard of living with the effects of tourism becoming a source of satisfaction for the host community by dealing with the problems in the country through tourism industry sustainability and the resulting economic benefits.

2. Background

2.1. Contextual Setting. The World Travel and Tourism Council [39] has been collecting evidence for more than 25 years that shows the economic impact and job creation from travel and tourism (All the numbers mentioned in this section have been prepared from reliable sources in Iran.). These statistics show that despite the unpredictable and growing shocks caused by terrorist attacks, political instability, natural disasters, and pervasive diseases, travel and tourism continue to grow. According to statistics released by the World Travel and Tourism Council in 2019, the direct share of travel and tourism in the world GDP in 2018 amounted to US$ 2.751 trillion https://wttc.org/Research/Economic-Impacton or 3.2% of the world's GDP. It is also projected to rise to US$ 4.346 trillion by 2025, accounting for 3.4% of the world's GDP.

Iran has many attractions, and the diversity of these attractions has attracted domestic and foreign tourists. Tourism in Iran has a high potential for growth. The most important tourist centers in Iran are historical and cultural areas, holy and religious places, and attractions in different cities.

According to the Tourism Organization, the share of Iran's tourism industry in GDP is about US$ 119 million (2.4%), which is projected to rise to 4% by 2023. Currently 475,000 Iranians work in the tourism industry and related industries accounting for 1.2% of the total workforce in Iran, and according to government plans, it should increase to 3.2% by 2023. According to statistics released by the World Tourism Organization, Iran's tourism grew by 12% in 2016, while global tourism growth was 4%. Perhaps, for this reason, private sector investments in tourism during 2016 grew by 20 to 30%, but according to the head of the Cultural Heritage, Handicrafts, and Tourism Organization, the number of foreign tourists entering the country was only 4.6% of the world's tourists in the last two years.

In 2012, about 4,800,000 people came to Iran, in 2013, about 5,100,000 people, in 2014, about 5,250,000 people, and in 2015, this figure rose to about 5,300,000. The number of European and American tourists visiting Iran has increased by 56.6% from 2015 to the end of the first quarter of 2016. From August, 2014, to the end of 2015, 478,826 Westerners (mostly Europeans) traveled to Iran. However, before January 2012, to July 2014, only 35,852 Europeans traveled to Iran. According to the latest forecast of the World Tourism Organization, the trend of attracting foreign tourists to Iran will continue until 2027.

Also in 2018, the direct share of travel and tourism in Iran to create employment is 468,000 jobs, equivalent to 1.9% of total employment in the country, and it is expected to reach 505,000 jobs in 2025, equivalent to 2% of total employment in the country. In 2018, investment in the travel and tourism sector in Iran at the current price of $ 2.5 billion was equivalent to 3.4% of the total investment in the country, and this share is expected to increase to 4.6% by 2025. In addition, tourism revenue in Iran in 2018 amounted to US$ 4.1 billion, equivalent to 4% of total exports, which is expected to reach 7.2% by 2025.

2.2. Literature Review

2.2.1. Tourism Industry in Iran (Ministry of Tourism and Tourism of Iran (2020))

(1) Historical Attractions. History and civilization are an integral part of the identity of any country. Countries that have this gift and have made good use of its tourism potential have made significant progress in their tourism industry [40]. Iran is also one of the countries that attract the attention of every tourist with its civilization and history of several thousand years. Iran, with relics from the ancient world, has 21 historical and archeological monuments registered on the UNESCO list so far. If we want to look at the past of Iran in the form of several identities and historical perspectives, we can mention the history of calligraphy and civilization, ancient Iran, and Safavid Islam as the most important sources of Iranian historical monuments.

(2) Natural Attractions. Iran is a country with a history and civilization of several thousand years, which attracts the attention of every tourist. So far, Iran has 21 historical and archeological monuments registered on the UNESCO list. From the perspective of civilization, the ancient region of Jiroft in the Kerman province with its history of 7,000 years is the center of the first glorious civilization in the world. But apart from this region, which seems more interesting for researchers and experts, ancient Iran is known around the world for the Persepolis with its famous Iranian antiquities registered in the UNESCO list, built during the reign of Darius the Great, Xerxes, and Ardashir I. From post-Islamic Iran, its Safavid monuments and buildings are the most famous around the world with the most prominent one being Naghsh Jahan Square in Isfahan. The square, which in the seventeenth century was known as one of the largest squares in the world, has 4 unique historical monuments connected to it: the Sheikh Lotfollah Mosque, the Imam Mosque, the entrance and bazaar of Qaisaria, and the High Palace of Aali Qapu Palace.

(3) Cultural Attractions. Iranian culture is extremely rich in the production of pleasure, art, and happiness and is full of unique delicacies. Delicacies are embedded in it to increase happiness and excitement and as a result more enjoyment of life. Examples of these subtleties can be seen from Persian poetry and literature with its global fame and influence (works of Rumi, Ferdowsi, Hafez, and Saadi) to the place of humor and music in Iranian culture. Visual arts and visual pleasures also have a special place in Iranian culture. Along with Iranian carpets that are famous for their beauty in the world, enameling, inlay work, woodcarving, pottery, and dozens of other works of art show the considerable interest of Iranians in beauty and elegance. Diverse Iranian food is another symbol of the elegance of Iranian culture. Despite the similarity of Iranian stews to some Indian dishes or the similarity of Iranian kebabs to Greek and Arabic kebabs, Iranian food still has many unique elements. The elements of Iranian culture are beyond the borders of the Islamic Republic, and its strong traces can be found in the neighboring independent countries of Afghanistan, Pakistan, Tajikistan, Uzbekistan, Turkmenistan, the Republic of Azerbaijan, Armenia, Georgia, and the Kurds of Iraq and Turkey have all more or less inherited a corner of Iranian culture. Nowruz and the solar calendar are very famous up to the Shiite religion along with Iranian music and architecture as well as the Persian language and national holidays of this country.

(4) Religious Attractions. Iran has a variety of religious places due to its ancient civilization and the presence of followers of different religions. There are nearly 9,000 religious sites in various parts of the country such as tombs of imams and tombs listed in the National Monuments List, mosques, religious schools, churches, synagogues, fire temples, and shrines. Religion has played a prominent role in the formation of cities such as Mashhad, Qom, Rey, Shiraz, Qazvin, Natanz, Damghan, Shahroud, Shush, Bastam, Lahijan, Amol, Ardabil, and Gonbad Kavous, and these cities have great potential to attract religious tourists. Iran can attract international tourists to all its religious areas with their existing cultural space, making the development of religious-cultural tourism possible. Due to the existence of numerous shrines, including the holy shrine of Imam Reza (AS) in Mashhad and the shrine of Imam Masoumeh (AS) in Qom). Iran is a pilgrimage destination for many travelers from Muslim countries with its unparalleled temples and churches that do not exist in other parts of the world. For example, the oldest church in the world is located in Iran.

(5) Medical Attractions. Due to the low cost of medical treatment in Iran on a global scale, it has an extraordinary capacity to attract medical tourists from Islamic countries and the region. To the extent that, given the favorable conditions created after the lifting of sanctions, the ground has been prepared for Iran to become a leading country in medical tourism in the region. Iran is one of the five most advanced countries in the world in the field of biotechnology and 9 out of 15 widely used biotechnological molecules are produced here. In many parts of Iran (including Sarein in Ardabil, Mahallat, GNU in Bandar Abbas, and Ferdows in Khorasan), there are mineral springs that welcome many patients. Infertility treatments, stem cell therapy, dialysis, heart surgery, cosmetic surgery, and eye surgery are also performed in Iran. Medical services in Iran are safer, more scientific, and cheaper. Currently, one-fourth of the country's hospitals are active in the field of health tourism, and we have a ranking of one to five in the specialized fields of eyes, heart, infertility, and nerves with cosmetic surgery (especially rhinoplasty) also having its tourists and is one of the most lucrative fields of medical tourism in Iran.

(6) Modern and Man-made Attractions. In the current view, Iran has become a more desirable historical destination for Western tourists. Unfortunately, over the past few decades, the Western media with their political motives and negative and destructive propaganda have succeeded in creating a backward, pre-tech image of Iran in the minds of their audiences, much to the surprise of most Western tourists when they arrive. Today, not only in the capital of Iran, but also in metropolises such as Isfahan, Shiraz, Mashhad, and Tabriz, or in tourist areas such as the northern cities or Kish Island, there are modern and advanced attractions for tourists ranging from places for fun and entertainment to state-of-the-art and new shopping malls, which due to the low cost of tourism in Iran compared to neighboring countries, offering an important competitive advantage to attract foreign tourists.

2.2.2. Tourism in Iran and GDP. According to the Tourism Organization, the share of Iran's tourism industry in GDP is about US$ 119 million (equivalent to 2.4%), which is expected to increase to 4% by 2025. There are currently 475,000 Iranians employed in the tourism industry and related industries, which is 1.2% of the total active labor force in Iran, and according to government plans, this should increase to 3.2% by 2025. According to statistics published by the World Tourism Organization, Iran's tourism grew by 12% in 2016, while global tourism growth was 4%. Perhaps, for this reason, private sector investment in tourism grew by 20 to 30% during 1995. However, according to the head of the Cultural Heritage, Handicrafts, and Tourism Organization, the number of foreign tourists entering the country in the past years has been only 4.6% of the world's tourists. Figure 2 shows the total share of travel and tourism in GDP and forecasts until 2027:

2.2.3. Iran's Position in the Tourism Competitiveness Index. According to statistics from the World Economic Forum [41] on Iran's tourism competitiveness indicators and its comparison with its regional competitors in the field of tourism, it can be said that Iran has had a favorable growth in many indicators in recent years. In 2011, Iran ranked 114th out of 139 countries, but by 2013, with 16 ascents, it ranked 98th out of 140 countries, in 2015 it ranked 97th out of 141 countries, and finally in 2017, with 4 steps upward, it ranked 93rd out of 136 countries in the world. Iran's score in the 2017 Tourism and Tourism Competitiveness Index is equal to 3.4, which in 2015 was 3.4. Iran has also risen from 9th

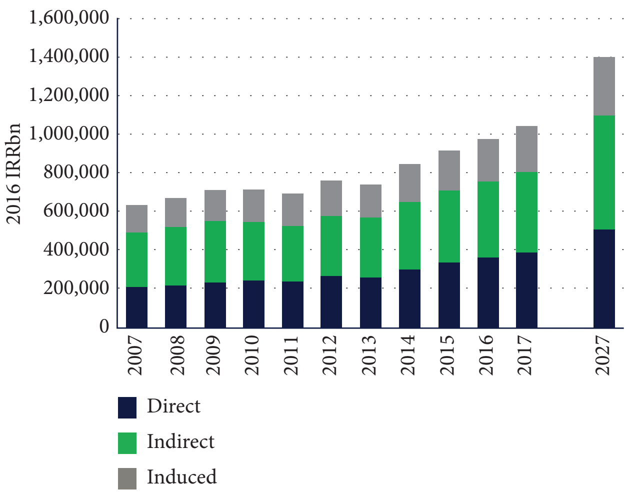

FIGURE 2: Total contribution of travel and tourism to GDP (WTTO, 2019).

place among Middle Eastern countries in 2015 to 8th place in 2017 in this group. The growing trend of tourists entering Iran and the very favorable situation in indicators such as competitive prices along with the growing trend in other indicators of competitiveness shows the investment attractiveness of Iran's tourism industry. Figure 3 shows the situation of Iran in terms of tourism indicators among the important countries in the region:

2.2.4. Residents of Touristic Areas and MCDM. Since tourism is strongly based on the goodwill of local residents, it needs their support for development. Therefore, it is necessary to identify the satisfaction indicators of residents in tourism targets. Various researchers have been researching this area for years because of the importance of the subject [33, 42–62]. Table 1 lists the methods studied by some researchers in recent years.

There have been six areas considered by researchers: economic, cultural, environmental, social, perceptual, and health. By examining the theoretical foundations, the most important indicators in previous research have been as follows:

(i) *Tourism creates more job opportunities for the community* (Nunkoo and Smith [76]; Mohd Hafiz Hanafiah et al. [77]).

(ii) *Tourism leads to more money in society* (Yoon et al. [78]; Gursoy and Rutherford [79]).

(iii) *Land and property prices rise due to tourism* (Yoon et al. [78]; Nunkoo and Ramkisson [15]).

(iv) *Cost of goods and services will increase due to tourism* (Yoon et al. [78]; Nunkoo and Ramkisson [15]).

(v) *Cost of developing tourism infrastructure is very high* (Yoon et al. [78]).

(vi) *Living standards in tourist areas are rising dramatically* (Mohd Hafiz Hanafiah et al. [77]).

(vii) *Tourism has economic benefits for locals and small businesses* (Yoon et al. [78]; Mohd Hafiz Hanafiah et al. [77]).

(viii) *Tourism encourages diversity of cultural activities for locals* (Mohd Hafiz Hanafiah et al. [77]).

(ix) *Tourism development moderates local culture and lifestyle* (Mohd Hafiz Hanafiah et al. [77]; Gurso and Rutherford [79]).

(x) *Tourism leads to cultural exchanges between tourists and community members* (Gursoy and Rutherford [79]; Yoon et al. [78]).

(xi) *Tourism institutionalizes development in local culture to attract more tourists* (Mohd Hafiz Hanafiah et al. [77]).

(xii) *The arrival of tourists to a region from a spatial perspective will transfer the culture to other areas and generations to come* (Azizi et al. [80]).

(xiii) *The arrival of tourists to an area from time to time will bring culture to other areas and generations to come* (Mohd Hafiz Hanafiah et al. [77]).

(xiv) *The arrival of tourists creates local and cultural cohesion in the tourist areas* (Rajabzadeh et al. [81]).

(xv) *Tourism has a positive impact on the cultural identity of a community* (Gursoy and Rutherford [79]).

(xvi) *Tourism does not generate more waste* (Azizi et al. [80]; Mohd Hafiz Hanafiah et al. [77]; Ko and Stewart [48]).

(xvii) *Tourism in the area does not cause traffic congestion, pollution, and noise* (Yoon et al. [78]; Mohd Hafiz Hanafiah et al. [77]).

(xviii) *Tourism does not lead to overcrowding of beaches, parks, and other tourist environments* (Yoon et al. [78]; Mohd Hafiz Hanafiah et al. [77]).

(xix) *Tourism does not increase the consumption of water, electricity, gas, and fuel* (Azizi et al. [80]).

(xx) *Building hotels and other tourism infrastructure destroys the natural environment* (Mohd Hafiz Hanafiah et al. [77]).

(xxi) *Tourism creates more parks and other recreational areas for the host community* (Yoon et al. [78]; Mohd Hafiz Hanafiah et al. [77]).

(xxii) *Income from tourists affects the way of life* (Mohd Hafiz Hanafiah et al. [77]; Nunkoo Ramkisson [15]; Ko and Stewart [48]).

(xxiii) *The arrival of tourists into the community is an honor. Tourism creates social relationships between individuals. Tourism makes it easier for locals to adopt new norms. Tourism is changing traditions and valuable culture* (Gursoy and Rutherford [79]).

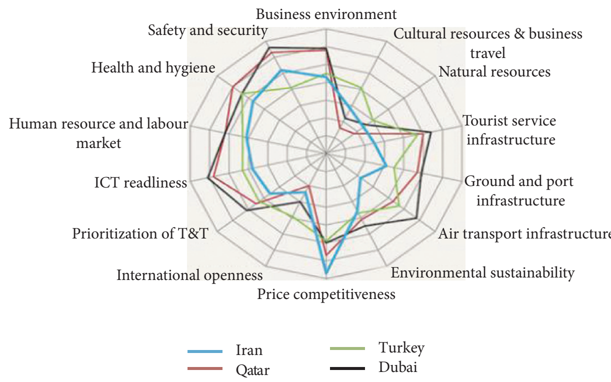

FIGURE 3: The travel and tourism competitiveness index [41].

TABLE 1: Satisfaction of the residents in tourism targets with a focus on the tourism development in terms of the method used.

Authors	Scope of research	Method/s	Country
Yang et al. [63]	Establishing a sustainable sports tourism evaluation framework	Bayesian BWM and VIKOR	Taiwan
Lim and lee [64]	Living as residents in a tourist destination	A phenomenological approach	Bulguk-Dong Gyeongju city
Gannon et al. [65]	The mediating role of resident perceptions toward tourism development	PLS	Iran
Martín et al. [66]	Resident perception towards tourism	Fuzzy-hybrid cluster and TOPSIS	Gran Canaria
Escudero Gómez [67]	Resident opinions and perceptions of tourism development	Statistical analysis	Spain
Alrwajfah et al. [68]	Resident perceptions and satisfaction toward tourism development	Regression analysis	Jordan
Ki¸si [69]	Sustainable tourism development	AHP-SWOT	Turkey
Foroni et al. [23]	Resident satisfaction with tourism and the European tourism	Statistical analysis	South sardinia
Lopes et al. [70]	Resident perceptions of tourism activity	Cluster analysis	Portugal
Sánchez-Teba et al. [71]	Resident negative perceptions towards tourism, loyalty, and happiness	PLS-LISREL	Spain
Liu and Li [21]	Sustainability and support for tourism development	Statistical analysis	India
Yu et al. [72]	Perceived tourism impacts and community quality of life perspective	LISREL	USA
Lin et al. [73]	Resident-tourist value co-creation	PLS	China
Ninh do and shih [74]	Factors influencing a traveler's destination decision-making process	DEMATEL-ANP	Taiwan
Almeida-García et al. [75]	Resident perceptions of tourism development	Statistical analysis	Spain

(xxiv) *Tourism increases sabotage and vandalism* (Nunkoo and Gursoy [82]).

(xxv) *Tourism increases the crime rate in the society* (Yoon et al. [78]; Mohd Hafiz Hanafiah et al. [77]).

(xxvi) *The arrival of tourists reduces the security of the area* (Nunkoo and Gursoy [82]).

(xxvii) *Tourism increases prostitution* (Gursoy and Rutherford [79]).

(xxviii) *Tourism destroys the natural environment* (Nunkoo and Smith [76]).

(xxix) *The development of tourism causes economic inflation in the region* (Nunkoo and Gursoy [82]; Ko and Stewart [48]).

(xxx) *The development of tourism facilities is a waste of taxpayers' money* (Yoon et al. [78]).

(xxxi) *Tourism provides new opportunities for local businesses* (Nunkoo and Smith [76]; Mohd Hafiz Hanafiah et al. [77]).

(xxxii) *Tourism contributes to the development of the region* (Nunkoo and Smith [76]; Ko and Stewart [48]).

(xxxiii) *Tourism stimulates the region's economic growth* (Rajabzadeh et al. [81]).

(xxxiv) *Tourism contributes to the development and improvement of infrastructure. Tourism promotes self-sufficiency and strengthens the* *foundation of local communities* (Gursoy and Rutherford [79]).

(xxxv) *The arrival of tourists improves the region's health* (Gondos [7]).

(xxxvi) *Health care centers in the area have been provided for tourist arrivals* (Tichaawa and Mhlanga [8]).

(xxxvii) *People in the region are more diligent in providing health services than ever before* (Kim et al. [83]).

(xxxviii) *Health facilities and infrastructure have improved* (Fun et al. [84]).

When a community becomes a tourist destination, the lives of its inhabitants are affected by tourism activities ([83]; 528). However, in order to take advantage of tourism and develop rural areas through tourism, residents of tourist areas need to have a good view of tourism and support its development. According to the theory of social exchange, residents react to the development of tourism based on the perceived economic, social, and environmental costs and benefits, and the level of support is a function of the perceived benefits and costs of tourism development [1]. In fact, if residents are optimistic about the positive effects of tourism and its benefits, they will be willing to support and cooperate in this area. If they believe that the benefits of tourism outweigh its costs, they will be interested in engaging in this exchange ([85]; 669), but if the host community believes that the development of tourism is effective in destroying their social and physical environment and that tourists are the cause of this trend, the quality of interactions between residents and tourists may decline. In fact, tourism may have a negative impact on the tourist destination and the attitude of the host community ([84]; 65). In the other hand, if the perception of the positive effects (benefits) from tourism is greater than the potential negative consequences, residents are more likely to support tourism. In this way, resident perception of tourism must be considered to be successful in developing and exploiting important tourism ([57]; 262).

In order to develop tourism for various purposes, the lifestyle of the host community may be affected by structural changes in the tourism industry. The results of tourism development can be attributed to factors such as changes in the local economy [86, 87], social changes [87, 88], cultural changes [87, 89, 90], and environmental changes [87, 89, 91]. Tourism is of great importance in the global economy and is one of the important sources of foreign exchange earnings, so it has a large share of planning and investment by countries around the world ([92]; 29). With the global boom in the tourism industry, many regions in developing countries have realized the importance of tourism as an important factor for developing regional economy [93]; 144). Creating jobs, currency, and regional equilibrium, helping global peace, helping to invest in cultural heritage, building the environment, helping build wildlife habitats, developing areas with tourist attractions, and preventing population migration have been some of the benefits of this industry [94].

2.2.5. Tourism in Iran and Employment. According to global statistics (World Trade Organization, 2020), Iran is one of the five countries capable of attracting foreign tourists to various attractions (cultural, religious, natural, and historical), but Iran ranks 97th out of 141 countries in the world and 12th out of 16 countries in the Middle East and North Africa. According to the report of the World Travel and Tourism Council [95], the share of Iran's total tourism in job creation last year was 5.6% of total employment (1,398,500 jobs), which is expected to reach 1,967,000 jobs by 2026, which would cover 6.1% of total employment. According to the statistics of the Tourism Organization, about 5.015 million people entered Iran in 2016 and over 7 million people traveled abroad. The average cost of each tourist entering Iran is US$ 1,710. Despite the growth of the tourism industry in recent years, the number of foreign tourists is less than 0.4% of the number of tourists in the world. Also, Iran's income from tourism is not more than 0.5% of the total global income of tourism. According to the World Travel and Tourism Council [95], if Iran could host 10 million foreign tourists, travel and tourism participation would reach about 2 million jobs. Therefore, one of the goals for 2025 is to attract 20 million foreign tourists in order to reach about 4 million jobs.

2.2.6. Description of Selected Areas. Iran is one of the most important countries in the field of tourism in the region and the world with its numerous attractive tourist areas. The variety of attractions and important tourist areas led the researchers to select 16 tourist attractions that have attracted tourists the most over the past two years:

(1) *T-1: Qeshm Salt Cave (Namakdan Cave)*. Qeshm Salt Cave is the largest salt cave in the world and is 6,600 meters long. This cave is located 90 km from Qeshm city and 2 km from the beach, so this 570-year-old cave can be visited while touring the beach.

(2) *T-2: Zoroastrian Crypts*. Yazd Silent Tower is a mysterious place that introduces you to the world of the dead. This tower is located on a low mountain 15 km away from Yazd city and near the Safaieh area. It may be interesting to note that this burial method was common before the Pahlavi period, but was banned during this period.

(3) *T-3: Kandovan Village*. Kandovan is one of the most beautiful villages in Iran. The history of Kandovan caves dates back to 7,000 years ago, but about 700 years ago, when the Mongols invaded Iran, the people of the East Azerbaijan region fled to these caves to save their lives that now look like beehives 18 km from the city of Osko.

(4) *T-4: Kariz Underground City*. Kariz Kish is an underground city with historical architecture and one of the most stunning sights in Iran. This kariz is located in the heart of the only coral island in the world. Shells and corals dating back thousands of years have covered the city. The only coral mosque

in the world with a roof full of marine fossils has been built in this underground city.

(5) *T-5: Maharlu Lake*. The strangest tourist attraction of Shiraz is Maharlu salt lake. The amazing thing about this lake is its pink color. The lake turns red in mid-summer because of the high evaporation rate and salt concentration, which causes the formation of algae.

(6) *T-6: Dasht-e Lut*. If you want to touch the highest sand pyramids in the world, just travel to the Lut plain. These pyramids are like clumped skyscrapers in the distance and some call this area the city of ghosts.

(7) *T-7: Nasir al-Mulk Mosque (Pink Mosque)*. The Nasir al-Mulk Mosque was built near the tomb of Shahcheragh during the Qajar period. The pink color of the tiles and glass has made this place known as the Pink Mosque. The light decoration and eye-catching architecture of this mosque have created a mystical atmosphere.

(8) *T-8: Stars Valley, Qeshm*. This valley is located 5 km from the village of Barake Khalaf. Scientifically, soil erosion has shaped the valley, but villagers believe it was formed by a falling star.

(9) *T-9: Shushtar Historical Hydraulic System*. Shushtar is a small but historical city in the north of Khuzestan province and is 90 km from Ahvaz. The Karun and Dez rivers flow through this city, and the Shushtar water structures are among the sights of Iran that are registered as part of the UNESCO World Heritage List. These water structures date back to the reign of Darius the Achaemenes.

(10) *T-10: Ganj Lake*. Lake Ganj or Lake Takht-e Soleiman is located 45 km from the city of Takab in East Azerbaijan Province. The natives believe that this lake was created with the beating of Solomon's staff and that countless treasures have been hidden in this area.

(11) *T-11: Chogha Zanbil Ziggurat*. Chogha Zanbil Ziggurat is one of the first tourist attractions in Iran to become registered with UNESCO. It is located near Shush in the Khuzestan province with the ziggurat dating back to the thirteenth century BC and the Elamite civilization. When employees of the Anglo-Iranian Oil Company were digging for oil in 1935, they came across inscribed bricks that later led to the discovery of Chogha Zanbil.

(12) *T-12: Katale Khor Cave*. Katale Khor Cave is located near the city of Garmab, 155 km south of Zanjan. In Turkic areas, the low mountains are called masses. This cave is located on one of these masses and the sun rises behind it, hence it is called the sun mass or the mass eater.

(13) *T-13: Babak Fort*. Babak Fort is a historical fortress 13 km from the city of Kalibar in the East Azarbaijan Province. Babak Fort was built during the Sassanid era. When the Abbasids invaded the area, Babak Khorramdin took over the leadership of the people and fought the invaders in this fort during 20 years.

(14) *T-14: Yazd Chek Chek Shrine*. Chek chek or Chekcheko is one of the most important Zoroastrian shrines, 43 km from Ardakan city and is one of the lesser known places in Iran. The interesting name of this spectacular place is taken from the sound of water drops dripping from the rock. This shrine receives Zoroastrian worshipers every year in June for 4 days.

(15) *T-15: Hormuz Island*. Hormoz Island, 16 km from Bandar Abbas, has been called the land of colors and is one of the most beautiful and special places of interest in Iran. Red soil and yellow, white, and red mountains will give you a unique view.

(16) *T-16: Biston and Bostan Arch*. Kermanshah has 3,000 historical monuments, 716 of which have been registered as national monuments. This spectacular place is called Biston, which is located 30 km northeast of Kermanshah. The location of this spectacular place along the Silk Road has attracted the attention of many kings. Biston, with its striking beauty, has many impacting ancient inscriptions. Many historians have mentioned the description of this ancient city and the carvings of Biston and Bostan Arch in their books.

3. Research Methodology and Analysis

This study focuses on evaluating and ranking the satisfaction indices of residents in touristic areas for the purpose of tourism development. Descriptive research consists of a set of methods designed to describe the conditions and phenomena under study. Conducting descriptive research can be merely to better understand the current situation or to aid the decision-making process. Due to the specialized nature of the subject and the limitation of identifying experts, a small number of experts were selected, including 20 individuals, who were selected by convenience sampling and willingness to participate in this research. The information for selecting experts is in Table 2.

After reviewing the theoretical foundations, 42 indicators were identified (Table 2) that need to be examined by experts regarding their role or not in the subject under study in Iran with the fuzzy Delphi method being used to screen the criteria.

3.1. Fuzzy Delphi Method (FDM). The FDM was proposed by Ishikawa et al. [96] to overcome the issues surrounding membership degree and is the result of the traditional fuzzy technique and fuzzy set theory. Noorderhaben [97] shows that the use of FDM for group decision-making can solve the issue of a fuzzy common understanding of expert opinions. This study uses triangular membership functions and fuzzy theory to solve group decisions and uses FDM to solve group decisions. The fuzziness of expert common understanding

Table 2: Selection of experts.

Row	Education	Work experience (years)	Field of study	No.	Job
1	PhD	12	Tourism	2	Faculty member
2	PhD	15	Tourism	2	Faculty member
3	PhD	8	Tourism	2	Faculty member
4	PhD	22	Tourism	2	Faculty member
5	PhD	25	Tourism	2	Faculty member
6	PhD	16	Tourism	2	Faculty member
7	PhD	15	Tourism	2	Faculty member
8	PhD	14	Tourism	2	Faculty member
9	PhD	24	Tourism	2	Faculty member
10	PhD	20	Tourism	2	Faculty member

can be solved using fuzzy theory and evaluated on a more flexible scale. The efficiency and quality of questionnaires can be improved. Therefore, more objective evaluation factors can be screened through statistical results [98]. The FDM steps are as follows:

(1) Collect all possible criteria that can affect the Satisfaction of Residents in Touristic Areas. Questionnaires are provided to the specialist to determine the importance of each evaluation indicator. Because human judgments are always vague and cannot be quantified accurately, each analyst must choose the appropriate linguistic expressions in order to integrate the opinions of all experts to eliminate trivial criteria (Table 3).

(2) Determine triangular fuzzy numbers (Figure 4, Table 4) by calculating the evaluation value of the triangular fuzzy number of each criterion specified by experts. A triangular fuzzy number (TFN) is a type of fuzzy number that is represented by three real numbers as $F = (l, m, u)$. These types of fuzzy numbers are very common due to their very high computational efficiency. In addition, calculations with this type of numbers are very simple and understandable. Fuzzy logic works by introducing fuzzy sets and then fuzzy numbers and introducing triangular fuzzy numbers has played an important role in the growth of fuzzy computing.

This study uses the geometric mean model of the general mean model proposed by Klir and Yuan [100] for FDM to find a common understanding of group decision-making. Suppose that the value of the importance of element number j by the expert of number i is from among n experts that $\widetilde{w}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$. Then, the fuzzy weight $\widetilde{w}_{ij}$ of element number j is

$$\widetilde{w}_j = \left(a_j, b_j, c_j\right), \quad j = 1, 2, \ \ldots, m, \tag{1}$$

where

$$\begin{aligned} a_j &= \mathrm{Min}\left\{a_{ij}\right\}, \\ b_j &= \frac{1}{n}\sum_{i=1}^{n} b_{ij}, \\ c_j &= \mathrm{Max}\left\{c_{ij}\right\}. \end{aligned} \tag{2}$$

(3) De-fuzzy: using the simple gravity center method to de-fuzzy, the fuzzy weight $\widetilde{w_J}$ of each alternative element to determine the value of S_j is obtained as follows:

$$S_j = \frac{a_j + b_j + c_j}{3}, \quad j = 1.2 \ldots .m. \tag{3}$$

(4) Screening evaluation criteria: finally, appropriate criteria can be determined using a multicriteria screening by setting and α threshold. The principle of screening is as follows: if $S_j \geq a$, then factor number j is the evaluation index. If $S_j < a$, then factor j is removed.

Therefore, the output of the first phase of fuzzy Delphi is given in Table 5.

As it is clear from the first round of analyses that in 12 criteria, the threshold level is lower than 0.70, they were removed from the analyses and the second round was performed. What is clear is that in the second round, all the experts reached a consensus on the criteria, and all the remaining criteria have a threshold above 0.70. In other words, the indicators of satisfaction of the target residents of tourism in Iran were accepted by the experts of these criteria. Next, the weight of the criteria is determined using Fuzzy SWARA.

Multicriteria decision-making is a large body of operations research that helps managers make decisions based on multiple and conflicting criteria. This field of study is referred to as multiple criteria decision-making and abbreviated as MCDM. In such decisions, several indicators or goals that are sometimes contradictory are considered. If the criterion in MCDM is the attribute index, it is known as MADM multicriteria decision-making. If the multiple criteria are meant to be objective, it is called MODM with multiple objectives. The use of these methods is very appropriate in organizational issues where managers deal with criteria that have different scales for measurement. The use of multicriteria decision-making methods in solving organizational problems is well compatible with the complex nature of organizations. Decision-making is one of the most important and basic tasks of management, and reaching organizational goals depends on its quality. According to decision-making expert Herbert Simon, decision-making is the essence of management. One of the decision-making techniques using quantitative data is multicriteria decision

Table 3: Factors identified in satisfaction.

Row	Components	Validity	Reliability
1	Tourism creates more job opportunities for the community.	KMO = 0.91 Bartlett's Test of sphericity Sig = 0.000	Cronbach's alpha = 0.87
2	Tourism leads to more money in society.		
3	Land and property prices rise due to tourism.		
4	Cost of goods and services will increase due to tourism.		
5	Cost of developing tourism infrastructure is very high.		
6	Living standards in tourist areas are rising dramatically.		
7	Tourism has economic benefits for locals and small businesses.		
8	Tourism encourages diversity of cultural activities for locals.		
9	Tourism development moderates local culture and lifestyle.		
10	Tourism leads to cultural exchanges between tourists and community members.		
11	Tourism institutionalizes development in local culture to attract more tourists.		
12	The arrival of tourists to a region from a spatial perspective will transfer the culture to other areas and generations to come.		
13	The arrival of tourists to an area from time to time will bring culture to other areas and generations to come.		
14	The arrival of tourists creates local and cultural cohesion in the tourist areas.		
15	Tourism has a positive impact on the cultural identity of a community.		
16	Tourism does not generate more waste.		
17	Tourism in the area does not cause traffic congestion, pollution, and noise.		
18	Tourism does not lead to overcrowding of beaches, parks, and other tourist environments.		
19	Tourism does not increase the consumption of water, electricity, gas, and fuel.		
20	Building hotels and other tourism infrastructure destroy the natural environment.		
21	Tourism creates more parks and other recreational areas for the host community.		
22	Income from tourists affects the way of life.		
23	The arrival of tourists into the community is an honor.		
24	Tourism creates social relationships between individuals.		
25	Tourism makes it easier for locals to adopt new norms.		
26	Tourism is changing traditions and valuable culture.		
27	Tourism increases sabotage and vandalism.		
28	Tourism increases the crime rate in the society.		
29	The arrival of tourists reduces the security of the area.		
30	Tourism increases prostitution.		
31	Tourism destroys the natural environment.		
32	The development of tourism causes economic inflation in the region.		
33	The development of tourism facilities is a waste of taxpayers' money.		
34	Tourism provides new opportunities for local businesses.		
35	Tourism contributes to the development of the region.		
36	Tourism stimulates the region's economic growth.		
37	Tourism contributes to the development and improvement of infrastructure.		
38	Tourism promotes self-sufficiency and strengthens the foundation of local communities.		
39	The arrival of tourists has improved the region's health.		
40	Health care centers in the area have been provided for tourist arrivals.		
41	People in the region are more diligent in providing health services than ever before.		
42	Health facilities and infrastructure have improved.		

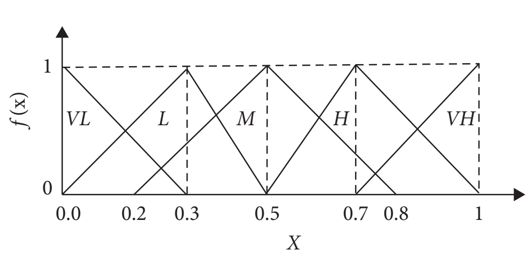

Figure 4: Linguistic scale for fuzzy Delphi.

Table 4: Triangular fuzzy numbers [99].

TFN	Fuzzy value	Verbal variables	
(0, 0, 0.25)	$\tilde{1}$	VL	Very low
(0, 0.25, 0.5)	$\tilde{2}$	*L*	Low
(0.25, 0.5, 0.75)	$\tilde{3}$	*M*	Middle
(0.5, 0.75, 1)	$\tilde{4}$	*H*	High
(0.75, 1, 1)	$\tilde{5}$	VH	Very high

Table 5: Percentage of consensus of results from first and second round questionnaire.

Components	Fuzzy value			De-fuzzy	Percentage of consensus first round	Percentage of consensus second round
	L	*M*	*U*			
1	3	4.609	5	4.304	70	75
2	4	4.182	5	4.341	80	80
3	3	4.031	5	4.015	85	80
4	4	4.136	5	4.318	85	85
5	3	4.641	5	4.323	80	75
6	1	3.452	4	2.976	75	85
7	3	4.751	5	4.375	90	80
8	3	3.942	4	3.721	95	82
9	1	1.555	3	1.777	45	Delete
10	4	4.676	5	4.588	70	75
11	3	3.961	5	3.980	70	80
12	2	3.907	5	3.703	90	95
13	4	4.727	5	4.614	75	72
14	3	4.289	5	4.144	70	75
15	2	3.931	5	3.715	72	75
16	1	1.597	3	1.798	50	Delete
17	1	1.657	3	1.828	65	Delete
18	1	1.813	4	2.156	40	Delete
19	1	1.629	3	1.814	50	Delete
20	4	4.676	5	4.588	70	85
21	3	4.873	5	4.436	95	80
22	4	4.835	5	4.666	85	85
23	3	3.270	4	3.385	70	78
24	3	3.183	4	3.343	79	75
25	4	4.044	5	4.272	95	90
26	1	2.023	4	2.261	40	Delete
27	1	2.187	5	2.593	45	Delete
28	1	1.952	5	2.476	35	Delete
29	1	1.578	4	2.039	50	Delete
30	1	2.027	5	2.513	55	Delete
31	1	1.634	4	2.067	45	Delete
32	2	3.159	4	3.079	70	75
33	1	1.354	3	1.677	65	Delete
34	4	4.182	5	4.341	80	85
35	3	4.766	5	4.383	85	90
36	3	3.092	4	3.296	89	90
37	2	3.995	5	3.747	80	85
38	3	3.249	5	3.624	80	80
39	4	4.889	5	4.694	90	95
40	4	4.781	5	4.640	80	85
41	4	4.044	5	4.272	95	90
42	4	4.090	5	4.295	90	90

making, and by using its techniques, the manager can make rational decisions by considering different decision-making criteria that are sometimes in conflict with each other. These methods are in the category of operations research and have many applications in industrial management and engineering.

3.2. Fuzzy SWARA. The use of fuzzy SWARA is less common in decision-making literature [101] with some researchers working on this in recent years [102, 103]. Crisp SWARA developed by Keršuliene et al. [104] is inadequate to handle uncertainty, so the fuzzy extension of this method was developed. The reason for using the fuzzy SWARA approach is the inherent uncertainty of deciding on medical tourism destinations, and it was used due to the qualitative nature of most of the criteria and the ease of collecting the opinions of decision makers. Using a fuzzy approach will bring the results closer to the real world. SWARA gives decision makers and policymakers the opportunity to prioritize based on the current state of the environment and the economy. The ability to estimate the opinion of experts about the importance of the criteria in determining their weight is a key element of this method. In addition, this method is useful for coordinating and collecting data from experts.

Also, the SWARA method is uncomplicated and specialists can easily work together. The most important advantage of this method in decision-making is that in some issues, priorities are defined based on the policies of companies or countries and do not need to be evaluated to rank criteria.

The process of determining the relative weight of the criteria using the SWARA method according to the following steps can be shown in detail [105].

We arranged the criteria in descending order.

According to Table 6, the relative importance of factor *j* was determined compared to the previous factor (*j*-1) which is of higher importance.

(1) Calculate the value of $\widetilde{k}_j$ using equation (4). It should be noted that the fuzzy parameters are shown with the symbol ~:

$$\widetilde{k}_j = \begin{cases} \widetilde{1}\, j = 1, \\ \widetilde{s}_j + 1, \quad j > 1, \end{cases} \tag{4}$$

where $\widetilde{k}_j$ is the value of the comparative importance coefficient.

(2) Calculate the value of $\widetilde{q}_j$ using equation:

$$\widetilde{q}_j = \begin{cases} \widetilde{1}\, j = 1, \\ \dfrac{\widetilde{k}_{j-1}}{\widetilde{k}_j} \quad j > 1, \end{cases} \tag{5}$$

where $\widetilde{q}_j$ is value of the fuzzy weights of the criteria.

(3) Calculate the weight of the criteria using the following equation:

$$\widetilde{W}_j = \frac{\widetilde{q}_j}{\sum_{k=1}^{n} \widetilde{q}_k}, \tag{6}$$

where n is the number of criteria and $\widetilde{W}_j$ is the weight of criterion *j*.

Table 7 shows the weighting process for the indicators:

After determining the weight of the indicators in the six areas studied, the Fuzzy EDAS technique was then used to identify 16 important tourist areas in Iran and prioritized by experts. These areas have been selected by a survey of several experts from among dozens of attractive tourist areas in Iran.

Table 6: Fuzzy and linguistic values [106].

Linguistic scale	Response scale
Equally important	(1, 1, 1)
Moderately less important	(2/3, 1, 3/2)
Less important	(2/5, 1/2, 2/3)
Very less important	(2/7, 1/3 , 2/5)
Much less important	(2/9, 1/4, 2/7)

Note. Table 6 is reproduced from Mavi et al. [106] [https://link.springer.com/article/10.1007%2Fs00170-016-9880-x].

3.3. Fuzzy Evaluation Based on Distance from Average Solution (Fuzzy EDAS). The EDAS methodology was developed by Keshavarz Ghorabaee et al. [107], and the method ranks material on the basis of the average solution [108]. The average solution is arrived at by calculating the positive distance from average (PDA) and negative distance from average (NDA). The alternative that has higher PDA values and lower NDA values are the best-ranked material alternative. In the case of the fuzzy-EDAS methodology, alternatives are ranked in accordance with the decreasing value of the de-fuzzified appraisal score. In methods such as TOPSIS or VIKOR, we measure the optimal option based on the distance from the positive and negative ideal, that is, the optimal option that has the shortest distance from the positive ideal and the maximum distance from the negative ideal.

But in the EDAS method, the best solution is the distance from the average solution (AV). In this method, we do not need to calculate the positive and negative ideals but consider two criteria for evaluating the desirability of options (PDA and NDA).

The steps involved in the fuzzy EDAS method have been delineated in the ensuing discussion.

Let $\widetilde{A}$ denote the fuzzy decision matrix, i.e.,

$$\widetilde{A} = \left[\widetilde{a}_{ij}\right]_{n\times m} = \begin{bmatrix} \widetilde{a}_{11} & \cdots & \widetilde{a}_{1m} \\ \vdots & \ddots & \vdots \\ \widetilde{a}_{n1} & \cdots & \widetilde{a}_{nm} \end{bmatrix}, \tag{7}$$

where j is the number of alternatives and I signifies the criteria. The following steps are traced in order to solve a decision-making problem using fuzzy EDAS methodology:

Step 1: in this step of the framework proposed, objective weights are determined for each of the criteria Ci using Bellow equations. Objective weights are determined for the decision matrix supplied by all the decision-makers:

$$w_j^* = \frac{\sum_{i=1}^{m}\sum_{r=1}^{m}\left|p_{ij} - p_{rj}\right|}{\sqrt{\sum_{j=1}^{m}\left[\sum_{i=1}^{m}\sum_{r=1}^{m}\left|p_{ij} - p_{rj}\right|\right]^2}},$$

$$w_j^o = \frac{w_j^*}{\sum_{j=1}^{m} w_j^*}. \tag{8}$$

Step 2: a fuzzy average decision matrix is developed with respect to all the criteria considered using Table 8 and Bellow equation:

Table 7: Criteria obtained by fuzzy SWARA.

Main criteria	Criteria	b_j	k_j	q_j	W_j	Global weight	Total weight
1	Economic		(1, 1, 1)	(1, 1, 1)	(0.335, 0.455, 0.392)	0.395	0.0658443
7		(0.4, 0.5, 0.667)	(1.4, 1.5, 1.667)	(0.714, 0.666, 0.599)	(0.239, 0.303, 0.235)	0.259	0.0431739
6		(0.23, 1.5, 0.465)	(1.23, 2.5, 1, 465)	(0.58, 0.266, 0.408)	(0.194, 0.121, 0.160)	0.159	0.0265044
2		(1, 1, 1)	(2, 2, 2)	(0.29, 0.133, 0.204)	(0.097, 0.060, 0.080)	0.079	0.0131689
3		(0.540, 0.650, 0.23)	(1.540, 1.650, 1.23)	(0.188, 0.08, 0.165)	(0.063, 0.036, 0.064)	0.055	0.0091682
4		(0.53, 1.74, 0.37)	(1.53, 2.74, 1.37)	(0.122, 0.029, 0.120)	(0.040, 0.013, 0.047)	0.034	0.0056676
5		(0.444, 0.5, 1.36)	(1.444, 1.5, 2.36)	(0.084, 0.019, 0.050)	(0.028, 0.008, 0.019)	0.019	0.0031672
8	Culture		(1, 1, 1)	(1, 1, 1)	(0.407, 0.462, 0.501)	0.456	0.0760127
10		(0.5, 0.66, 1.12)	(1.5, 1.66, 2.12)	(0.666, 0.602, 0.471)	(0.271, 0.278, 0.236)	0.262	0.0436739
11		(1.04, 1.5, 1)	(2.04, 2.5, 2)	(0.326, 0.240, 0.235)	(0.133, 0.110, 0.117)	0.121	0.02017
14		(0.42, 0.373, 0.5)	(1.42, 1.373, 1.5)	(0.229, 0.174, 0.156)	(0.093, 0.080, 0.078)	0.084	0.0140023
15		(1, 1, 1)	(2, 2, 2)	(0.114, 0.087, 0.078)	(0.046, 0.040, 0.039)	0.042	0.0070012
12		(0.63, 1.2, 1)	(1.63, 2.2, 2)	(0.069, 0.039, 0.039)	(0.028, 0.018, 0.019)	0.022	0.0036673
13		(0.444, 0.76, 0.1.42)	(1.444, 1.76, 2.42)	(0.047, 0.022, 0.016)	(0.019, 0.010, 0.008)	0.013	0.002167
21	Environmental		(1, 1, 1)	(1, 1, 1)	(0.583, 0.600, 0.625)	0.603	0.1005168
20		(0.4, 0.5, 0.667)	(1.4, 1.5, 1.667)	(0.714, 0.666, 0.599)	(0.416, 0.399, 0.374)	0.397	0.0661777
23	Perceptual factors		(1, 1, 1)	(1, 1, 1)	(0.705, 0.741, 0.705)	0.717	0.1195199
22		(1.36, 1.87, 1.39)	(2.36, 2.87, 2.39)	(0.418, 0.348, 0.418)	(0.294, 0.258, 0.294)	0.282	0.0470078
38	Social		(1, 1, 1)	(1, 1, 1)	(0.381, 0.545, 0.428)	0.451	0.0751792
37		(0.53, 1.74, 0.37)	(1.53, 2.74, 1.37)	(0.653, 0.364, 0.729)	(0.248, 0.198, 0.312)	0.253	0.0421737
36		(0.454, 0.58, 1.38)	(1.454, 1.58, 2.38)	(0.449, 0.230, 0.306)	(0.171, 0.125, 0.131)	0.143	0.0238373
34		(1, 1, 1)	(2, 2, 2)	(0.224, 0.115, 0.153)	(0.085, 0.062, 0.065)	0.071	0.0118353
35		(0.5, 0.66, 1.12)	(1.5, 1.66, 2.12)	(0.149, 0.069, 0.072)	(0.056, 0.037, 0.030)	0.042	0.0070012
32		(1.04, 1.5, 1)	(2.04, 2.5, 2)	(0.073, 0.027, 0.036)	(0.027, 0.014, 0.015)	0.019	0.0031672
25		(0.42, 0.373, 0.5)	(1.42, 1.373, 1.5)	(0.051, 0.019, 0.024)	(0.019, 0.010, 0.010)	0.014	0.0023337
24		(1, 1, 1)	(2, 2, 2)	(0.025, 0.009, 0.012)	(0.009, 0.004, 0.005)	0.007	0.0011669
39	Health		(1, 1, 1)	(1, 1, 1)	(0.377, 0.454, 0.547)	0.460	0.0766794
42		(0.404, 0.76, 0.1.32)	(1.404, 1.76, 2.32)	(0.712, 0.568, 0.413)	(0.268, 0.258, 0.226)	0.251	0.0418403
41		(0.303, 0.5, 0.616)	(1.303, 1.5, 1.616)	(0.546, 0.378, 0.255)	(0.206, 0.171, 0.139)	0.173	0.0288381
40		(0.4, 0.5, 0.607)	(1.4, 1.5, 1.607)	(0.390, 0.252, 0.158)	(0.147, 0.114, 0.086)	0.116	0.0193366

Table 8: Linguistic terms for alternatives ratings [3, 12].

Linguistic term	Membership function
Very low (VL)	(0, 0, 0.1)
Medium low (ML)	(0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (F)	(0.3, 0.5, 0.75)
High (H)	(0.5, 0.75, 0.9)
Medium high (MH)	(0.75, 0.9, 1)
Very high (VH)	(0.9, 1, 1)

Note. Table 8 is reproduced from [108] [https://link.springer.com/book/10.1007%2F978-981-32-9072-3].

$$AV_j = \frac{\sum_{i=1}^{n} \tilde{a}_{ij}}{k}. \tag{9}$$

Step 3: the distance of optimal solution from negative feasible solutions must be maximum, whereas it should be minimum from the negative feasible solution. In this step of the Fuzzy EDAS methodology, matrices for fuzzy positive distance from average (PDA) and fuzzy negative distance from average (NDA) are calculated using Bellow equations:

$$\begin{aligned} PDA &= \left[pda_{ij}\right]_{n\times m}, \\ NDA &= \left[nda_{ij}\right]_{n\times m}, \end{aligned} \tag{10}$$

where for beneficial criteria,

$$\begin{aligned} pda_{ij} &= \left\{ \frac{\psi\left(\tilde{a}_{ij} - AV_j\right)}{k\left(AV_j\right)}, \right. \\ nda_{ij} &= \left\{ \frac{\psi\left(AV_j - \tilde{a}_{ij}\right)}{k\left(AV_j\right)}, \right. \end{aligned} \tag{11}$$

and for nonbeneficial criteria,

$$\begin{aligned} pda_{ij} &= \left\{ \frac{\psi\left(AV_j - \tilde{a}_{ij}\right)}{k\left(AV_j\right)}, \right. \\ nda_{ij} &= \left\{ \frac{\psi\left(\tilde{a}_{ij} - AV_j\right)}{k\left(AV_j\right)} \right. \end{aligned} \tag{12}$$

Step 4: in this step of the methodology, matrices are developed for fuzzy weighted positive and fuzzy weighted negative distances. Bellow equations are used for this purpose:

$$\begin{aligned} sp_i &= \sum_{j=1}^{m} \left(\widetilde{w}_j + pda_{ij}\right), \\ sn_i &= \sum_{j=1}^{m} \left(\widetilde{w}_j + nda_{ij}\right). \end{aligned} \tag{13}$$

Step 5: fuzzy normalized values for fuzzy weighted positive and fuzzy weighted negative distances are computed using Bellow equations:

$$\begin{aligned} nsp_i &= \frac{sp_i}{\max_i\left(k\left(sp_i\right)\right)}, \\ nsp_i &= 1 - \frac{sn_i}{\max_i\left(k\left(sn_i\right)\right)}. \end{aligned} \tag{14}$$

Step 6: in the penultimate step, fuzzy appraisal score for different alternatives is calculated using the Bellow equation:

$$as_i = \frac{nsp_i + nsn_i}{2}. \tag{15}$$

Step 7: in the last step, alternative materials are ranked in accordance with the decreasing value of de-fuzzified appraisal score. The best choice of the alternative material is the one with the highest value of appraisal score.

Finally, these 16 important tourism areas in Iran were prioritized using the opinions of experts and based on the six areas studied (Table 9):

Therefore, after identifying the priorities, it is necessary to perform sensitivity analysis in six areas. For this purpose, Fuzzy COPRAS (FC), Fuzzy MABAK (FM), and Fuzzy TOPSIS (FT) were used to provide a more detailed analysis of the accuracy of the results (Table 10):

It is clear that the model is well designed and the results of sensitivity analysis of the model proposed with alternative models show the same.

4. Discussion and Conceptual Cross-Check of Results

The present study shows good results. These results can be very effective in providing a practical and hybrid model in the field of tourism. Researchers first identified the satisfaction indicators of tourism target residents using a meta-combined model and using the discussions in previous research with 42 criteria being identified. Then, these indicators were screened using the fuzzy Delphi technique and the opinions of experts. The screening results show the elimination of 12 criteria that were identified as less in developing the satisfaction of tourists in Iran. Indicators 9, 16, 17, 18, 19, 26, 27, 28, 29, 30, 31, and 33 were removed.

Then, based on the results of the first stage, the indicators were classified into 6 areas and weighed with the fuzzy SWARA technique. The results of this stage show that in the economic field, index 1 has the highest weight with 0.395 and index 5 has the lowest weight with 0.019. In the cultural field, index 8 has the highest weight with 0.456 and index 13 has the lowest weight with 0.013. In the field of environment,

Table 9: Ranking of important tourism areas in Iran.

Alternatives	Ranking					
	Economic	Culture	Environmental	Perceptual factors	Social	Health
T-1	5	12	7	8	7	1
T-2	6	5	10	12	8	9
T-3	4	6	2	9	10	10
T-4	9	8	5	1	9	11
T-5	8	10	3	11	5	8
T-6	10	9	4	10	6	7
T-7	11	3	9	2	2	15
T-8	7	13	8	3	12	16
T-9	3	11	11	5	14	3
T-10	2	16	1	13	13	2
T-11	13	1	13	16	4	14
T-12	12	15	16	14	16	5
T-13	16	7	14	15	15	6
T-14	15	4	15	4	1	13
T-15	14	14	12	7	11	4
T-16	1	2	6	6	3	12

Table 10: Verification of the results.

	FC	FM	FT	FC	FM	FT	FC	FM	FT	FC	FM	FT	FC	FM	FT	FC	FM	FT
Alternatives	Economic			Culture			Environmental			Perceptual factors			Social			Health		
T-1	5	5	5	12	12	12	7	7	7	8	8	8	8	7	7	1	2	1
T-2	4	6	6	5	6	5	10	10	10	12	12	12	7	8	8	9	11	9
T-3	6	4	4	6	5	6	3	2	2	9	9	9	10	10	10	10	6	10
T-4	9	9	9	8	8	8	4	5	5	1	1	1	5	9	9	11	9	11
T-5	8	8	8	14	10	10	2	3	3	11	11	11	6	12	5	8	15	8
T-6	10	11	10	9	9	9	5	4	4	10	10	10	6	6	6	7	8	7
T-7	11	10	11	4	3	3	9	9	9	2	2	2	4	1	2	15	7	15
T-8	7	7	7	13	14	13	8	8	8	3	3	3	12	5	12	16	16	16
T-9	3	3	3	11	11	11	11	11	11	5	5	5	14	11	14	3	3	3
T-10	2	2	2	16	16	16	1	1	1	13	13	13	13	13	13	2	1	2
T-11	13	15	13	2	1	1	13	13	13	16	16	16	1	4	4	14	9	14
T-12	12	12	12	15	15	15	16	16	16	14	14	14	16	16	16	5	10	5
T-13	16	16	16	7	7	7	14	14	14	15	15	15	15	15	15	6	11	6
T-14	15	13	15	3	4	4	6	15	15	4	4	4	2	3	1	13	8	13
T-15	14	14	14	10	13	14	12	12	12	7	7	7	11	14	11	4	7	4
T-16	1	1	1	1	2	2	15	6	6	6	6	6	3	2	3	12	15	12

index 21 has the highest weight with 0.603 and index 20 has the lowest weight with 0.397. In the field of perceptual factors, index 23 has the highest weight with 0.717 and index 22 has the lowest weight with 0.282. In the social sphere, index 38 has the highest weight with 0.451 and index 24 has the lowest weight with 0.007. Finally, in the field of health, index 39 has the highest weight with 0.460 and index 40 has the lowest weight with 0.116. The output results of Fuzzy SWARA also generally show that index 23 has the highest weight with 0.119 and index 24 has the lowest weight with 0.001.

Finally, the indicators were prioritized into 6 areas and 16 important tourism regions in Iran. These areas are one of the most beautiful and important tourist areas in Iran. From an economic point of view, Biston and Bostan Arch, from a cultural point of view, ChoghaZanbil Ziggurat, from an environmental point of view, Ganj Lake, from perceptual factors, Kariz Underground City, from a social point of view, Yazd Chek Shrine, and from a health point of view, Qeshm salt cave. The sensitivity analysis of the model is also based on the following graph (Figure 5):

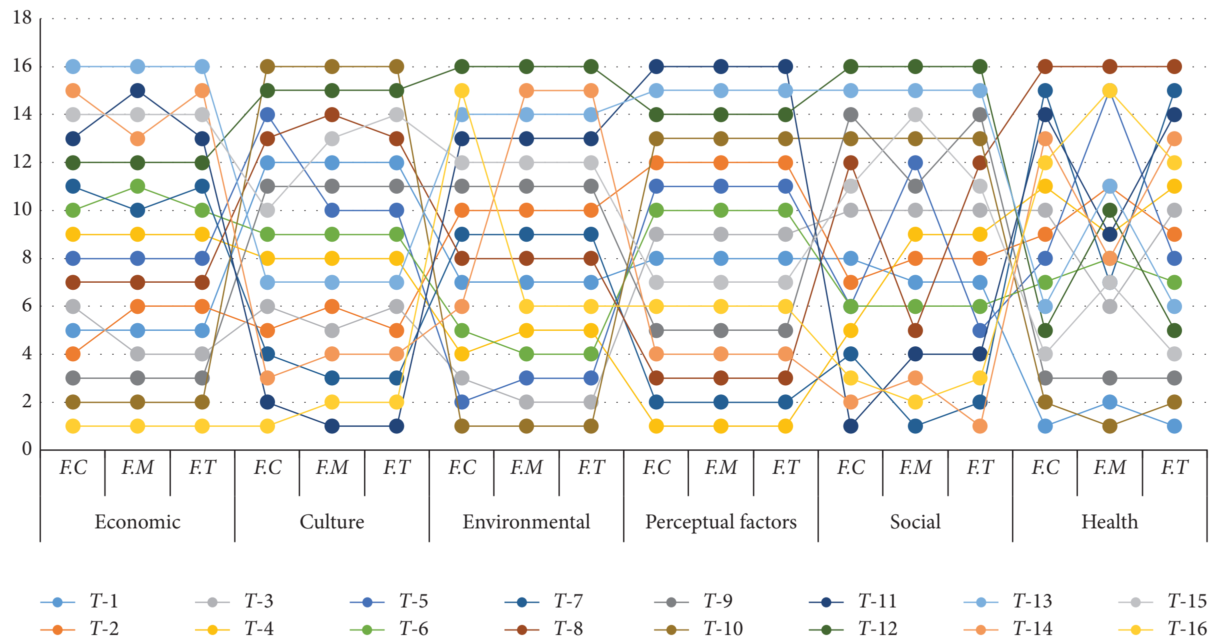

Figure 5: Sensitivity analysis.

5. Conclusion

Resident satisfaction with the purpose of tourism and the development of tourism are two sides of the same coin. Certainly, the future of tourism is closely tied to the support of the residents at the target areas on the one hand and the hospitality of local residents and their interaction with tourists on the other. In order to achieve sustainable tourism development, it is necessary to have an advantage in upstream documents for both the target population and the tourist. Ignoring the demands of the residents and not providing them with satisfaction and support will hurt the future of tourism in the country.

Resident satisfaction with the presence of tourists as well as their support for the development of tourism and their loyalty to tourism and the presence of tourists has a tremendous impact on the future of tourism in any region. Tourism requires the hospitality of local residents and their interaction with tourists. In the tourism industry, management must be such that the value, quality, and commitment of both parties are created. In other words, tourism has an advantage for both tourists and residents. If the demands of the residents and their satisfaction and support are ignored in tourism, the country will certainly not achieve the targets set in the field of tourism.

According to the research results, in order to achieve the development of the tourism industry in the communities, it is necessary to have the support of the local community for the development of tourism as one of the important stakeholders. This is also achieved through the satisfaction of the residents. In order to achieve their level of satisfaction, it is necessary for their attitude and understanding of tourism to be in the direction that the benefits of development outweigh its disadvantages and efforts need to be made in order to achieve this goal. If it turns out that the results of tourism activities are not harmful (or have limited harm) and may have benefits, each person will work together to enter and develop the industry. According to the research findings, infrastructural works should be done in the five main dimensions of tourism to create this feeling in the host communities, namely, economic, cultural, environmental, social, and health dimensions, which can be considered according to the components proposed and existing fields. As in any tourism situation, the necessary activities must be planned before their implementation, so this information can be used to prioritize the activities of the programs in question.

5.1. Research Limitations. Despite the results obtained in this study, there is an important limitation and research constraint that made it very difficult during the research, which was the issue of the coronavirus and the constraints that the researchers faced in conducting the field study. Also, the hybrid model was used to exploit the six criteria under study with perhaps the technological factors and limitations of the coronavirus crisis being ignored. Perhaps as a suggestion for future researchers is the need for the impact of these factors to be considered on the satisfaction of tourism target residents.

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Optimization of Tourism Real Estate Development Project Based on Option Premium Model

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Compared with that of traditional housing real estate, the development of tourism real estate is time-consuming, complex, and irreversible. It is hard to guide investment decision-making on tourism real estate with the conventional discount cash flow (DCF) method. This paper aims to demonstrate that the real option method can improve and optimize the investment decision-making on tourism real estate. Through case analysis, the real option model, i.e., the classic American real option model, and binary tree value distribution model were adopted to analyze the factors affecting the real option of tourism real estate, optimize the development sequence of tourism real estate project, and demonstrate the phased development value of tourism real state, thereby enhancing the development value of tourism real estate projects. The case analysis proves that tourism real estate investment is fully consistent with real option in the uncertain spatiotemporal attributes: uncertainty, irreversibility, and timeliness. Therefore, tourism real estate project carries obvious features of real option. The decision-making by the real option model is much more scientific and superior than that by the conventional DCF method. Since the application of real option theory has been emphasizing housing real estate over tourism real estate, the research results enrich the theory on real option-based investment decision-making for real estate and expand the application scope of real option.

1. Introduction

At present, tourism real estate enterprises still rely on traditional metrics to analyze and evaluate project investment, such as internal rate of return (IRR), payback time, and net present value (NPV) [1]. During project analysis and evaluation, these metrics are theoretically supported by the discount cash flow (DCF) method and suitable for small construction projects requiring one-time investment. In real life, however, tourism real estate development is often highly uncertain [2] as it tends to span across several regions, last a long time, and cover multiple phases. According to the traditional theory, the excessive uncertainty brings a huge risk to the projects. From the perspective of option, the uncertainty will push up the option value [3].

Since its proposal in the 1970s, real option and its pricing method have been applied to various emerging industries and venture capital industries. The application is particularly successful in the real estate sector, producing lots of representative research results (Table 1).

Chinese scholars started to examine real option in the early 21st century. Currently, real option theory is mainly adopted to discuss land market and housing real estate in real estate investment analysis [12].

Some scholars tried to apply real option theory in commercial real estate [13], and some tried to apply in water management [14].

However, by the practice of tourism real estate investment, the author found that very few scholars introduced the theory to other segments of real estate, namely, industrial real estate and logistics real estate by Wu et al. [15], especially in the tourism real estate, which still uses the backward NPV method.

This article attempts to apply the latest real options theory to tourism real estate innovatively.

We use option thinking instead of traditional net present value (NPV) thinking and give options for tourism real

Table 1: Representative foreign studies of real estate based on real option theory.

Field	Main topics	Representative works
Real estate mortgage	Mortgage pricing	McDonald and Siege [4]
Mortgage-backed security	Design and pricing of mortgage-backed security	Anderson et al. [5] Yeh and Lien [6]
Formulation of real estate purchase and sales strategies	Analysis on the housing provident fund system; presale pricing strategy for commercial housing	Yao and Pretorius [7]
Lease design and pricing	Design and pricing of different forms of lease; credit difference analysis under default risk	AlShelahi et al. [8]
Investment in real estate development	Analysis on land price structure; investment decisions on real estate development and redevelopment; conversion and hybrid development decisions between different land uses	Jang et al. [9] Dahan [10] Glascock et al. [11]

estate projects. By analyzing the real option value of tourism real estate projects, we can calculate the best development time of tourism real estate projects and realize dynamic optimization under uncertainty and demonstrated that Real Options can better optimize the investment decision-making on tourism real estate than net present value (NPV).

This paper is mainly composed of three parts: Introduction, Real Option Model, and Case Analysis. The first part explains the dilemma of investment decision-making in tourism real estate and summarizes that real option theory is mainly applied in land market and housing market, rather than tourism real estate. The second part interprets the diagram of option value, solves the real option tourism real estate model, and evaluates the influence of relevant variables on the model. The third part calculates the real option value of tourism real estate and determines the binary tree value distribution in each phase.

2. Modeling Basis

Black and Scholes and Merton pioneered the correct way to real options in 1973 and even won the Nobel Prize in Economics in 1997. Myers first proposed the concept of real options in 1977. The real options analysis framework believes that decision makers have the right to invest, expand, and abandon a project based on the new information obtained.

Considering the characteristics of tourism real estate, this article adopts the "classic, continuous, open," stochastic integral methods for pricing American options and innovatively discusses the effect of real options factors on tourism real estate project value.

2.1. Option Value Diagram. Option value was divided into two parts: internal value and time value [16]. The internal value of option is the sum of the two parts (Figure 1).

Specifically, the intrinsic value of the call option = the market price of the underlying asset–the exercise value of the option (present value).

The time value of an option refers to the profit potential value during the validity period.

The value of the option is the lower limit of the intrinsic value and the upper limit of the call option underlying asset price.

Obviously, the higher the volatility of the underlying asset price, the greater the time value of the option. And the volatility of the underlying asset is more advantageous than the disadvantages for the option owner.

This asymmetry leads to the willingness of the bulls to pay more options for the volatility over a period of time, thus generating time value.

2.2. Classic American Real Option Model. Suppose the project value V changes by the following geometric Brownian motion (GBM):

$$\mathrm{d}V = \alpha V \mathrm{d}t + \sigma V \mathrm{d}z, \quad (1)$$

where α is the percentage growth rate of GBM, i.e., the drift coefficient of simple Brownian motion; σ is the fluctuation rate of GBM, i.e., the change parameter of Brownian motion; and Dz is the increment of Wiener process. Formula (1) shows that the current project has a known value. However, the future value of the project obeys lognormal distribution. The variance will grow linearly with the change of time period. Hence, the project will have an indefinite future value. As a result, the investment opportunity of the project is equivalent to the long-term call option. Then, the meaning of investment decision-making is to decide when to exercise the option. Therefore, investment decision-making can be treated as an option pricing problem and solved through dynamic planning.

2.2.1. Solution Features. Through dynamic planning, the solution features can be obtained by option pricing (contingent debt) [16]. Then, it is necessary to find the rule to maximize $F(V)$, the value of option investment. At time t, investment has a return of $V_t - I$. Thus, the expected present value can be maximized by

$$F(V) = \max E\left[(V_T - I)e^{-\rho T}\right], \quad (2)$$

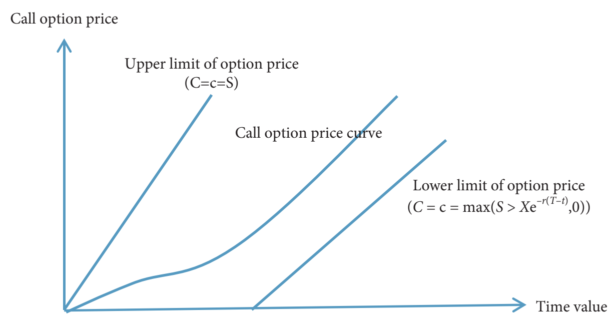

Figure 1: European call option price curve of no income assets.

where p is the discount rate; T is the time of decision-making in the future; and E is the expectation. To maximize constraint (2) on project v, it must be assumed that $\alpha < p$.

α is the percentage growth rate of GBM; if $p < \alpha$, the e^{-pT} factor will become infinite and the value growth rate of the project will be infinite too, causing the formula insolvent.

So, we have to assume that $\alpha < p$ and assume that $\delta = p - \alpha > 0$ later and constrain the value of α to solve the formula solution.

There is also the optimal stopping problem in continuous time. The investment opportunity $F(V)$ will not generate any cash flow prior to the time of investment T. The only return is the capital gain. For the investor, V does not have an optimal value. Thus, the continuous-time Bellman equation can be established as follows:

$$pF\mathrm{d}t = E(\mathrm{d}F). \tag{3}$$

Formula (3) shows that, for the investment opportunity, the expected total return $pF\mathrm{d}t$ equals the expected added value in the period $\mathrm{d}t$. Expanding $\mathrm{d}F$ by Itô's lemma,

$$\mathrm{d}F = F'(V)\mathrm{d}V + \frac{1}{2}F''(V)(\mathrm{d}V)^2. \tag{4}$$

Substituting $\mathrm{d}V$ of formula (1) to the above formula and making $E(\mathrm{d}z) = 0$,

$$E(\mathrm{d}F) = \alpha VF'(V)\mathrm{d}t + \frac{1}{2}\sigma^2V^2F''(V)\mathrm{d}t. \tag{5}$$

Dividing the above formula by $\mathrm{d}t$, the Bellman equation can be obtained as follows:

$$\frac{1}{2}\sigma^2V^2F''(V) + \alpha VF'(V) - pF = 0. \tag{6}$$

If α is substituted with $p - \delta$, it must be assumed that $\delta > 0$ or $\alpha < p$ to ensure the existence of the optimal solution. After the substitution, $F(V)$ must satisfy the following:

$$\frac{1}{2}\sigma^2V^2F''(V) + (p - \delta)VF'(V) - pF = 0. \tag{7}$$

In addition, $F(V)$ must meet the following boundary conditions:

$$F(0) = 0, \tag{8}$$

$$F(V^*) = V^* - I, \tag{9}$$

$$F'(V^*) = I. \tag{10}$$

Condition (8) means $F(V) = 0$ under $V = 0$. Thus, if $V = 0$, the investment option has no value. The other two conditions are designed for investment optimization. As the value of optimal investment, V^* can reflect the net return $V^* - 1$ obtained by the enterprise. Formula (10) is the smooth boundary condition. If a weak $F(V)$ is not continuous and if the critical exercise point V^* is not smooth, then the return can be increased by dispersing the investment across different points.

Formula (7) is a second-order differential equation, which needs to conform to both boundary conditions. Although the first boundary has a known position, the second boundary is unknown. That is, the second boundary is necessary to make V^* a part of the solution. Formula (9) can also be explained after being converted into $V^* - F(V^*) = I$. If an enterprise makes an investment, t could obtain a project of value V. However, the investment option or opportunity whose value is $F(V)$ will be discarded. Hence, the net income is the value-opportunity cost: $V - F(V)$. At the point of critical value V^*, the net income equals the tangible or direct investment cost I. Similarly, the equation can be transformed to $V^* = I + F(V^*)$ so that the total cost of project value and investment is the sum of opportunity cost and direct cost.

Formula (7) must be solved under constraints (8)–(10) to obtain $F(V)$ rapidly. The functional form can be speculated. If it is effective, then the actual solution can be determined by substituting the form into the formula. We firstly described and derived some features of the solution, before giving its details.

To satisfy formula (6), the following form must be adopted for the solving process:

$$F(V) = AV^{\beta}. \tag{11}$$

Here is a modification of the formula. β and A are all calculated by each parameters.

And all parameters satisfy Brownian motion and Wiener formula (1) where α is the percentage growth rate of GBM, i.e., the drift coefficient of simple Brownian motion; $\delta = \rho - \sigma$ is the fluctuation rate of GBM, i.e., the change parameter of Brownian motion; and ρ is the risk-free drift rate, i.e., the risk-free yield.

The two constants, namely, critical value V^* of optimal investment and constant A, can be solved by substituting boundary conditions (9) and (10) into formula (11):

$$V^* = \frac{\beta}{\beta - 1}I, \tag{12}$$

$$A = \frac{V^* - I}{(V^*)^{\beta}} = \frac{(\beta - 1)^{(\beta-1)}}{\beta^{\beta}I^{\beta-1}}. \tag{13}$$

Formulas (11)–(13) define the optimal investment rule, i.e., the critical value V^*, and the value of investment opportunity. Investing on that point can optimize the features. The features of the solution will be described in detail in the subsequent analysis.

2.2.2. Solving β. Since tourism real estate project has an optimal development time, the said solution is important to the project.

[Footnote: Dixit and Pindyck [17]].

Notably, it can be derived from $\beta > 1$ that $(\beta/\beta - 1) > 1$ and $V^* > I$. Therefore, the NPv rule is proved sufficiently accurate. For tourism real estate project, there is a wedge between investment cost I and critical value V^* due to the irreversibility and uncertainty of the project. The wedge size equals the factor $\beta/\beta - 1$. The factor should be considered fully in order to examine the response of the wedge to the changes of some parameters, as well as the magnitude of the parameter values. For this purpose, it is necessary to analyze the solution to formula (9) in greater details.

Factor (7) is linearly correlated with dependent variable F and its derivative. Hence, the general solution of (7) can be considered a linear combination of two independent solutions. If the function AV^{β} is selected, it can be assumed that β is the root of homogeneous equation. Thus, we have

$$\frac{1}{2}\alpha^2\beta(\beta - 1) + (\rho - \delta)\beta - \rho = 0. \tag{14}$$

The two roots of the equation can be expressed as follows:

$$\begin{aligned} \beta_1 &= \left(\frac{1}{2} - \frac{\rho - \delta}{\alpha^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{\rho - \delta}{\alpha^2}\right)^2 + \frac{2\rho}{\alpha^2}} > 1, \\ \beta_2 &= \left(\frac{1}{2} - \frac{\rho - \delta}{\alpha^2}\right) - \sqrt{\left(\frac{1}{2} - \frac{\rho - \delta}{\alpha^2}\right)^2 + \frac{2\rho}{\alpha^2}} < 0. \end{aligned} \tag{15}$$

Since $\beta > 0$, β_1 is the root of the equation.

β_1 is a definite value; as long as each parameter is determined, it is unique. This formula reflects the relationship between σ, p, and δ.

So that we can also calculate V^*, A, and $F(V)$, which just is the best real option value by formulas (11)–(13).

2.2.3. Influence of Real Option Factor. As the effects of project value, α, δ, and p can be evaluated by a standard static comparison:

(1) α is the percentage growth rate of GBM, i.e., the drift coefficient of simple Brownian motion. It can be understood as the expected yield.

If α is larger, it indicates that the investor's expected rate of return is higher, and it also indicates that the investor is willing to take greater risks.

If α changes with time or the variable V, it will become more uncertain when determining the optimal investment rule.

Different decision makers have different expectations, which directly affects the valuation results of real option price.

With the growth of α and decrease in β_1, the value of $\beta_1/\beta_1 - 1$ will increase. Then, value V will become more uncertain in the future, resulting in a larger project value $F(V)$.

(2) $\delta = p - \sigma$ is the fluctuation rate of GBM, i.e., the change parameter of Brownian motion. It can be understood as the fluctuation rate of the project. $\delta = p - \sigma$ describes the deficiency of return or convenience yield.

Because generally we believe that a competitive product market will prevent prices from being too high or too low. Product prices fluctuate based on the intrinsic value of the product and obey the mean reversion.

Therefore, the distribution of product prices is more in line with the normal distribution, that is, in line with the Brownian motion on the function. This is why we put forward the geometric Brownian motion (GBM) formula at the beginning.

And more importantly, $\delta = p - \sigma$ can just express the extent of price deviation from value, which is also the volatility of price. Therefore, δ can be regarded as the volatility of the project price.

Since β_1 increases with δ, a higher δ leads to a smaller wedge $\beta_1/\beta_1 - 1$. The growth of δ will stabilize the future value V and suppress the project value $F(V)$ in the future.

(3) p is the risk-free drift rate, i.e., the endogenous discount rate and correlation coefficient in dynamic planning. It can be understood as risk-free yield.

Since β_1 has a negative correlation with p, a higher p means a larger wedge $\beta_1/\beta_1 - 1$. The growth of p will destabilize the future value V,] and bolster the project value $F(V)$ in the future.

2.3. Influence of Real State. Therefore, it can be discovered that

(1) When ρ and δ remains unchanged, the real option value will increase with α, i.e., the expected yield, and decrease with α.

The α value is deeply affected by the bounded rationality of tourism real estate investors. Optimistic investors often overestimate the expected yield, and conservative investors tend to underestimate the expected yield.

Therefore, when the expected yield of tourism real estate project is overestimated, the real option value must have been overestimated; when the expected yield is underestimated, the latter must have been underestimated, even to a level below the investment cost, making the project seemingly unsuitable for investment. In this case, if investors are not confidence about the benefit of tourism real estate project or strictly control the development risks of tourism real estate, they could wait for another investment opportunity or give up the investment opportunity in order to avoid investment risks.

In general, a project with high investment difficulty has a high-risk factor. It is often believed that a high-risk is often accompanied by a high benefit. Thus, investors may expect more benefits from difficult projects. For tourism real estate investment, man-made tourism real estate is more difficult and uncertain than natural tourism real estate or human tourism real estate. Therefore, man-made tourism real estate has a higher expected yield than the latter two tourism real estates.

(2) When ρ and δ remain unchanged, the real option value will decrease with the growing convenience rate of tourism real estate δ, i.e., the dividend yield implied in the fund invested in tourism real estate or the opportunity cost of fund utilization, and increase with the decrease in δ.

Therefore, there is a cost to utilize the fund invested in tourism real estate. The utilization of the fund does not bring any excessive income. If the investment fund has a high dividend yield, conservative investors would rather wait than invest in tourism real estate. The investment in tourism real estate can be stimulated by a low convenience yield, a low dividend yield, and the bounded rationality of investors. Table 2 shows the relationship between classic real option parameters and project value.

3. Case Analysis

3.1. Real Option Value of Project A. After summarizing the incomes and costs of project development, the net cash flow of the tourism real estate project can be clarified as Table 3. The NPV of Project A can be calculated by taking the discount rate of 4%. According to the NPV formula, simply adopt the bank five-year average loan interest rate of 4%, as the discount rate.

3.1.1. Calculation of Real Option Value. According to the abovementioned formula, real option value can be calculated by

$$\beta_1 = \left(\frac{1}{2} - \frac{\rho - \delta}{\alpha^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{\rho - \delta}{\alpha^2}\right)^2 + \frac{2\rho}{\alpha^2}} > 1. \tag{16}$$

The real option value is optimal (maximum) when $V = V^*$.

The first step is to calculate the expected growth rate α. From Table 3, it can be seen that the total investment cost is 3,755,970,000 yuan, the total investment income is 4,396,520,000, and time T is 7. Then, $\alpha = 2.66\%$ can be solved by the growth rate formula as follows:

$$4,396,520,000 = 3,755,970,000 * (1 + \alpha)(7 - 1). \tag{17}$$

Taking the discount rate of 4%, the convenience yield equals 4%. Then, it can be computed that $\beta = 11.145$ and $A = 9.62798E{-}59$ (close to zero). Setting the cost I to 3,755,970,000 yuan, then

$$\begin{aligned} V^* &= 4,126,201,100 \text{ yuan}, \\ F(V) &= 370,231,100 \text{ yuan}. \end{aligned} \tag{18}$$

3.1.2. Optimal Development Cycle. For real option investment decision-making for tourism real estate, a key consideration is the optimal development cycle. After analyzing the project development, the initial year discount and initial value of the project enterprise were both 3,755,970,000.

The optimal development cycle of real option can be defined by

$$\begin{aligned} T &= \frac{1}{\alpha}\ln\left[\frac{\rho I}{(\rho - \alpha)X_0}\right], \\ T &= \frac{1}{2.66\%}\ln\left[\frac{4\%}{(4\% - 2.66\%)}\right] = 41.11 \text{ (years)}. \end{aligned} \tag{19}$$

Under the discount rate of 4%, if the tourism real estate project maintains an annual yield of 2.66%, then the optimal development cycle of the project is 41.11 years. The option value of the project will peak in the 41.11 year. That is, the optimal lifecycle of the project is 41.11 years.

Note that the later operating phase faces a very high uncertainty. The development and operation must be adjusted according to the actual environment. After each adjustment, the cash flow and real option value must be recalculated. This reflects the agility and managerial flexibility of real option.

3.2. Real Option Value Distribution. By real option premium, the housing subprojects were ranked and subjected to phased development. As shown in Figure 2, the project development covers four phases:

(i) *Phase I.* Tourism project I (rainbow forest and tourism facilities): Give full play to the role of the rainbow forest and the supporting facilities, creating an elegant, safe, and harmonious atmosphere for the tourism real estate project. In this way, the premiums of the land and real estate project will be further improved.

(ii) *Phase II.* Real estate project I (mall high-rises): Because of the large option premium, start construction immediately when rainbow forest is about to complete, to avoid affecting follow-up construction.

(iii) *Phase III.* Tourism project II (man-made resources): Develop dream islands and children's playground, providing the necessary resources for subsequent real estate development.

(iv) *Phase IV.* Real estate project II (real estate project): Develop high-rises block and villa block following the relevant procedures, aiming to obtain option premium and maximize project income.

Table 2: Relationship between classic real option parameters and project value.

Parameter	Meaning	Correlation with F
α	Expected yield	Positive
σ	Fluctuation rate	Positive
P	Discount rate, risk-free yield	Positive
Δ	Convenience yield (dividend yield)	Negative

Table 3: Cash flow of the tourism real estate project under Project A (unit: yuan).

Development plan	Total	2016	2017	2018	2019	2020	2021	2022
Development cost-housing	2,455,650,000	887,650,000	387,970,000	257,580,000	379,760,000	410,550,000	132,120,000	0
Development costs-tourism	1,300,320,000	477,800,000	0	74,400,000	35,050,000	406,800,000	254,830,000	51,430,000
Total investment cost	3,755,970,000	1,365,450,000	387,970,000	331,980,000	414,810,000	817,350,000	386,960,000	51,430,000
Housing sales revenue	3,310,520,000	0	476,160,000	734,400,000	214,400,000	1,122,790,000	762,760,000	0
Tourism sales revenue	1,086,000,000	0	0	0	276,000,000	0	405,000,000	405,000,000
Total investment income	4,396,520,000	0	476,160,000	734,400,000	490,400,000	1,122,790,000	1,167,760,000	405,000,000
Net cash flow	327,770,000	−1,365,450,000	88,180,000	402,410,000	75,580,000	305,440,000	780,800,000	353,560,000

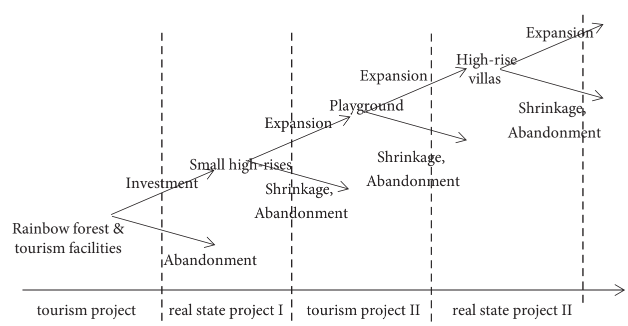

Figure 2: Improved development phases of tourism real estate project.

In the light of the actual situation, the binary tree value of the tourism real estate project was analyzed and calculated. The first is to solve the fluctuation rate. The rate was obviously 37.9%, as mentioned in the above analysis. In our plan, the values of S and X are already given: 439,652 (10,000 yuan) and 375,597 (10,000 yuan). Besides, $\alpha = 0.2539$, $T = 7$, and $\rho = 0.04$.

Then, the rise factor, fall factor, and risk neutral probability can be, respectively, calculated by

$$u = e^{\sigma\sqrt{\xi T}} = e^{0.3790*\sqrt{1/7}} = 1.056,$$
$$d = e^{-\sigma\sqrt{\xi T}} = \frac{1}{u} = \frac{1}{1.056} = 0.947, \tag{20}$$
$$p = \frac{e^{P(\zeta T)} - d}{u - d} = \frac{e^{4\%(1/7)} - 0.947}{1.056 - 0.947} = 0.539.$$

Next, the tourism real estate project was decomposed by the seven periods (years). The binary tree model of real option was derived for each period (Figure 3 and Table 4).

Different from the traditional market-driven development strategy, our development strategy, which is based on the optimal value of the real option premium model, integrates high-rises, multistory buildings, with villas, and develops all these subprojects at once, thereby avoiding the construction difficulty in cross-development in the preliminary phase. In addition, the least popular subproject, i.e., the high-rises, was developed first, and the priciest villas were developed at the end of the project such that the villas can be sold at a high price.

After being improved by the real option method, Project A can obtain option premium and live up to development needs. The improved project plan is highly feasible.

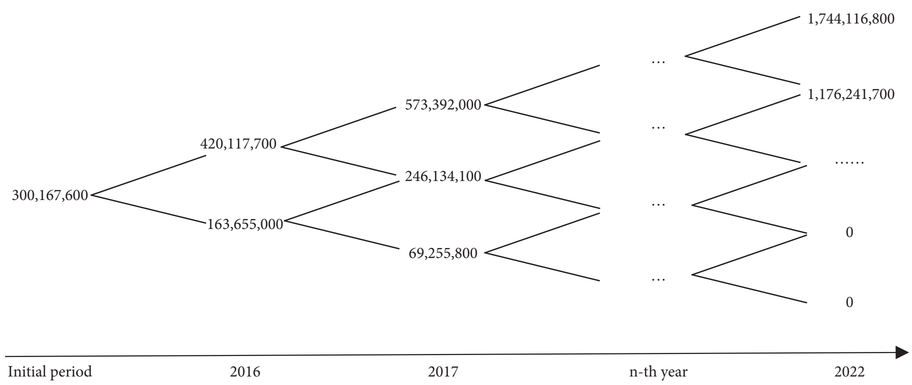

Figure 3: Real option value distribution of tourism real estate project (unit: yuan).

Table 4: Real option value of tourism real estate project in each period (unit: yuan).

Initial period	2016	2017	2018	2019	2020	2021	2022
300,167,600	420,117,700	573,392,000	760,774,700	978,607,300	1,218,980,400	1,473,877,100	1,744,116,800
0	163,655,000	246,134,100	361,434,900	515,545,800	709,733,000	936,114,200	1,176,241,700
0	0	69,255,800	114,385,500	185,743,400	294,913,500	453,874,500	666,998,700
0	0	0	17,351,400	32,376,400	60,411,900	112,724,000	210,334,300
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	00	0	0
	0	0	0	0	0	0	0
	0	0	0	0	0	0	0

4. Conclusions

Through drawing real option theory to the tourism real estate investment decision, this article has achieved certain results. However, there are also some shortcomings, such as the limitation of data access, the simplified application of formula models, and the lack of consideration of more special circumstances.

In the future, it is necessary to further deepen the discussion on the option game and behavioral economics of tourism real estate.

After reviewing the dilemma of investment decision-making in tourism real estate, this article innovatively applies real options to the tourism real estate, which is very different from the previous net present value (NPV) method that cannot adapt to tourism real estate.

And this article further uses real option factor parameters to explain the changes in tourism real estate, derives the real option tourism real estate model, and applies the model to the development of an actual project.

It is concluded that tourism real estate project carries obvious features of real option; real option-based decision-making is much better than market-driven decision-making; and the tourism real estate project becomes more valuable after being improved by the real option tourism real estate model. It greatly deepens research on options in tourism real estate.

The research results provide a good reference for applying real option in the investment decision-making for tourism real estate.

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Research on Intelligent Recommendation Business Model of Tourism Enterprise Value Platform from the Perspective of Value Cocreation

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With the rapid development of China's economy, people pay attention to their own quality of life, and tourism has become the first choice for people from all walks of life to relax themselves. Tourism travel has mainly developed from the form of travel agency registration to the form of online registration based on the network platform business model. Considering the value cocreation and the diversity of tourism enterprise platform, this paper puts forward the business model research of intelligent recommendation of tourism enterprise platform from the perspective of value cocreation. Firstly, the commonly used recommendation algorithms are introduced, which are collaborative filtering recommendation algorithm, content filtering recommendation algorithm, and association rule recommendation algorithm. Secondly, it analyzes the number of tourists and economic benefits of the business platform of tourism enterprises from April 2020 to April 2021 and also analyzes the business models of five modules under the tourism platform on different platforms. Finally, three recommendation algorithms are used to compare the comprehensive performance of five modules in different business models. Finally, we find that the rate of accuracy and recall of business is above 88%, which can have good economic benefits and provide customers with high-quality recommendation service and good satisfaction.

1. Introduction

This paper discusses the intelligentization of tourism recommendation system based on WebGIS and gives the organization mode of urban tourism recommendation knowledge base based on WebGIS and the design scheme of inference engine in literature [1] using JSP and MapXtreme to realize the city tourism recommendation system. This scheme is very suitable for establishing intelligent city tourism information system. Applying data mining technology [2] to provide services for users' personalized needs is a hot spot in current tourism research. This paper introduces a tourism service intelligent recommendation system based on Apriori-MD algorithm, which is twice as efficient as Apriori algorithm. It has a wide application prospect in the tourism market. Because of the large error of data calculation in traditional recommendation system, literature [3] proposes an intelligent recommendation system for tourist attractions based on collaborative filtering. The overall structure diagram of the system is designed. The results show that the intelligent recommendation system has small data calculation error and good recommendation effect. Literature [4] deals with big data and its value-added tourism, which provides a better understanding of customer behaviors and preferences for making decisions. The rapid spread of new technologies in Morocco's tourism industry has created new demands and challenges, predicting the behaviour of tourists and providing personalized services. The new big data system helps tourism stakeholders make appropriate strategic decisions and promotes the development of tourism in Morocco. Literature [5] proposes an ontology-based CBR system for intelligent recommendation of tourism products and proposes an ontology-based case representation method and corresponding case retrieval method. It is proved that the system is effective. The characteristics of tourism show its importance to economic growth and the influence of information technology system. The TAST model proposed in literature [6] can effectively collect the personalized characteristics of tourism information. After generating the TAST model, the cocktail method is used to generate the recommended list of tourism packages, and the cocktail method is more effective in recommending tourism packages. The Internet has become the media of choice for many travelers to access travel information, as well as in Turkey. Literature [7] provides a new method for the marketing strategy of Turkish travel agencies. Using case-based reasoning algorithm, an intelligent system is established as a recommendation tool for travel planning. In mobile travel applications, active recommendation is particularly practical. Literature [8] proposes a method and research prototype based on smart space and active recommendation system technology, and the system implementing the proposed method helps tourists use their mobile devices. Literature [9] proposes the overall structure and functionality of an intelligent recommendation system that enables a user to identify his/her own destination, bundle a set of products, and make a travel plan for personalized travel. Literature [10] proposes an intelligent context-aware recommendation system, which makes intelligent reasoning to determine the weight or importance of different types of environment and time context. Tour guide applications rely heavily on location, resulting in inappropriate advice, which can be mitigated if proper personalization and content filtering are performed. Travel reviews and travel notes are two major ways to share social travel. More and more people are willing to share their travel experiences and feelings on the web, forming fragmented travel knowledge. Literature [11] proposes a multisource social media data fusion method, Crowd Travel, which provides users with travel information through crowd intelligent mining. Data mining, web mining, and knowledge management can be used to customize individual or group information services to improve tourists' satisfaction. For the concept of intelligent tourism electronic portal, literature [12] put forward the basic framework of intelligent tourism electronic portal.

2. Recommendation Algorithm Analysis

2.1. Collaborative Filtering Recommendation Algorithm. The core part of collaborative filtering recommendation algorithm is the selection of nearest neighbors [13]. The effectiveness and efficiency of this algorithm depend on the effectiveness and efficiency of neighbor user similarity calculation. There are three common calculation methods: cosine similarity, modified cosine similarity, and Pearson correlation coefficient, which will be introduced below.

The basic steps of collaborative filtering recommendation algorithm are as follows.

Input: current user ID, user-item scoring matrix UR, number of nearest neighbors K, maximum recommended value top-N;

Output: Recommended item list L;

Step 1: in the recommendation system based on user CF, input the scoring data of all users for all items, and construct a matrix R of $M * N$ as shown in Table 1 (M users and N items), and R_{ij} represents the scoring value of the ith user for the jth item. The rating of a user is considered as a vector in the n-dimensional term space. If the i user does not rate the j term, the matrix is expressed as $R_{ij} = 0$.

In the recommendation in Table 1, the user and project scoring matrix reflects the recommendation relationship. If the score of the matrix is high, it means that the user has a high recommendation for this product and its commercial value is obvious. If there is a similar product recommendation value between different users, the product recommendation between different users will be compared, and different products will be recommended between different customers, thus increasing income.

Step 2: calculate the nearest neighbor; that is, calculate the user similarity value between the current user and all M users, and select K users with the largest user similarity as the nearest neighbors of the current user. As mentioned earlier, there are multiple methods to calculate user similarity, and the commonly used ones are the following.

2.1.1. Cosine-based similarity. Assuming that the set of items that users i and j have commented on together is represented by i, the similarity between the two users, sim(i, j), is defined as

$$\operatorname{sim}(i, j) = \frac{\sum_{c\in \mathrm{I}} R_{i,c} R_{j,c}}{\sqrt{\sum_{c\in \mathrm{I}} R_{i,c}^2}\sqrt{\sum_{c\in \mathrm{I}} R_{j,c}^2}}. \quad (1)$$

Among them, $R_{i,c}$ and $R_{j,c}$ represent the scores of users i and j on item C, respectively.

2.1.2. Modified cosine similarity. The modified cosine similarity calculation method subtracts the user's average score for all items from the user's score for a certain item, which avoids the calculation method of formula (1) not considering the difference between the average user scores. For example, some users tend to score high scores and low scores, thereby solving the problem of scoring scale among different users, and the calculation formula is defined.

$$\operatorname{sim}(i, j) = \frac{\sum_{c\in \mathrm{I}_{ij}} \left(R_{i,c} - R_i\right)\left(R_{jf} - R_j\right)}{\sqrt{\sum_{c\in \mathrm{I}_i} \left(R_{i,c} - R_i\right)^2}\sqrt{\sum_{c\in \mathrm{I}_j} \left(R_{if} - R_j\right)^2}}. \quad (2)$$

Table 1: User-item scoring matrix.

User/item	I_1	I_2	I_3	...	I_n
U_1	R_{11}	R_{12}	R_{13}	...	R_{1n}
U_2	R_{21}	R_{22}	R_{23}	...	R_{2n}
...	...	...	...	...	...
U_m	R_{m1}	R_{m2}	R_{m3}	...	R_{mn}

Among them, R_i and R_j represent the average scores of users i and j on the project, respectively.

2.1.3. Person correlation coefficient

For similarity between users i, j, sim(i, j) is also measured by Pearson correlation coefficient as follows:

$$\operatorname{sim}(i,j)=\frac{\sum_{c\in \mathrm{I}_{ij}}\left(R_{i,c}-\overline{R}_i\right)\left(R_{j,c}-\overline{R}_j\right)}{\sqrt{\sum_{c\in \mathrm{I}_{ij}}\left(R_{i,c}-\overline{R}_i\right)^2}\sqrt{\sum_{c\in \mathrm{I}_j}\left(R_{j,c}-\overline{R}_j\right)^2}}. \tag{3}$$

Step 3: K nearest neighbors of the current user are obtained through the above methods, and the corresponding recommendation results are generated in the next step. If the nearest neighbor set of user u is represented by N, the prediction score $P_{u,i}$ of user u for item i is calculated as follows:

$$P_{u,i}=R_u+\frac{\sum_{n\in N}\operatorname{sim}(u,n)\times\left(R_{n,i}-R_n\right)}{\sum_{n\in N}\left(|\operatorname{sim}(u,n)|\right)}, \tag{4}$$

where sim_{nu} denotes the similarity between users u and n, R denotes the score of user n on item i, and R_u and R_n denote the average score of users u and n on item i, respectively.

Step 4: through the above method, the current user can calculate the prediction scores of all commodities without interactive behaviors and finally select the list L of top-N recommended items with the highest prediction scores to the current user.

2.2. Content Filtering Recommendation Algorithm. In the tourism platform resource representation model and user consumption preference model, it has been proposed that, due to the variety of commodity types and different commodity characteristics and attributes involved in e-commerce, all categories of commodities are represented as a set $\{R_i\}$. It is a class t commodity, which is represented by binary groups $<d_i, g_i>$, where d_i denotes the ith attribute of the tth commodity and g_i denotes the set of values of the attribute d_i. The user's preferences on all categories of goods are expressed as a set $\{U_t\}$, where U_t is the user's preferences on category t goods. U_t is represented by the triple $<a_i, v_i, w_i>$, $i=1,\ldots, m$, where a_i represents the ith attribute of the tth commodity. If the value of the attribute a_i is numeric, v_i denotes the value preferred by the user on the attribute; if the value of the attribute a_i is nonnumeric, v_i denotes the set of attribute values preferred by the user on the attribute; W_i represents the user's weight on the attribute a_i, which is used to describe the degree to which the user pays attention to the attribute, and satisfies that $\sum_{i=1}^{m} w_i = 1$ and m is the number of T-type commodity attributes.

2.2.1. Mining Algorithm of Consumer Preference. Input is user's consumption preference on category t goods $<a_i, v_i, w_i>$.

(i) Step 1: data preprocessing: extract the historical consumption records of users on the T-type goods, and sort them according to the time sequence of users' consumption. For each attribute a_i of the t-type goods, the value set $v_i=\{v_i^1, v_i^2,\ldots, v_i^n\}$ is obtained, and n is the number of times the user consumes the t-type goods. For each attribute a_i, execute step 2 through step 4, and then go to step 5.

(ii) Step 2: attribute value distribution probability calculation: if the value of a_i is continuous, it is discretized by interval partition, and the partitioned interval is represented by b_k, and $v_i^1, v_i^2,\ldots, v_i^n$ is mapped to each interval. If a_i is a discrete value, its value is expressed by b_k. The probability that the attribute a_i has a value of b_k is $p(b_k)=n_{b_k}/n$, where n_{b_k} represents the number of times that the commodity consumed by the user has a value of b_k on the attribute a_i or is located in the interval b_k.

(iii) Step 3: calculate attribute weight through information entropy. The information is $H(a_i)=-\sum_{b_k\in v_i} p(b_k)\log p(b_k)$of the attribute a_i, the information entropy is normalized $H'(a_i)=H(a_i)/\sum_{i=1}^{m} H(a_i)$, and the weight of the attribute a_i is $W_t = 1-H'(a_i)$.

(iv) Step 4: adjust the attribute weight according to the change frequency of attribute value. The change frequency of attribute value v_i is $q_i=n^*/n-1\,(n\geq 2)$, where $n*$ is the number of times the values of adjacent attributes actually change. The weight of adjustment attribute is $w_i = w_i\times(1-\beta\times q_i)$, β is the adjustment range parameter, and the larger β is, the larger the adjustment range is.

(v) Step 5: normalization of attribute weights: the normalization formula is $W''_t = W'_i/\sum_{i=1}^{m} W'$.

(vi) Step 6: attribute value preference calculation: the user's score is based on ten-point system, and the mapping relationship between score θ and score coefficient η is= $\xi=\theta-\delta/10-\delta$, which is the lowest score of all goods consumed by users. The numerical attribute value preference is adjusted by forgetting factor, the calculation formula of forgetting factor is $\lambda=\xi\times p(v_i^{\text{new}})$, v_i^{new} is the value of the latest consumer goods on attribute a_i, $p(v_i^{\text{new}})$ is the probability of attribute a_i taking v_i^{new}, and the adjustment formula is $V'_i=\lambda v_i^{\text{new}}+(1-\lambda)V_i$. There are at most i elements stored in the preference set of nonnumerical attribute values, and the preference attribute values are updated according to the first-in-first-out principle, and the size of i is the empirical value 5.

Output is user's new consumption preference$\langle a_i, v_i', w_i'' \rangle$.

The recommendation algorithm based on consumer preference calculates the similarity between consumer preference $\langle a_i, v_i', w_i'' \rangle$ and commodity$\langle d_i, g_i \rangle$, matches the consumer preference and commodity, generates a recommendation list according to the matching degree, and recommends the top-N commodities to users in turn. The recommended process is as follows:

(i) Step 1: obtain the attributes, attribute values, and attribute weights of T-type commodities from the current user consumption preference model U_t and commodity model R_t, respectively.

(ii) Step 2: if the value of the attribute a_i is numerical data, the similarity between the user's consumption preference and the commodity on the ith attribute is $S_i = |v_i - g_i|/\max\{v_i, g_i\}$. If the value of the attribute a_i is nonnumerical data, the similarity between the user's consumption preference and the commodity on the ith attribute is $S_i = v_i \cap g_i / v_i \cup g_i$. The similarity between consumer preference and commodity issim$(U_t, Rt) = \sum_{i=1}^{m} w_i \times s_i$.

(iii) Step 3: sort the goods from high to low according to the similarity, and return the top-N goods list to the user.

2.3. Traditional Association Rule Recommendation Algorithm. Because the sites in the field of e-commerce are built based on the Internet and the convenience of using the Internet to obtain information, each site can provide very personalized, transparent, and humanized recommendations. In recent years, knowledge discovery has been paid more and more attention in the field of artificial intelligence, and an important research direction of knowledge discovery is the mining of association rules. Association rules are also known as "shopping basket" analysis, because its main research object is e-commerce order database, and its main purpose is to find some association and combination relationships between transaction items from the order database. Apriori algorithm is the most commonly used core algorithm in association rules mining. Its core idea is to find the elements whose frequent item sets are K first and then find the elements whose frequent item sets are $K+1$ according to K-frequent item sets. It is mainly divided into two steps:

(1) enerating all K-frequent item sets, firstly scanning the transaction database to obtain an item set data, calculating the support degree of an item set (i.e., the number of times the data item set X appears in the transaction database), eliminating the result that the support degree is less than the preset minimum support threshold, and retaining an item frequent set. Then, binomial set is constructed; that is, the results of a frequent set are combined in pairs, and its support degree is calculated, and the item set whose support degree is not less than the preset minimum support degree is reserved. Similarly, K-frequent item sets can be generated by mining.

(2) The second is generating trusted association rules from K-frequent item sets; the confidence level (the ratio of the number of transactions containing both X and Y in the transaction database D to the number of transactions containing X in D) is calculated for the frequent item sets obtained by mining. The minimum confidence threshold is the boundary of whether the association rules generated are trusted association rules, and the value of confidence level indicates the degree to which the association rules can be trusted.

From the above analysis, it can be seen that Apriori algorithm has always been searching for frequent item sets in iteration, so the biggest problem is to scan the database many times and produce a large number of quasifrequent item sets or candidate sets, which is inefficient and low in performance, especially when facing massive data. Of course, since Agrawal first proposed association rules, many experts and scholars in the field of data mining at home and abroad have made in-depth research on association rule mining methods and proposed many algorithms. Most of them are improved and extended based on Apriori algorithm.

(1) By scanning the transaction database DB for the first time, the set F of frequent items and the support degree of each frequent item are obtained, F is sorted in descending order of support degree, the result L is obtained, and the Header Table is constructed accordingly.

(2) Scan the transaction database DB for the second time. After removing infrequent items from each read transaction, press L in the first step. After sorting, create a path of FP tree with null as the root node, and add 1 to the count of items on the path. In the process of inserting FP tree, find the corresponding items in the header table and establish a pointer index. And so on, continue to insert other transactions until their complete FP tree is built.

As can be seen from the above steps, FP-Growth algorithm only needs to scan the database twice. Compared with Apriori algorithm, FP-Growth algorithm greatly reduces traversal times, which will greatly improve the efficiency of the algorithm. In addition, FP-Growth algorithm does not need to generate candidate sets like Apriori algorithm, but it adopts divide-and-conquer strategy, which compresses the database providing frequent item sets into an FP tree and generates association rules, which also greatly improves the efficiency of the algorithm.

3. Data Analysis of Tourism Enterprise Value Platform

3.1. Travel Analysis of Tourism Platform. Taking May 1, 2021, as the research time point, this paper analyzes the correlation between the flow of people and tourism income from the number of people on May 1 in different periods, as shown in Figure 1.

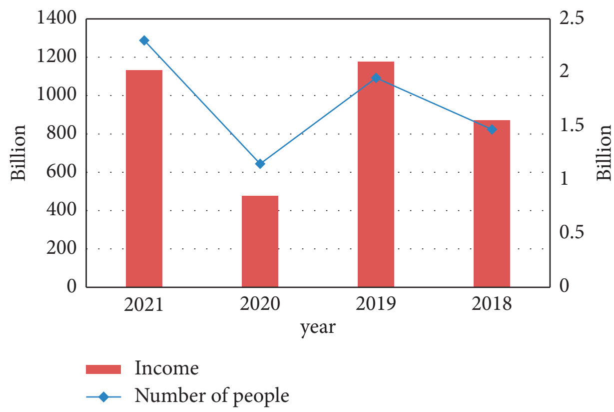

FIGURE 1: Correlation between tourism income and number of tourists.

It can be seen from Figure 1 that there is a positive correlation between tourism income and population. Due to the serious epidemic situation in 2020, the number of tourists is relatively small, the number of tourists in the region increases, and the cost is relatively small. In 2019 and 2018, the relationship between the number of tourists and income and expenses is more obvious, mainly due to the large number of people traveling out of the province and the large cost. In 2020, the number of people is relatively small, mainly due to the epidemic situation. Many scenic spots and tourist areas implement strict policies, resulting in a small number of people and less tourism revenue. In 2021, only when the epidemic situation is well controlled will the number of tourists increase obviously and the income increase.

However, under different platforms, mobile APP is more used to realize travel reservation and travel strategy, and different regions and times can realize relative APP travel services such as strategy information, travel reservation, hotel accommodation, transportation, food, and beverage. Figure 2 shows the number of mobile APP visits from June 2019 to December 2020.

It can be seen from Figure 2 that, due to the epidemic situation, the number of people visiting APP in February 2020 was small, mainly because the national tourism was suspended and the number of visits was relatively small. With the effective control of the epidemic situation, the number of tourists nearby gradually appeared, and the number of people visiting the travel APP also increased from March to December. However, compared with the number of visits before January 2020, the minimum number of visits before the epidemic is equivalent to the maximum number of visits after the epidemic.

Nowadays, users have already adapted to the whole process of corresponding tourism projects by using the network, and tourism users have become accustomed to preparing trips and spending and sharing in advance on the travel app. This also indicates that the urgent need of the tourism mobile market has always existed. Judging from the number of newly added tourism apps every day, the tourism mobile applications in the market have maintained steady growth. Take April 2021 as an example to illustrate the increase of APP in Figure 3.

The increase of APP data in April showed irregularity, but the number of weekends such as April 3rd, April 4th, April 10th, and April 11th decreased obviously. Overall, the highest points have the largest number on Wednesdays and Thursdays.

In the tourism industry, the functions that can be realized on the APP are mainly as follows: hotel accommodation, ticketing platform, comprehensive tourism services and travel, etc. The distribution ratio of the above functions in the vertical APP is shown in Figure 4.

The choice of travel mode under various tourism platforms is also an important link in tourism. In the mainstream mode of travel, people use APP to choose the number of visits in different time periods, as shown in Figure 5.

As can be seen from Figure 5, the number of visits to the platform increased significantly in August, September, and October 2020. In these three months, it shows that the epidemic situation is well controlled, and people have more holidays, especially in October, with the largest increase. It shows that there are more people who have tourism plans in the three months of a year; so long as the tourism routes and reasonable tourism plans are arranged reasonably, tourism income can be provided.

Nearly 80% of tourism consumers use tourism-related apps to arrange trips, including information inquiry, accommodation, and delivery.

It is used most in the three links of reservation. Nowadays, tourism consumers have become accustomed to preparing their journeys in advance on the travel App, and the travel App has been able to provide travel services in the whole process chain, which greatly enhances users' willingness to download and use. The specific scale is shown in Figure 6.

3.2. Market Application Analysis of Tourism Value Platform.

This section analyzes the resources under the tourism value platform from the aspects of strategy information, travel reservation, hotel accommodation, transportation, and food and beverage. From the perspective of various domestic tourism platforms, this paper mainly analyzes the main application scenarios of tourism platforms in these aspects, and the specific tourism enterprises are shown in Table 2.

The following form the various functions to analyze the application of the tourism platform, for the tourism platform access data analysis. Through relative data, this paper analyzes the tourism distribution under different platforms and explains five functions: strategy information, travel reservation, hotel accommodation, transportation, and food and beverage.

3.2.1. Attractions Ticketing.

In the Raiders information, it mainly focuses on the platforms of Xiaohongshu, Qunar, Ma Honeycomb, and Public Comment. The specific data distribution is shown in Figure 7.

In the past, where the mainstream travel strategy platform went, Ma Honeycomb was no longer brilliant. Although there was still a steady increase in downloads every month, it was no longer the first echelon of travel strategy app.

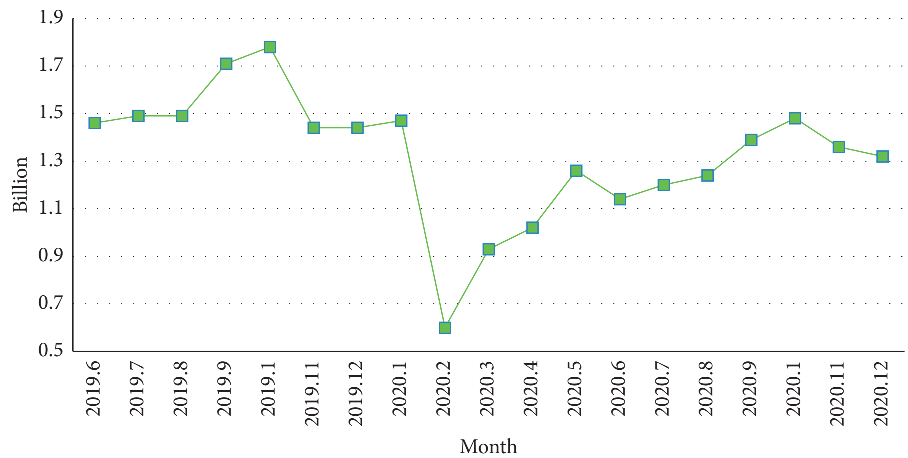

Figure 2: Number of apps visited in April.

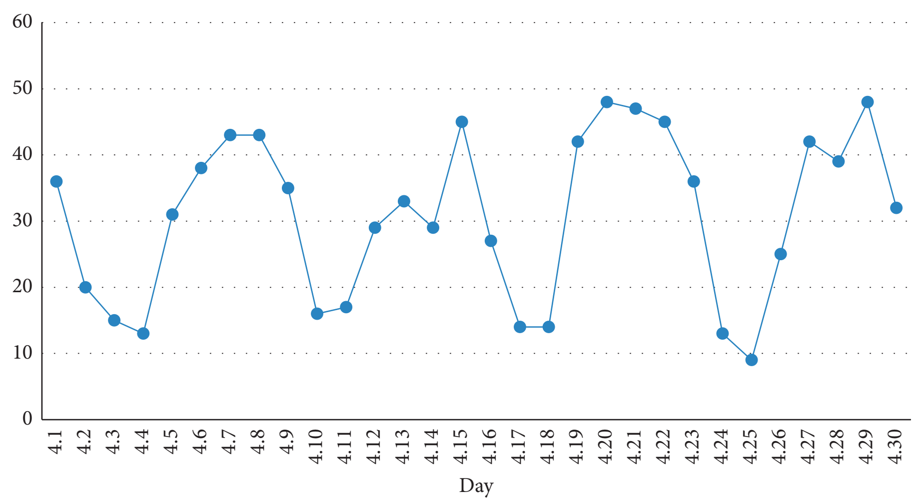

Figure 3: Daily APP increase in April.

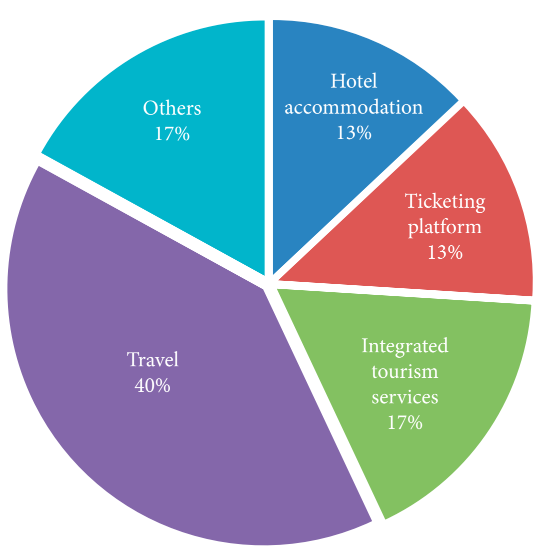

Figure 4: Function comparison relationship of tourism platform.

3.2.2. Scheduling. In the travel reservation information, the analysis mainly focuses on the platforms of Qunar, Same Trip, Ctrip Travel, and Flying Pig Travel. The specific data distribution is shown in Figure 8.

3.2.3. Hotel Accommodation. In the hotel accommodation information, the analysis is mainly concentrated on the platforms of Same Trip, Ctrip Travel, Flying Pig Travel, China Living Club, Airbnb, Bird Famous Residence, and Booking. The specific data distribution is shown in Figure 9.

3.2.4. Traffic Reservation. In the traffic travel information, the analysis mainly focuses on the platforms of Where to Travel, DiDi Travel, Hello Travel, and Hua Xiaozhu Taxi, among which Hua Xiaozhu Taxi is a rising star in 2020, and the specific data distribution is shown in Figure 10.

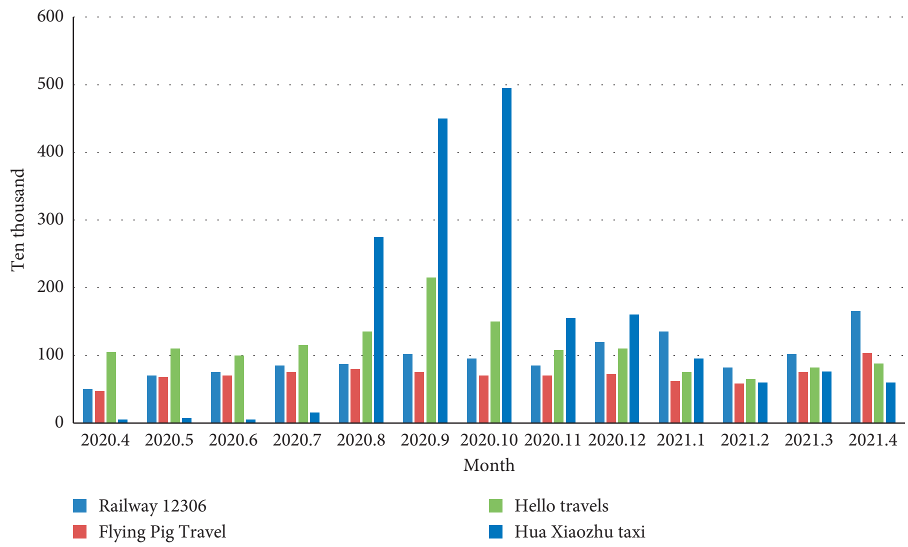

Figure 5: Travel visits of tourism platform.

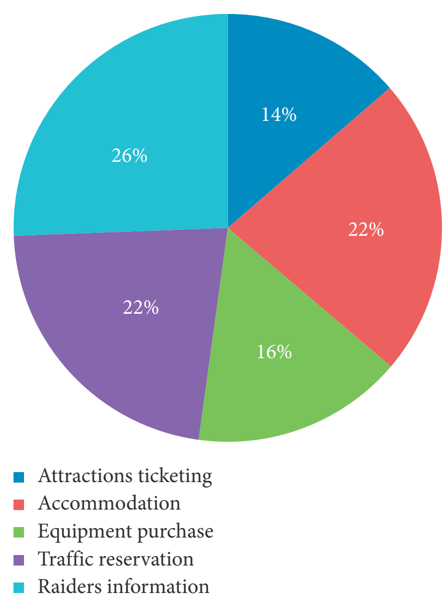

Figure 6: Utilization rate of tourism platform.

Table 2: Application of main functions of tourism platform.

Tourism project	Tourism enterprise
Attractions ticketing	Ctrip, Where to travel, Hornet's Nest, Public Comment, Little Red Book
Scheduling	Ctrip, Where To Travel, Same Journey, Flying Pig Travel
Hotel accommodation	Flying Pig Travel, China Residential Association, Airbnb
Traffic reservation	Drip Travel, Flower Piglet, Harrow Trip, Tick-Tock Trip
Raiders information	Meituan, Are You Hungry, Public Comment

Under the tourism platform, passengers analyze road conditions through navigation, which can effectively improve the ability of accurate location. In Gaode Map, Baidu Maps, and Tencent Maps, the growth rate of Gaode Map is much higher than the latter two from August 2020, and the specific distribution is shown in Figure 11.

3.2.5. Raiders Information. In the food and beverage information, the analysis is mainly concentrated on Meituan, ELEME, Public Comment, and Baidu Glutinous Rice. The specific data distribution is shown in Figure 12.

The catering platform with take-out function occupies an important position in the tourism catering market.

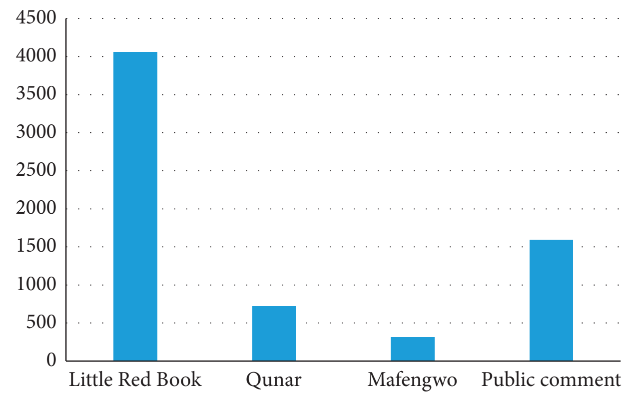

Figure 7: Raiders' information distribution information of tourism platform.

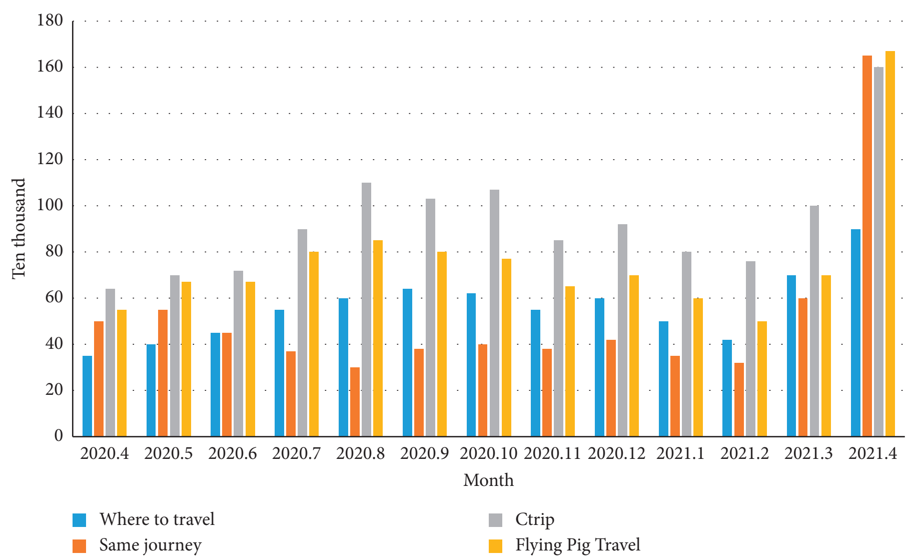

Figure 8: Travel platform access information for travel reservation.

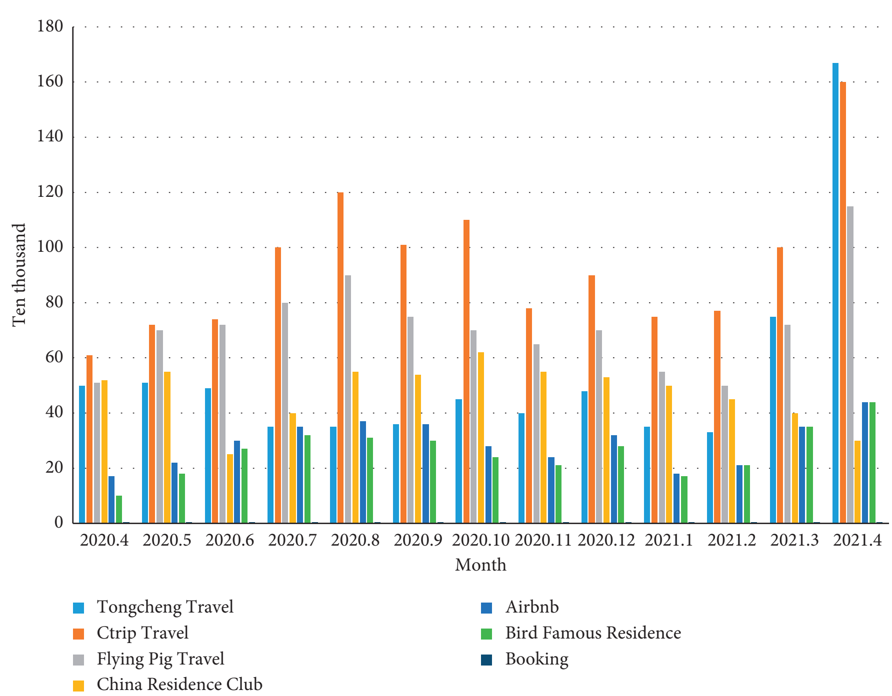

Figure 9: Travel platform access information for hotel accommodation.

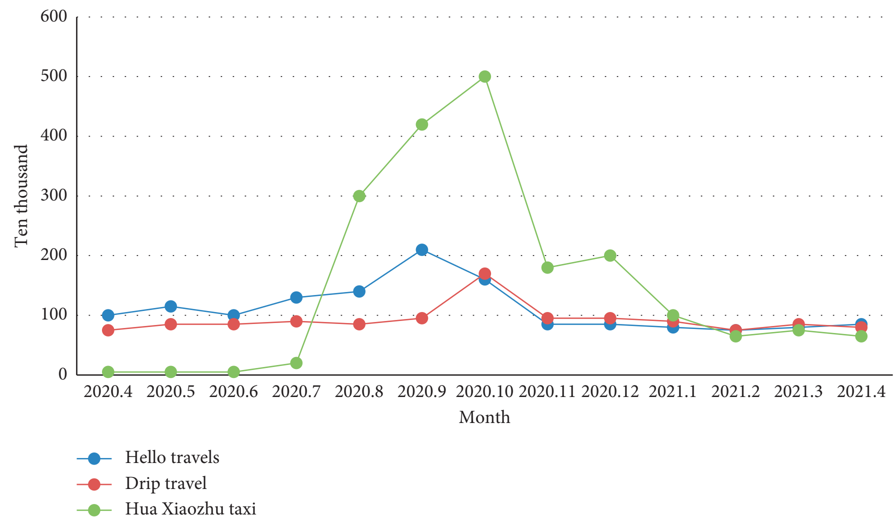

Figure 10: Platform information distribution of travel.

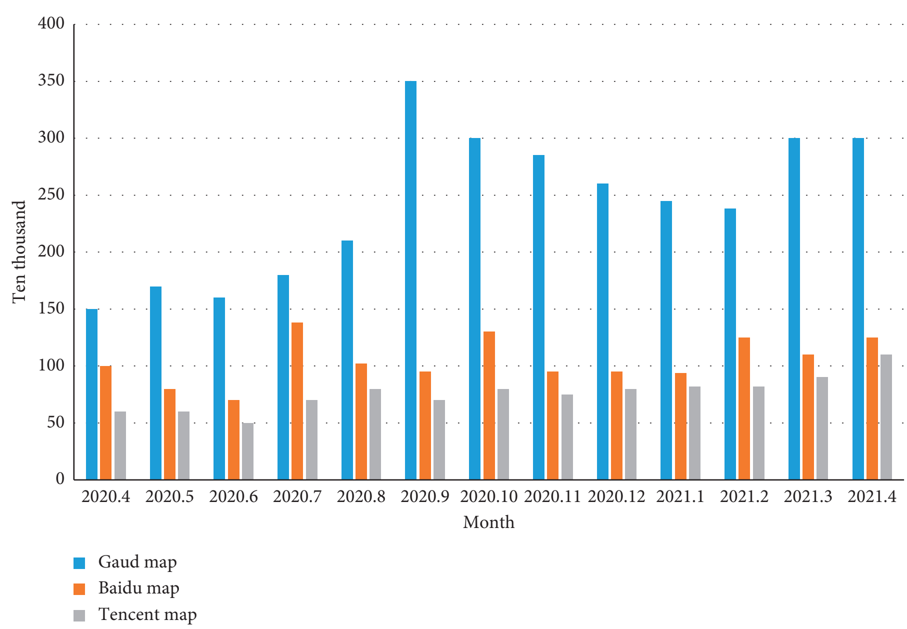

Figure 11: Travel platform distribution information of itinerary navigation.

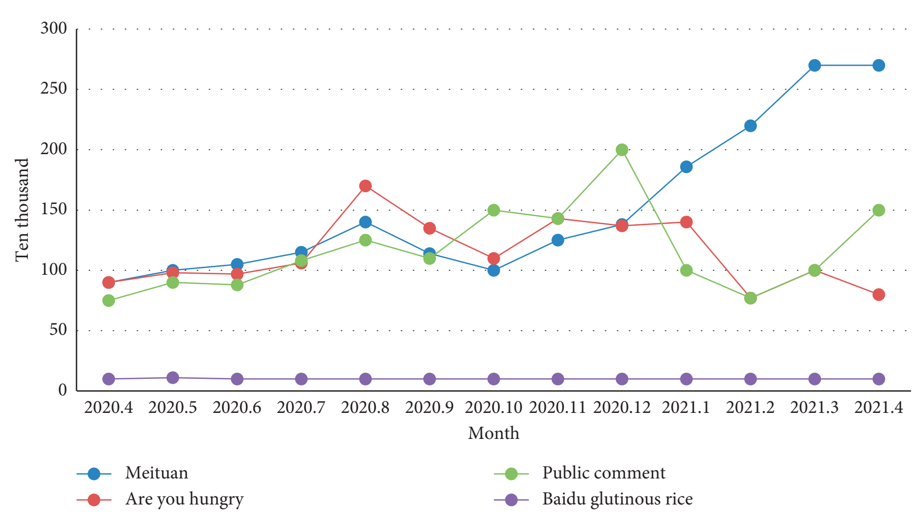

Figure 12: Distribution information of tourism platform for catering and gourmet food.

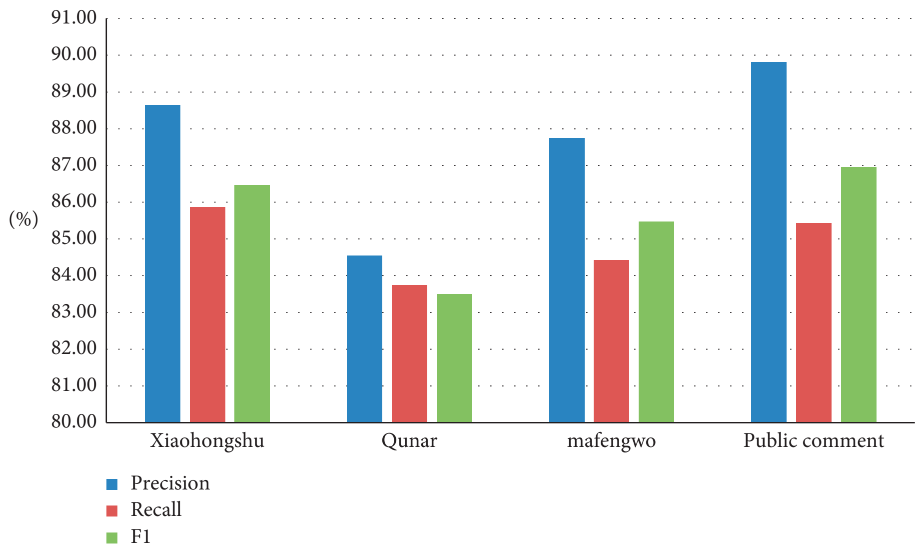

FIGURE 13: Comparison of Raiders' information recommendation performance of tourism platform.

Represented by Meituan Takeaway and Hungry Noodles, from the performance of downloads in the past year, Meituan Takeaway has a strong momentum, and since 2021, it has gradually cast off Hungry Noodles as a direct competitor. The Public Comment, which integrates comment, group purchase, and preferential payment, performed stably. The recommendation of "foodies" provides a credible reference for new visitors, which also makes Public Comment have strong vitality in the domestic tourism market all the year round. The development momentum of gourmet group buying applications is weak. Baidu Glutinous Rice and other platforms focusing on food group buying have weak development momentum, so perhaps focusing on a single group buying field is not the most suitable choice at present.

4. Research on Recommendation Business Model under Multiplatform from the Perspective of Value Cocreation

In the second section, three recommendation methods are introduced. Because of the differences in usage between recommendation methods, enterprises under many tourism platforms have effective analysis on different recommendation methods under various platforms. In order to maximize the operating benefits of the business model, maximizing the commercial value based on multiple platforms is the goal pursued, and achieving good user experience and sharing good tourism can effectively improve the commercial value of the tourism platform.

The following studies the business models of the above problems from different recommendation methods combined with various tourism platforms and analyzes the business models of recommendation algorithms such as collaborative filtering, association rules, and content filtering under different platforms, so as to realize the selection of the best tourism business platform and obtain the maximum benefits and results.

In order to reflect the actual test effect of the above indicators, the mean absolute error (MAE) can be used to express the score prediction accuracy, which has the advantages of simplicity and easy understanding. The MAE calculation formula is shown as follows:

$$\text{MAE} = \frac{\sum_{u,i\in T}\left|r_{ui} - \widehat{r}_{ui}\right|}{|T|}, \tag{5}$$

where r_{ui} indicates the actual score of the user U on the commercial service I provided by the travel platform and $\widehat{r}_{ui}$ indicates that the recommendation system predicts the score of the commercial service I provided by the user U on the travel platform. In this paper, the difference of MAE overall error evaluation is not obvious, so this index will not be discussed.

The prediction accuracy of tourism business platform recommendation can accurately predict the user's definite preference for recommended tourism platform, which is expressed by two parameters: accuracy and recall.

$$\begin{aligned}
\text{Precision} &= \frac{\sum_{u\in U}|R(u)\cap T(u)|}{\sum\limits_{u\in U}|R(u)|},\\
\text{Recall} &= \frac{\sum_{u\in U}|R(u)\cap T(u)|}{\sum_{u\in U}|T(u)|},\\
F_1 &= \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}.
\end{aligned} \tag{6}$$

Through the above indicators to analyze the recommendation effect under various tourism platforms, the recommendation of each platform business is still evaluated by five main modules: strategy information, travel reservation, hotel accommodation, transportation, and food and beverage under the tourism platform.

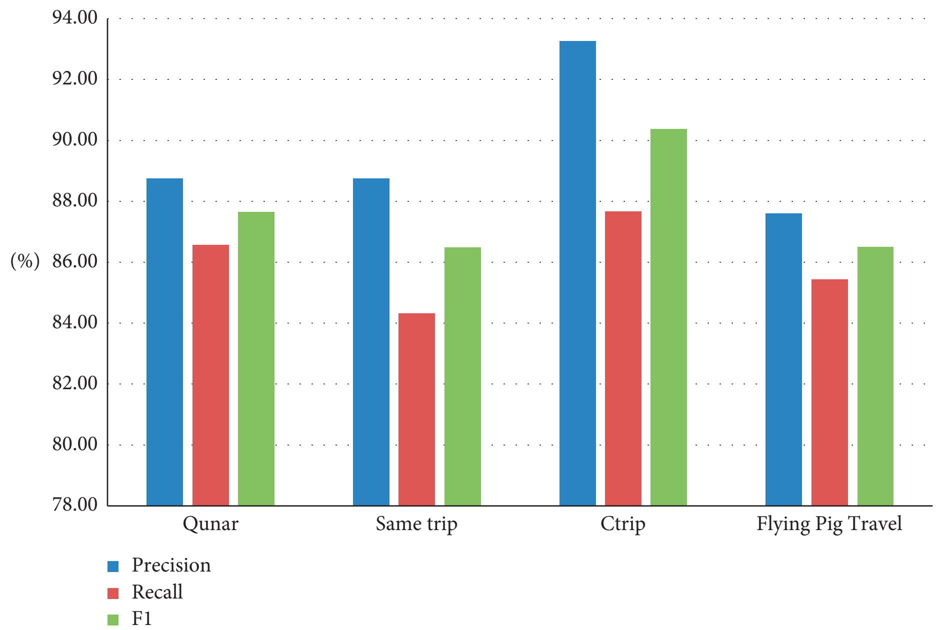

FIGURE 14: Comparison of travel booking recommendation performance of travel platform.

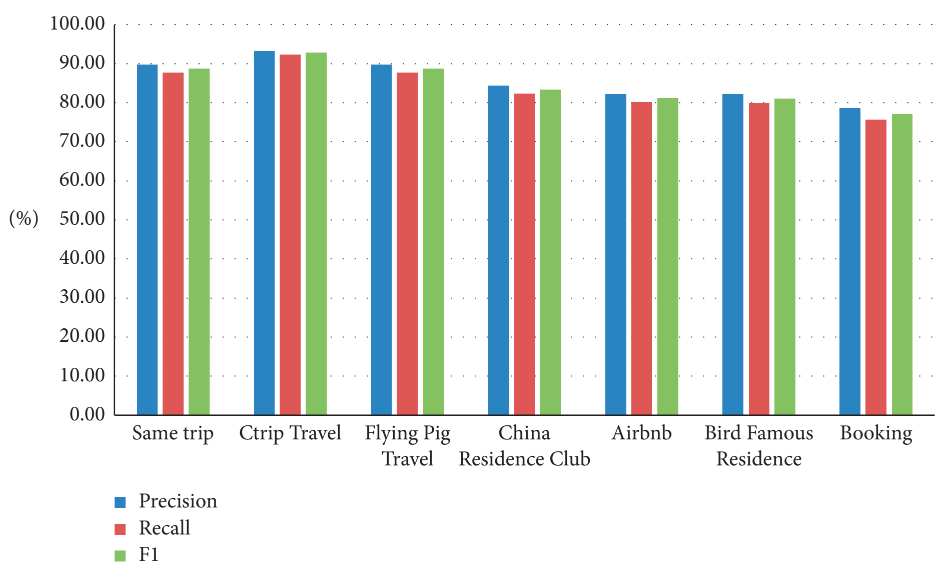

FIGURE 15: Comparison of hotel accommodation recommendation performance of tourism platform.

4.1. Attractions Ticketing. In the strategy information of tourism platform, the predetermined information of Xiaohongshu, Qunar, Ma Honeycomb, and Public Comment is mainly concentrated as the research target, and data collection and sharing are adopted. The specific data distribution is shown in Figure 13.

4.2. Scheduling. In the travel reservation information, the analysis mainly focuses on the platforms of Where to Travel, Same Trip, Ctrip Travel, and Flying Pig Travel and analyzes the accuracy rate, recall rate, and *F*1 under various recommendation algorithms. The specific data distribution is shown in Figure 14.

4.3. Hotel Accommodation. In the hotel accommodation information, the accuracy rate, recall rate, and F_1 are mainly analyzed under several recommendation algorithms, such as Same Trip, Ctrip Travel, Flying Pig Travel, China Living Club, Airbnb, Bird Famous Residence, and Booking, and the specific data distribution is shown in Figure 15.

4.4. Traffic Reservation. In the traffic travel information, it mainly focuses on DiDi Travel, Hello Travel, Hua Xiaozhu Taxi, and so on. Road condition analysis through navigation can effectively improve the ability of accurate location. Gaode Map, Baidu Maps, and Tencent Maps are mainly used for navigation path. Accuracy rate, recall rate, and *F*1 are analyzed on several platforms under various recommendation algorithms, among

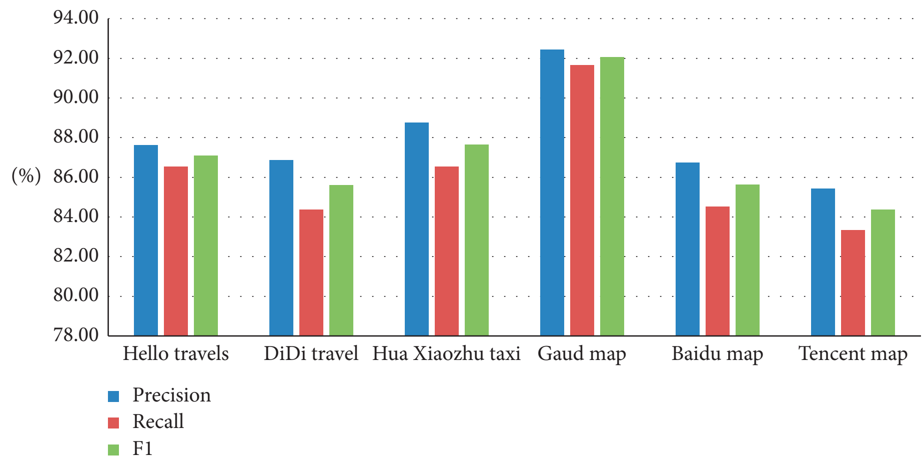

Figure 16: Comparison of transportation recommendation performance of tourism platform.

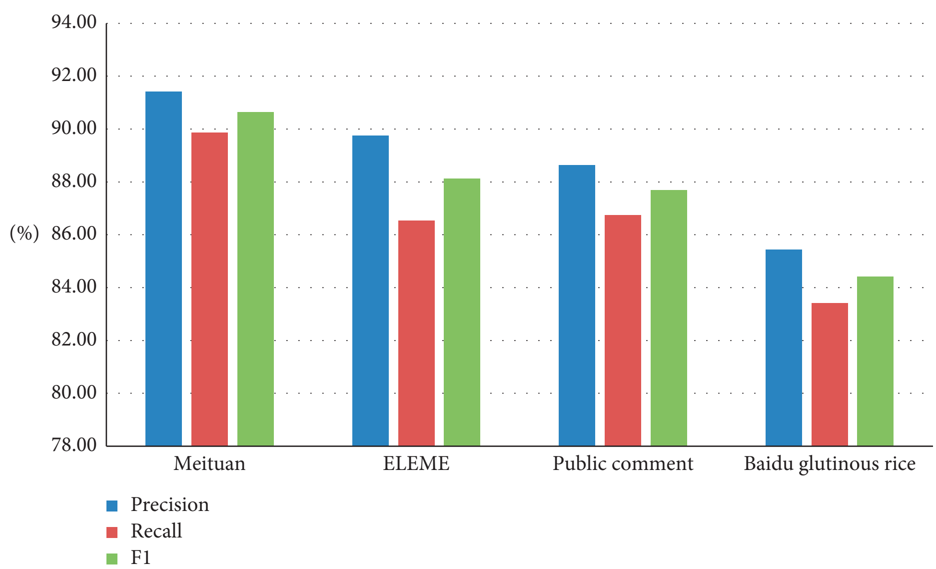

Figure 17: Comparison of food and beverage recommendation performance of tourism platform.

which Hua Xiaozhu Taxi's performance is also very good, and the specific data distribution is shown in Figure 16.

4.5. Raiders' Information. In the food and beverage information, it mainly focuses on Meituan, Hungry, Public Comment, and Baidu Glutinous Rice. The accuracy rate, recall rate, and *F*1 are analyzed on several platforms under various recommendation algorithms. The specific data distribution is shown in Figure 17.

Analysis of the performance of the abovementioned modules, generally in the accuracy and recall rate of more than 88%, all show good performance. These business models can provide better services and get better attention.

5. Conclusion

Considering the commercial value, the service value platform provided by tourism enterprises provides customers with high-quality services and gains the satisfaction of users in order to realize commercial value. The three service recommendation algorithms proposed in this paper are applied to the business service recommendation of tourism platform. Different recommendation algorithms have different requirements, and the optimal recommendation method is used to realize recommendation under different platforms. From the recommendation effect, the overall optimal recommendation effect is over 88%, and the service requests and recommendations put forward by customers can achieve the purpose of commercial services. The future research work should analyze the difference of multiplatform recommendation, make the best recommendation method according to the customer's request, and then provide value-added services to meet the customer's needs and maximize the commercial benefits.

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7

Study on Regional Control of Tourism Flow Based on Fuzzy Theory

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In order to solve the problems of poor regional control effect and high control difficulty coefficient of a traditional tourism flow, this paper puts forward the research of a regional control of tourism flow based on fuzzy theory. The capacity of regional tourism is determined by analyzing the factors that influence the regional control of the tourism flow. The regional tourism flow is divided into different time series by automatic clustering algorithm, the same sample data is fused, and the Euclidean distance between traffic is obtained. The regional tourism flow prediction model is constructed according to fuzzy theory. On this basis, the real-time capacity of regional scenic spot flow is calculated, and the regional tourist flow control model is constructed to realize the regional tourist capacity control. The experimental results show that the regional control error of tourism flow is always lower than 0.40, and the difficulty coefficient of control is low, which has certain advantages.

1. Introduction

Global tourism has developed rapidly in recent years. More and more countries will speed up the development of tourism as a strategic decision, and our country will position tourism as a strategic pillar industry and modern service industry to cultivate it and issued the Tourism Law to ensure and promote the sustainable and healthy development of tourism [1]. Tourism's share of GDP continues to rise. The focus of the development of world tourism is gradually moving eastward, and the tourism market in Asia, especially in China, accounts for more and more of the global tourism market. Worldwide, the external environment of tourism in China is further optimized, and the development trend of popular tourism is becoming more and more obvious. At the same time, tourism has become a hot field of industrial investment. Tourism is called "the promotion catalyst of national economy," " forever sunrise industry," and the demand for tourism service of our people is gradually increasing [2]. On the one hand, the development of tourism can meet the increasing material and cultural needs of people; on the other hand, it can directly or indirectly promote the development of national economy. At the same time, tourism is a very related industry. In the process of its operation, it can not only promote the development of six tourism characteristic industries, such as travel, housing, purchase, entertainment, food, and travel, but also promote the development of a series of industries, such as business and service industry. Regional tourism demand has become the foundation of tourism development [3].

At present, the regional tourism demand is rising. If the forecast result of tourism demand is not accurate, it will lead to waste of resources and repeated construction. The phenomenon of low tourism service quality and excessive reception load caused by tourism demand is [4]. The accurate forecast of tourism demand is the basic basis and reference of tourism policy making and investment development, and also the fundamental of regional control of tourism flow [5]. Therefore, the related research has carried on a lot of research and has obtained certain results.

A tourism flow prediction model based on a gradient lifting regression tree is proposed in [6]. The accurate prediction of tourist flow is the key problem in tourism economic analysis and development planning. Based on the idea of integrated learning, a tourism flow prediction model based on gradient lifting regression tree is proposed. In this model, the tree generation algorithm of the original model is optimized to minimize the nonanalytical solution of the objective function, and the person correlation coefficient is used to analyze the correlation of each influencing factor to construct the feature vector to predict the tourist flow accurately. Taking Guilin tourist flow from 2015 to 2018 as an example, the prediction accuracy of the exponential smoothing algorithm and support vector machine algorithm is analyzed by comparing the average error, mean square error, and error. This method has higher prediction accuracy and better application value in tourist flow prediction, but little consideration is given to regional tourist flow control. Literature [7] puts forward the real-time tracking and prediction method of tourist flow data in scenic spots under cloud computing. This method can accurately track and predict the tourist flow data of scenic spots in real time. It is necessary to consider the continuous passenger flow state of scenic spots under cloud computing and complete the real-time tracking of tourist flow data through the state equation of scattered passenger flow data. The traditional real-time tracking method of tourist flow data in scenic spots does not consider the state of continuous passenger flow in scenic spots, which leads to poor tracking accuracy. The real-time tracking and prediction method of tourist flow data in scenic spots under cloud computing is put forward. The state parameters of continuous passenger flow under cloud computing are modeled, the unidirectional passenger flow and the aggregation passenger flow are estimated effectively, and the state equation and observation equation of dispersed passenger flow data are obtained. Based on the adaptive Kalman filter algorithm to monitor the dynamic change of scattered passenger flow data in cloud computing, and to correct the system state noise and observation noise variance, finally, on the basis of data prediction sorting and similar clustering, the effective tracking of tourist traffic data in scenic spots under cloud computing is realized. The method has higher tracking accuracy and stable and reliable performance, but the control and prediction are time-consuming and have some limitations.

Mobile computing is a new technology emerging with the development of mobile communication, Internet, database, distributed computing, and other technologies. Mobile computing technology will enable computers or other information intelligent terminal devices to realize data transmission and resource sharing in the wireless environment. Its role is to provide useful, accurate, and timely information to any customer anytime and anywhere. This will greatly change the way people live and work.

Based on the shortcomings of the above methods, this paper proposes a regional control method of tourism flow based on fuzzy theory. By analyzing the factors that affect the regional control of tourism flow, the capacity of regional tourism is determined, the regional tourism flow is divided into different time series by automatic clustering algorithm, the same sample data is fused, and the Euclidean distance between traffic is obtained. The technical route of this method is as follows:

(1) To determine the capacity of regional tourism by analyzing the factors affecting the regional control of tourism flows

(2) The regional tourism traffic is divided into different time series by automatic clustering algorithm, the same sample data is fused, and the Euclidean distance between traffic is obtained, and the regional tourism traffic prediction model is constructed according to fuzzy theory

(3) On this basis, the real-time traffic capacity of regional scenic spots is calculated, and the regional tourist flow control model is constructed to realize the regional tourist capacity control

(4) Experimental analysis

(5) Concluding remarks

2. Regional Tourism Demand and Capacity Analysis

2.1. Analysis of Factors Influencing Regional Tourism. Due to time constraints, regional tourism has become the most popular choice in current tourism. Before controlling the regional tourism flow, it is necessary to analyze the influencing factors of regional tourism. On this basis, the regional tourism capacity is divided to lay the foundation for the subsequent regional control of tourism flow [8]. Regional tourism impact factors include the following:

(1) Seasonal factors

Seasonality is a prominent feature of the tourism industry. The phenomenon of seasonal characteristics in tourism industry is not only limited to individual countries or regions to fully understand this important feature of tourism industry but also the premise of rational development and utilization of tourism resources. Seasonal characteristics are the part that needs to be attached great importance to in the process of tourist volume prediction. For a long time, how to grasp the seasonal volatility of tourist volume in the process of tourist volume analysis has been an important and complex issue. In the literature of tourist volume analysis, there are two ways to deal with the seasonal variation of tourist volume, that is, it is regarded as random or definite. As to which of the two methods will produce more accurate prediction results in the process of tourist volume prediction, there is no conclusion at present [9]. There are many complicated reasons behind the phenomenon that the tourist volume fluctuates with the season, including the reason of the tourist destination itself. It also includes the reasons from tourists and the comprehensive role of the whole tourism industry chain. Therefore, in the process of tourist volume prediction, we may need to consider the seasonal characteristics of tourism in different regions.

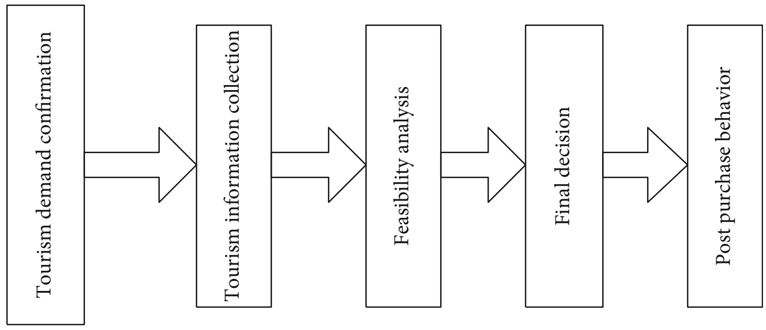

Figure 1: Traveller's regional tourism decision-making process.

(2) Sudden events

The impact of various unexpected special events on local tourism is very significant. For example, during natural disasters such as earthquakes and tsunamis, during severe outbreaks or during terrorist attacks and people's riots, tourism will suffer heavy losses due to these unpredictable emergencies. These natural or perceived events have caused huge losses to the number of visitors. The method used to measure the specific losses caused by these sudden events is to model and analyze the data before the event occurs, and to predict the local tourist volume under normal conditions. Then, compared with the actual observations at the time of occurrence, the difference between them is regarded as the loss caused by the event to the local tourist volume.

(3) Policy change

With the development of global international trade, economic and political exchanges between countries are frequent. In this context, tourism is also ushered in more foreign tourists. Countries' economic, political, and other related policies have a real-time impact on domestic tourism development. Therefore, this influence factor also becomes the important influence factor which affects the tourism industry progress and the development.

2.2. Regional Tourism Capacity Analysis. The so-called tourism market usually refers to the tourism demand market or the tourist source market, that is, the frequent buyers and potential buyers of tourism products: tourism consumption refers to people in the process of playing, the act and activity of meeting the needs of individual enjoyment and development by purchasing one or some tourism products. Tourism products are not stored as tangible products that are common in everyday life. They are essentially "perishable," [10] for example, hotel rooms, flight seats, and ticket tickets at a particular time and place will lose their current product value if they are not sold in time. Therefore, for the tourism market, it is very important to study and analyze the consumer's purchase behavior and make accurate tourism demand forecast.

A consumer purchase behavior model is an important theoretical reference for marketing activities. Through this model, we can determine the factors that affect consumers' decisions before and during the purchase of goods or services. In order to help marketers better carry out sales work, the decision-making process of consumer purchase is one of the important components of this behavior model and the decision-making process of tourists' regional tourism as shown in Figure 1.

When tourists make regional tourism decisions, they first "confirm the demand," and the purchase behavior will not occur for no reason. It must be because of some reason or stimulation that the demand for a certain commodity or service will trigger the desire to buy. The inducement may be accumulated for a long time, or may be temporarily stimulated by the behavior of acquaintances and friends, the effect of advertising, etc., such as seeing the photos of friends playing on social networks, suddenly producing the desire to travel outside. Then, we "collect information "; most people have to collect information to help make decisions before making decisions, information is the basis for decision-making, and purchase decisions are the same. Especially when it comes to larger amounts of money, consumers want to have a comprehensive understanding of information about goods or services, or to consult their own information, or to ask for advice from family and friends, or to study and analyze different package preferences, and so on. The larger the amount, the more detailed the information collection is. The characteristics of tourism services (inseparability, quality differences, family names, nonstorage, and nontransferability of ownership) determine that tourism consumption decisions are usually accompanied by higher risks, so consumers are more likely to conduct extensive information searches to reduce risk; again," evaluate goods ", which is based on the various types of information collected in the previous link, aggregate and further compare them, thus forming a consumer perspective and evaluation of a commodity or service, deciding whether to enter the next link or to give up buying. The final "decision to buy," that is, after confirming the availability of goods or services, occurs naturally, but this does not mean that the purchase is terminated [11].

When the regional tourism consumption of the above tourists is terminated, the regional tourist attractions need to plan the capacity to realize the control of the regional tourism capacity. The capacity of regional tourist attractions analyzed in this paper is shown in Figure 2.

The tourism capacity is the total capacity of the regional tourist attractions, and the composition of the capacity set to Z includes three parts of the influence factors, which are set

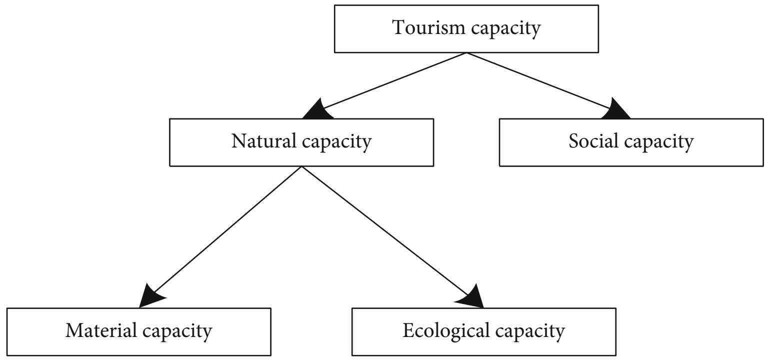

Figure 2: The capacity of regional tourist attractions analyzed.

to P, E, and S, respectively. The calculation formula can be expressed as

$$Z = P + E + S. \quad (1)$$

The content of formula (1) is not a simple addition, indicating that there is a vector relationship between the three, which is an inclusive relationship. Natural capacity is a supply-oriented capacity calculation, which mainly includes basic material capacity and natural ecological environment capacity. Among them, material capacity is a kind of facility capacity, according to the facility capacity of regional tourism to regional tourism. Social capacity is a kind of demand-oriented capacity, which is constructed on the psychological capacity of tourists and residents in tourist areas [12].

3. Regional Control of Tourism Flows

3.1. Construction of Regional Prediction Model of Tourism Flow Based on Fuzzy Theory. In order to realize the regional control of tourism flow, a regional prediction model of tourism flow is constructed to determine the flow of the tourism area.

First, the regional tourism traffic is divided into different time series by automatic clustering algorithm, and the historical sample is set as

$$y_i = (y_1, y_2, \cdots y_n). \quad (2)$$

By reordering the samples in formula (2), the same sample data is fused and [13], and the sorted sample data are expressed as follows:

$$y_i^{'} = \left(y_1^{'}, y_2^{'}, \cdots y_n^{'}\right). \quad (3)$$

On this basis, the mean value of the sample data is obtained, namely,

$$\text{arv} = \frac{\sum_{i=1}^{n}\left(y_{i+1} - y_i^{\prime}\right)}{n-1}. \quad (4)$$

Then, the Euclidean distance between different sample data is calculated, that is,

$$d\left(x_i, x_j\right) = \sqrt{\left(x_i - x_j\right)^2\left(x_i - x_j\right)}. \quad (5)$$

According to formula (5), the clustering center can be obtained as

$$c_j = \frac{1}{n}\sum_{i=1} d. \quad (6)$$

Finally, the regional prediction model of tourism flow is constructed according to fuzzy theory. A logical relation existing in fuzzy theory sets the interval between sample data as a set of fuzzy theories; fuzzy processing of sample travel flow data [14] obtained is as follows:

$$\begin{cases} A_1 = \dfrac{f_{11}}{u_1} + \dfrac{f_{12}}{u_2} + \cdots \dfrac{f_{1n}}{u_n}, \\ A_2 = \dfrac{f_{21}}{u_2} + \dfrac{f_{22}}{u_2} + \cdots \dfrac{f_{2n}}{u_n}, \\ \cdots, \\ A_i = \dfrac{f_{i1}}{u_1} + \dfrac{f_{i2}}{u_2} + \cdots \dfrac{f_{\text{in}}}{u_n}. \end{cases} \quad (7)$$

After the above fuzzy processing, the logical relationship in the sample data of tourism flow is determined, and on this basis, the prediction model is constructed, that is,

$$A_j = \frac{p + M[A_i]}{s+1}. \quad (8)$$

Construction of the regional prediction model of tourism flow based on fuzzy theory is shown in Figure 3

3.2. Regional Tourist Capacity Control. According to the prediction results of the regional tourism flow prediction model, the control method of regional tourist capacity is designed to achieve the expected goal. For regional tourist attractions, the real-time control of capacity should be achieved, which requires scenic spots to predict the daily capacity. Setting up the entrance capacity of regional tourist attractions, that is, the main factor limiting ticket sales, is calculated by formula (9) and obtained [15]:

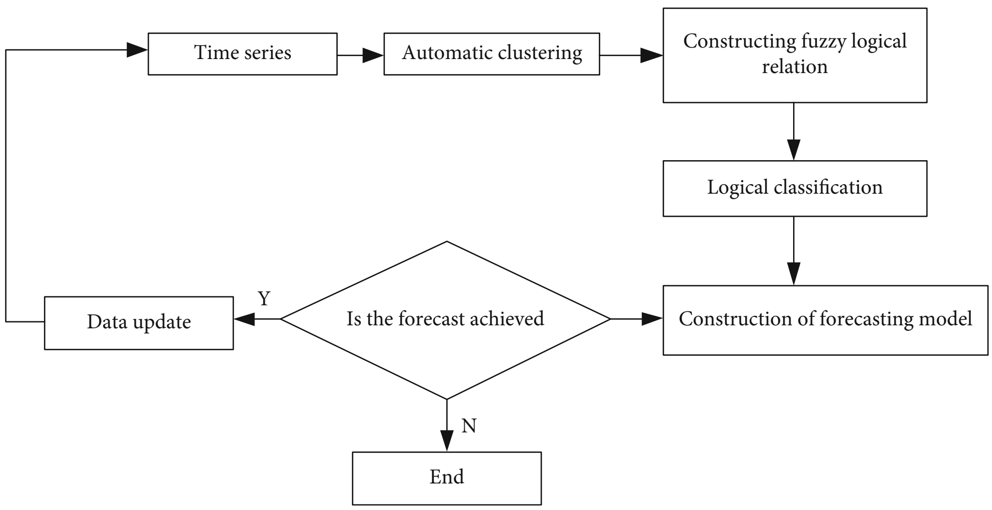

Figure 3: Flow of regional prediction model of tourism flow based on fuzzy theory.

$$T_i = \frac{(t - t_1)}{t_t \times F}. \tag{9}$$

In the formula, T_i represents the total entrance capacity of regional scenic spots, F represents the total number of tickets sold, and t_t represents the per capita flow of a single entry.

In the regional tourist capacity control, the key factor determining its capacity is the main play items in the scenic area, and the mathematical formula is as follows:

$$R_i = \frac{s_1}{s} \times \frac{t_{t-1}}{R_1 + R_2}. \tag{10}$$

In the formula, R_i represent the tourism facility application market, s_1 represents the landscape area, and R_1 represents the length of the tour.

According to the above analysis, [16] of regional tourist flow control model is constructed, and the following is obtained:

$$U = \frac{t_t - R_i}{T_i}. \tag{11}$$

In the regional tourist capacity control, according to the flow prediction model constructed by fuzzy theory, the real-time capacity of regional scenic spot flow is calculated, and the regional tourist flow control model is constructed to realize the regional tourist capacity control [17].

4. Experimental Analysis

4.1. Design of Experimental Scheme. In order to verify the scientific effectiveness of the proposed method, an experimental analysis was carried out. On the basis of the correlation analysis of real-time passenger flow data in a regional scenic spot, the data values with relatively high correlation degree are selected as the target research objects. Four data parameters in representative group 3 were selected as the main research objects. The experiment is carried out on the MATLAB platform. The experimental operating system is a WINDOWS XP system, and the system runs 16 GB of memory.

4.2. Design of Experimental Parameters. In order to verify the effectiveness of the proposed method, it is shown in Table 1.

Table 1: Experimental parameters.

Parameter	Short-cut process
Regional passenger flow (h)	500
Sampling interval (min)	5
Data statistics software	SPSS 7.0
Sample data volume	3000
Number of iterations (times)	10

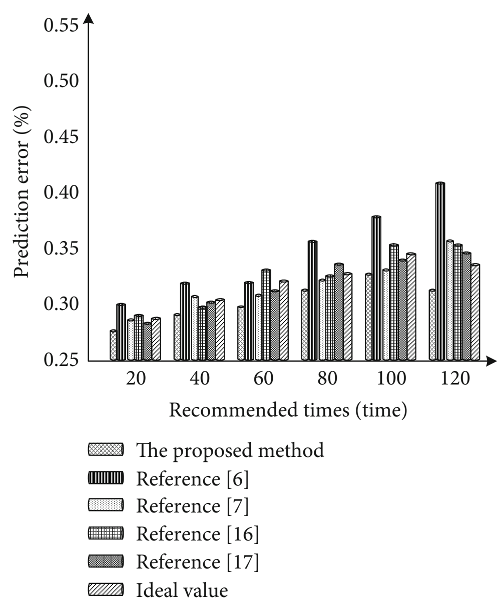

Figure 4: Comparison of regional traffic data prediction error in different methods.

Table 2: Comparison of the regional control coefficient of tourism flow with different methods.

Number of controls (times)	Methods of this paper	Document [6] methodology	Document [7] methodology	Document [18] methodology	Document [19] methodology
20	0.11	0.52	0.63	0.45	0.39
40	0.13	0.42	0.68	0.49	0.48
60	0.14	0.53	0.71	0.58	0.51
80	0.13	0.54	0.65	0.62	0.57
100	0.12	0.57	0.62	0.59	0.59

Under the above experimental environment and experimental parameter setting, the proposed method, literature [6] method, and literature [7] method are used to control the sample data, and the accuracy of regional flow prediction and the difficulty coefficient of control are taken as the experimental indexes. The prediction error is calculated by the following formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{c=1}^{N}(y_i - y\wedge_i)^2}. \quad (12)$$

In the formula, $\hat{y}_t$ and $\hat{y}_i$ represent two different observations of passenger flow and $\bar{y}_t$represents the average measured passenger flow.

4.3. Result. To verify the validity of the proposed method, the error of the proposed method, the literature [6] method, and the literature [7] method in predicting the sample flow data is analyzed experimentally as shown in Figure 4:

The analysis in Figure 4 shows that the error of sample data prediction by using the proposed method, literature [6] method, and literature [7] method. When the number of iterations is 40, the prediction error of the proposed method is about 0.29, which is lower than the ideal error value. The prediction error of the literature [6] method is about 0.33, and the prediction error of the literature [7] method is about 0.32. When the number of iterations is 80, the prediction error of the proposed method is about 0.31, which is lower than the ideal error value. The prediction error of the literature [18] method is about 0.38, and the prediction error of the literature [19] method is about 0.33. When the number of iterations is 100, the prediction error of the proposed method is about 0.30, which is lower than the ideal error value. The prediction error of the literature [18] method is about 0.45, and the prediction error of the literature [19] method is about 0.34. In contrast, the prediction error of the proposed method is low, which is due to the fact that the proposed method determines the capacity of regional tourism by analyzing the factors that affect the regional control of tourism flow. The regional tourism flow is divided into different time series by automatic clustering algorithm, the same sample data is fused, and the Euclidean distance between traffic is obtained. The regional tourism flow prediction model is constructed according to fuzzy theory, in order to improve the accuracy of the proposed method.

Table 3: Comparison of RMSE with different methods.

Methods	RMSE
Methods of this paper	0.56
Document [6] methodology	0.72
Document [7] methodology	0.65
Document [18] methodology	0.71
Document [19] methodology	0.61

To further verify the effectiveness of the proposed method, the experimental analysis of the proposed method, the literature [6] method, and the literature [7] method on the tourism flow regional control coefficient, the value of the control coefficient range between 0 and 1, where the lower value represents the better control effect; the results are shown in Table 2:

The analysis of the data in Table 2 shows that under the same experimental environment, there are some differences in the difficulty coefficient of sample data control using the proposed method, literature [6] method, and literature [7] method. When the control times are 40 times, the control difficulty coefficient of the proposed method is 0.13, the control difficulty coefficient of the literature [6] method is 0.42, and the control difficulty coefficient of the literature [7] method is 0.68. When the number of iterations is 80, the control difficulty coefficient of the proposed method is 0.13, the control difficulty coefficient of the literature [18] method is 0.62, and the control difficulty coefficient of the literature [19] method is 0.57. When the number of iterations is 100, the control difficulty coefficient of the proposed method is 0.12, the control difficulty coefficient of the literature [18] method is 0.59, and the control difficulty coefficient of the literature [19] method is 0.59. It has some advantages. In addition, the RMSE of each comparison method is given in Table 3.

5. Conclusion

In view of the shortcomings of traditional methods, this paper puts forward a regional control study of tourism flow based on fuzzy theory. The capacity of regional tourism is determined by analyzing the factors that influence the regional control of tourism flow. The regional tourism flow is divided into different time series by automatic clustering algorithm, the same sample data is fused, and the Euclidean distance between traffic is obtained. The regional tourism flow prediction model is constructed according to fuzzy theory. On this basis, the real-time capacity of regional scenic spot flow is calculated, and the regional tourist flow control model is constructed to realize the regional tourist capacity control. The experimental results show that the regional control error of tourism flow is always lower than 0.40, and the difficulty coefficient of control is low, which has certain advantages.

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The Development of a Tourism Attraction Model by Using Fuzzy Theory

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The purpose of this study is to develop a model to investigate the tourists' preference. Ten attributes of tourist destinations were used in this study. Fuzzy set theory was adopted as the main analysis method to find the tourists' preference. In this study, 248 pieces of data were used. Besides the evaluations for the factors, the overall evaluations (namely, satisfied, neutral, and dissatisfied) for every tourism destination were also inquired. After screening, 201 pieces of these data could be used. In these 201 pieces of data, 141 were classified into "satisfied" with the tourism destination, accounting for 70.15%, and 49 were "neutral," accounting for 24.38%, while 11 were "dissatisfied," accounting for 5.47%. Eight rules were obtained with the method of fuzzy preprocess. Regarding the condition attributes, three of the original ten attributes were found influential, namely, level of prices, living costs, information and tourist services, and tourist safety of the tourism destinations. From the results of this study, it is shown that top management of tourism destinations should put resources in these fields first, in order to allow limited resources to perform to maximum effectiveness.

1. Introduction

With the rapid economic and social development, the increase in GDP every year, and people's growing concern toward recreations, the tourism industry has been developing vigorously. In many countries, the tourism industry is a main industry that deserves our policy attention, and obviously it has become a global socioeconomic phenomenon [1]. A successful tourism industry can enhance regional economic development, as well as becoming a source of rich foreign exchange income [2]. The tourism industry is one of the main industries that determine the world's long-term economic growth [3].

The tourism industry has a far-reaching influence on many aspects such as social and economic development, culture, city development, and revival; in particular, it has the greatest influences on economics [4]. The output value of the tourism industry accounts for US$ 6 trillion of the global economy which is 9% of global GDP [5]. UNWTO (2011) [4] further estimated that, by 2020, the number of global tourists will reach 1.6 billion and 2 million people; global tourism earnings will reach as much as two trillion US dollars. The data indicates that tourism can bring in an enormous amount of economic benefits [6].

However, in modern society, no tourism industry can escape from international competition due to globalization. In this situation, how to increase international competitiveness of the tourism industry has become one of the greatest concerns.

This study investigated into tourist destinations. A tourist destination (such as city or region) is no longer viewed as a place that features unique natural landscape, culture, or art; instead, it is seen as a compound product that satisfies the tourists' need [1]. Now, many countries are actively developing their own tourist destinations' international competitiveness [2]. However, how to enhance tourist destinations' attractiveness to tourists relies on more than a single factor; it requires an overall plan to increase the tourist destinations' competitiveness in the international market [7].

The goal of this study is to establish a model for managing tourist destinations. The management of all tourism destinations should focus on enhancing their attractiveness and quality, as well as effectively using the limited resources in the current environment [8]. Therefore, this study explores various tourist destinations from the perspective of tourists. In addition, how these tourism destinations attract tourists and the tourists' evaluations are also included in this study [9].

Fuzzy model is similar to the thinking model of human beings [10, 11]. This study therefore uses fuzzy model to analyze the preference rules of tourist destinations. Hereby, this research aims to develop a model for investigation of tourist destinations management. It adopts fuzzy set theory as the main analysis method for tourism industry to find the tourists' preference. In the second part of this study, it does literature exploration on the competitiveness and attractiveness of tourism destination. The third section focuses on introduction of fuzzy set theory and fuzzy rules extraction algorithm [12]. The fourth section gives a possible explanation for the results. Finally, the authors draw a conclusion and the suggestions for future research in the last section.

2. Review and Discussion of the Literature

Tourism refers to people's temporary movement from their residence or working environment to a destination, and all related facility or services in the destination which are to be provided to tourists are covered in the tourism industry [13].

Gunn [14] reported that the so-called destination refers to local residents' "location"; on the other hand, it is a "playground" for tourists from other areas. A better explanation for a playground is a tourist destination, as it can be a specific tourist attraction, a town, a certain region in a country, an entire country, or even a bigger area on the planet [15]. Cracolici and Nijkamp [1] believed a tourist destination is a supplier that satisfies tourists physically and mentally; two parts are included: "structural" and "nonstructural." "Structural" refers to the natural landscape and cultural resources in a tourist destination, while "nonstructural" means human resources, perceptions, and so forth. Accordingly, if an area plans to develop tourism, the key point basically lies in how to present a destination that attracts tourists [16] and how to become more appealing and competitive than any other areas' destinations.

The critical factor model of tourist destinations' competitiveness established by Cracolici and Nijkamp [1] based on the concept of Crouch and Ritchie [8] encompasses physiography, culture and history, market ties, activities, events, and the tourism superstructure. Ten attractions of tourist destinations were compiled and used as the attributes in this study, as follows: (F1) reception and sympathy of local residents, (F2) artistic and cultural cities, (F3) landscape, environment, and nature, (F4) hotels and other accommodation, (F5) typical foods, (F6) cultural events (concerts, art exhibitions, festivals, etc.), (F7) level of prices, living costs, (F8) quality and variety of products in the shops, (F9) information and tourist services, and (F10) tourist safety.

3. Establishment of Fuzzy Decision Rules

3.1. Introduction of Fuzzy Concept. Fuzzy theory has been widely studied and successfully applied in various fields, which has got remarkable achievements so far. The fuzzy set defined by Professor Zadeh is represented by characteristic function $\mu_A(x)$ in mathematics, in which the value of membership function is the degree of element x belonging to a fuzzy set A. Therefore, the function matches the elements in the universal set to another set that is between 1 and 0:

$$\mu_A : X \longrightarrow [0, 1], \tag{1}$$

where $x \in X$, X indicates the universal set that is defined for the specific problem, while $[0, 1]$ refers to the range of real numbers between 0 and 1. Accordingly, this study will apply the two operating factors in the deduction of if-then fuzzy rules and membership function.

The vague linguistics between "yes" and "no" could be all represented by membership function values, which is the basic concept of fuzzy set theory. It aims to illustrate fuzzy phenomenon by clear and strict mathematic methods.

In this study, the tourism management of towns with cultural heritage is investigated. Ten attributes about tourism management of these towns were used for the study. In addition, fuzzy set theory is utilized to obtain the rules of tourist preference. During the fuzzy deduction, we collect various data from complicated environments and apply them in fuzzy deduction rules and membership functions to make the final decisions.

For the tourism management of cultural heritage towns, ten properties are investigated. Besides, the fuzzy set theory is also used to obtain the rules of tourists' preference. To sum up, the fuzzy system theory is scientific, advanced, and practical and can also provide correct guidance to our work. A new learning method for automatically deriving fuzzy rules and membership functions from a given set of training instances is proposed here as the knowledge acquisition facility [17]. Notation and definitions are introduced below.

Data preprocess and fuzzy rule establishment are included in the fuzzy learning algorithm. A set of training instances are collected from the environment. Our task here is to generate automatically reasonable membership functions and appropriate decision rules from these training data, so that they can represent important features of the data set. In order to avoid the disturbance of ineffective information, all the data should be preprocessed in advance [18].

The support set of fuzzy set D is a crisp set; it includes all the elements in the universe set U, but the membership value in D must be greater than 0 as follows:

$$\operatorname{supp}(D) = \{x \in U \mid \mu_D(x) > 0\}. \tag{2}$$

The center of a fuzzy set is defined as if the membership values which correspond to fuzzy set D from every element in supp(D) are finite (basically 1 is supposed to be the maximum value). In this situation, the position of the maximum value or the medium point of the maximum value is defined as the center of the fuzzy set as shown in Figure 1. The typical center of a fuzzy set is shown in Figure 1.

Fuzzy set includes all the points in the set U. Concerning set D, when the membership value is equal to 0.5, it is the vaguest point.

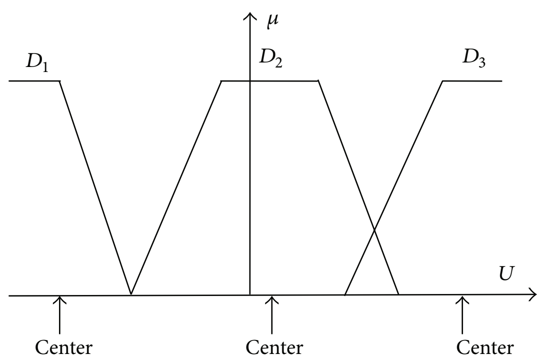

FIGURE 1: Typical centers in fuzzy set.

In order to obtain the support set higher than a certain level, α-cut is used to extract the support set and α-cut of fuzzy set D is a definite set D_α as follows:

$$D_\alpha = \{x \in U \mid \mu_D(x) \geq \alpha\}. \tag{3}$$

Fuzzy proposition includes two types, namely, atomic fuzzy proposition and compound fuzzy proposition. An atomic fuzzy proposition is a single fuzzy proposition as follows:

$$q_1 \text{ is } a_1, \tag{4}$$

where q is a linguistic variable and a_1 is the linguistic value of q_1.

A compound fuzzy proposition is using conjunctions such as "and," "or," and "not" to joint atomic fuzzy propositions to make fuzzy intersection set, fuzzy union set, and fuzzy compensate set. For example, q_1 stands for "information and tourist services," q_2 stands for "level of prices, living costs," a_1 and a_2 stand for linguistic values "very good" and "barely acceptable," and then the compound fuzzy proposition will be as follows:

$$q_1 \text{ is } a_1 \text{ and } q_2 \text{ is } a_2. \tag{5}$$

Fuzzy rules are made of "if-then" and fuzzy propositions as shown in rule r:

$$\begin{aligned} r\text{: If } q_1 \text{ is } a_1 \text{ and } q_2 \text{ is } a_2 \\ \text{Then } y \text{ is } b_1. \end{aligned} \tag{6}$$

In an "if fuzzy proposition," the questionnaire analysis is set as a condition attribute and, in a "then fuzzy proposition," the questionnaire analysis is set as a decision attribute. When linguistic variable q_1 is a_1 and q_2 is a_2, linguistic variable y will be b_1; therefore with fuzzy rules, the linguistic causal relationship can be inferred. All the fuzzy rules can be put together to make a fuzzy rule database and this database includes various corresponding fuzzy rules.

Fuzzy inferences mean making inferences with all the rules in fuzzy rule database. There are three types in fuzzy inferences, namely, type 1, type 2, and type 3, which stand for singleton, linguistic, and linear inference rules. In this study, linguistic inference rules were used, and the method proposed by Tsukamoto was applied.

3.2. Deleting Ineffective Data. In order to avoid the interruption from ineffective data, preprocessing is necessary before data analysis [19]. There are many different methods that can be used for preprocessing. However, one preprocessing method may not be suitable for all of the fields. In this study, a novel preprocessing method of screening ineffective data for questionnaires was proposed. Here we define the effective data as honest data and ineffective data as dishonest data. Some attributes and data might be deleted to let decision-makers obtain precise and useful data in questionnaire analysis process. In this process, it is supposed that data from some respondents can be neglected. This type can be considered as a form of majority verdict which can obtain the main consensus from the majority of the questionnaire respondents. Concerning the data analysis in this study, the answers from questionnaires responded by tourists were used for data analysis. The effective data are defined as responses from the majority of tourists. The ineffective data, on the other side, include dishonest data and data from respondents with special preference.

3.3. Establishing Questionnaire Rules. The method of deleting ineffective data will be reported in this part. First of all, the authors assumed that most people have similar perception. Therefore, concerning a specific tourism destination, it is supposed that the scoring toward a specific attribute from the questionnaire respondents would be aggregated in a range. In the space of condition attribute, every decision attribute forms a block space and has its own center; those data with bias might be far from the center and more likely to be ineffective data. In addition, in the space of condition attribute, the intersection with different decision attribute might be small or empty; this assumption is to make sure that the classification of decision attribute is identifiable.

With establishing fuzzy rules, the authors can screen ineffective data with the method of fuzzy inference. Concerning the content of the questionnaire, there are n subquestion items in each of the questions, and these n subquestion items stand for condition attribute items as follows:

$$Q = \{q_1, q_2, \ldots, q_n\}, \tag{7}$$

where $n \in N$ and N stands for the set of positive integers.

The overall evaluation a respondent made is the decision attribute y in a fuzzy rule. Supposing that a respondent answered a specific question item q_p, the set of linguistic values is as follows:

$$a^p = \left\{a_1^p, a_2^p, \ldots, a_{j_p}^p\right\}, \tag{8}$$

where $1 \leq p \leq n$ and $p \in N$, j_p is the number of the linguistic values of a specific condition attribute, and $j_p \in N$.

After answering all the subquestions, the respondent must select a linguistic value from set B as the overall evaluation, where set B is a set of linguistic values as follows:

$$B = \{b_1, b_2, \ldots, b_i\}, \tag{9}$$

where i is the number of decision attribute linguistic values and $i \in N$.

The data of the answers from respondents were transferred into fuzzy rules. For example, when the linguistic value of the decision attribute inference is b_h, the first fuzzy rule will be as follows:

$$r_1^h\colon q_1 \text{ is } a_{p_1}^1 \text{ and } q_2 \text{ is } a_{p_2}^2 \text{ and } \cdots \text{ and } q_n \text{ is } a_{p_n}^3 \longrightarrow y \text{ is } b_h, \tag{10}$$

where $1 \le h \le i$ and $h \in N$.

Then all the fuzzy rules would be put together in fuzzy rule database as follows:

$$R = \left\{r^1, r^2, \ldots, r^i\right\}. \tag{11}$$

The linguistic values of decision attribute in fuzzy rule of R could be classified into i categories and every category would correspond to the linguistic values in set B as follows:

$$r^h = \left\{r_1^h, r_2^h, \ldots, r_{k_h}^h\right\}, \tag{12}$$

where r^h stands for the fuzzy rule classification of b_h and the number of rules is k_h.

The previous part reported the principles of fuzzy rules for multiple condition attribute to single decision attribute. It is found from rule classification that the distribution space of b_h corresponds to set Q in (7) as follows:

$$F_h = \left\{a^{-1}\left(b_h\right), a^{-2}\left(b_h\right), \ldots, a^{-n}\left(b_h\right)\right\}, \tag{13}$$

where F_h is the linguistic value distribution space of b_h and $a^{-1}(b_h)$ stands for the distribution situation of a^1, which is corresponded from b_h.

4. Results and Discussion

4.1. Overview of the Research Data. In this study, 248 data used were retrieved. Most of the respondents are the office workers and young persons in Taiwan. In these 248 data, 201 of the tourist sites the respondents mentioned include the sites in northern parts, central parts, southern parts, and eastern parts of Taiwan. And the other 47 ones are international tourist sites out of Taiwan. In these data, tourists' evaluations for each of the factors about the tourism destinations were included. Besides the evaluations for the factors, the overall evaluations (namely, satisfied, neutral, and dissatisfied) for every tourism destination were also inquired. After screening, 201 of these data could be used. In these 201 data, 141 were classified into "satisfied" with the tourism destination, accounting for 70.15%, and 49 were "neutral," accounting for 24.38%, while 11 were "dissatisfied," accounting for 5.47%. The numbers and percentages of data classified into each category were shown in Table 1. The evaluation of the attribute "level of prices, living costs," has three fuzzy linguistic terms of levels ("good," "barely acceptable," and "poor.") On the other hand, the attribute "tourist safety" has four fuzzy linguistic terms of levels ("very good," "good," "poor," and "very poor.") The levels of these two attributes were shown in Table 2. Through the method of fuzzy preprocess, 8 rules were obtained. These fuzzy rules were shown in Table 3. Concerning the condition attributes, two of the original ten attributes were found influential, namely, level of prices, living costs (F7), and tourist safety (F10) of the tourism destinations.

Table 1: The numbers and percentages of overall evaluation.

	Satisfied	Neutral	Dissatisfied	Total
Numbers of data classified into each category	141	49	11	201
Percentage	70.15%	24.38%	5.47%	100.00%

4.2. Fuzzy Rules Analysis. The results of the fuzzy rules analysis were shown in Table 3. According to fuzzy mathematics, only two (F7, level of prices, living costs, and F10, tourist safety) of the 10 attributes were strongly influential attributes. From these rules, the following results can be obtained.

(1) From Rule 2 and Rule 3, when F7 (level of prices, living costs) received "good," the overall evaluations would be "satisfied" if F10 (tourist safety) received "good" or "very good."

(2) From Rule 1 and Rule 3, when F10 (tourist safety) received "very good," the overall evaluations would be "satisfied" even if F7 (level of prices, living costs) received "barely acceptable."

(3) From Rule 4 and Rule 5, when F7 (level of prices, living costs) received "barely acceptable," the overall evaluations would be neutral, if F10 (tourist safety) received the level of "good" or "poor."

(4) From Rule 6 and Rule 7, when F7 (level of prices, living costs) received "poor," the overall evaluations would be dissatisfied, if F10 (tourist safety) received the level of "poor" or "very poor."

(5) From Rule 6 and Rule 8, if F10 (tourist safety) received "very poor," the overall evaluations would be dissatisfied, no matter F7 (level of prices, living costs) received "barely acceptable" or "poor."

(6) Comparing Rule 1 and Rule 4, F7 (level of prices, living costs) received "barely acceptable" in both rules and at this time F10 (tourist safety) would be a key for the overall evaluations. F10 (tourist safety) received "very good" in Rule 1 and the overall evaluations were "satisfied," while, in Rule 4, the overall evaluations were "neutral" as F10 (tourist safety) received "poor."

(7) While comparing Rule 2 and Rule 5, F10 (tourist safety) received "good" in both of these rules. F7 (level of prices, living costs) would be a key for the overall evaluations in this situation. In Rule 2 F10 (tourist safety) received "good" and the overall evaluations were "satisfied"; in Rule 5, however, the overall evaluations were "neutral" as F7 (level of prices, living costs) received "barely acceptable."

Table 2: Levels of attributes.

Attributes	Numbers of levels	Fuzzy linguistic terms of levels (form high level to low level)
F7: level of prices, living costs	3 levels	"Good," "barely acceptable," and "poor."
F10: tourist safety	4 levels	"Very good," "good," "poor," and "very poor."

Table 3: The 8 rules derived from fuzzy analysis.

	F7 level of prices, living costs	F10 tourist safety	Evaluation
Rule 1	Barely acceptable	Very good	Satisfied
Rule 2	Good	Good	Satisfied
Rule 3	Good	Very good	Satisfied
Rule 4	Barely acceptable	Poor	Neutral
Rule 5	Barely acceptable	Good	Neutral
Rule 6	Poor	Very poor	Dissatisfied
Rule 7	Poor	Poor	Dissatisfied
Rule 8	Barely acceptable	Very poor	Dissatisfied

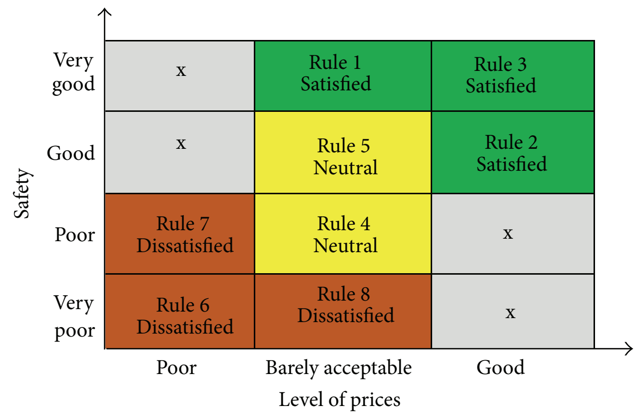

Figure 2: Fuzzy rule base (for all tourists).

(8) Comparing Rule 4 and Rule 7, as F10 (tourist safety) received "poor" in both rules, F7 (level of prices, living costs) would be a key for the overall evaluations. For example, F7 (level of prices, living costs) received "barely acceptable" in Rule 4 and the overall evaluations were "neutral," while, in Rule 7, F7 (level of prices, living costs) received "poor" and the overall evaluations turned to "dissatisfied" consequently.

(9) Comparing Rule 5 and Rule 8, when F7 (level of prices, living costs) received "barely acceptable," F10 (tourist safety) played a crucial role for deciding the overall evaluations. In other words, if F10 (tourist safety) received "good," the overall evaluations would be "neutral." On the other hand, if F10 (tourist safety) received "very poor," the overall evaluations would be "dissatisfied."

(10) From the comparison of Rule 1, Rule 4, Rule 5, and Rule 8, it was found that F7 (level of prices, living costs) received "barely acceptable" in each of the rules. In Rule 1, for example, the overall evaluations were "satisfied" since F10 (tourist safety) received "very good." The overall evaluations of Rule 4 and Rule 5 were "neutral" on the other hand as F10 (tourist safety) received either "good" or "poor." In Rule 8, however, the overall evaluations were "dissatisfied" when F10 (tourist safety) received "very poor."

In this section, the rules in Table 3 were represented as in Figure 2. In Figure 2, the upper right corner (areas of Rule 1, Rule 2, Rule 3, and Rule 5) shows that when the attribute "tourist safety" was evaluated as "good" or "very good," the attribute "level of prices, living costs" was also evaluated as "good" or "barely acceptable," and the overall evaluations were satisfied or neutral. The reason might be that most tourists already had sufficient information about the level of local living costs before they made decision for their destinations. The tourist might therefore think the level of price is agreeable. On the other hand, the lower left corner (areas of Rule 6, Rule 7, Rule 8, and Rule 4) shows that when the attribute "tourist safety" was evaluated as "poor" or "very poor," the attribute "level of prices, living costs" was evaluated as "poor" or "barely acceptable," and the overall evaluations were dissatisfied or neutral. It is believed that the poor safety might impair tourists' confidence. To sum up, tourist safety is the attribute the tourists care about the most.

In Figure 2, "x" stands for no rules in that exact area. According to Figure 2, no rules were found in the upper left corner; these areas stand for destinations with high safety and high price. The reason for no rules here might be that most respondents are office workers and young persons, they made very different evaluations about these destinations, and therefore no consistent rules could be produced. Besides, there are no rules either in the lower right corner. This lower right corner area stands for tourist destinations with poor safety. Since tourist safety was the attribute the tourists care about the most, very few tourists would select these destinations.

4.3. Comparison of the Results from Tourists of Different Ages. Tourism is getting more and more popular in the 21st century. However, tourists of different ages might have various demands and different preference regarding tourism destinations. In order to investigate the tourist preference of different ages, the authors divided the data of tourists into two groups: one group is of tourists above 30 years old and the other group is of tourists of 30 years old and below.

4.3.1. Results from Tourists of 30 Years Old and Below. In the group of tourists of 30 years old and below, there are 139 pieces of data collected from these tourists. After programming

Table 4: Levels of attributes (tourists of 30 years old and below).

Attributes	Numbers of levels	Fuzzy linguistic terms of levels (form high level to low level)
F7: level of prices, living costs	3 levels	"Good," "barely acceptable," and "poor."
F9: information and tourist services	3 levels	"Good," "barely acceptable," and "poor."
F10: tourist safety	4 levels	"Very good," "good," "poor," and "very poor."

Table 5: The 13 rules derived from fuzzy analysis (tourists of 30 years old and below).

	F7 level of prices, living costs	F9 information and tourist services	F10 tourist safety	Evaluation
Rule 1	Barely acceptable	Barely acceptable	Very good	Satisfied
Rule 2	Barely acceptable	Good	Good	Satisfied
Rule 3	Barely acceptable	Good	Very good	Satisfied
Rule 4	Good	Barely acceptable	Good	Satisfied
Rule 5	Good	Barely acceptable	Very good	Satisfied
Rule 6	Good	Good	Good	Satisfied
Rule 7	Good	Good	Very good	Satisfied
Rule 8	Barely acceptable	Barely acceptable	Poor	Neutral
Rule 9	Barely acceptable	Barely acceptable	Good	Neutral
Rule 10	Poor	Poor	Very poor	Dissatisfied
Rule 11	Poor	Barely acceptable	Very poor	Dissatisfied
Rule 12	Barely acceptable	Poor	Very poor	Dissatisfied
Rule 13	Barely acceptable	Poor	Poor	Dissatisfied

with fuzzy set theory, three of the attributes were found to be crucial, namely, "level of prices, living costs" (F7), "information and tourist services" (F9), and "tourist safety" (F10). The evaluations of both of the attributes "level of prices, living costs" and "information and tourist services" were divided into three fuzzy linguistic terms of levels "good," "barely acceptable," and "poor" while the evaluation of the attribute "tourist safety" could be divided into four fuzzy linguistic terms of levels "very good," "good," "poor," and "very poor" as shown in Table 4. Thirteen fuzzy rules were derived from fuzzy computing as shown in Table 5.

According to the fuzzy rules obtained from the data of tourists of 30 years old and below, the following results can be obtained.

(1) Comparing Rule 4 and Rule 9, F9 (information and tourist services) received "barely acceptable" and F10 (tourist safety) received "good" in both rules; at this time F7 (level of prices, living costs) would play a crucial role in deciding the overall evaluations. For example, when F7 received "good" in Rule 4, the overall evaluation would be "satisfied" while, in Rule 9, F7 received "barely acceptable" and the overall evaluation was then "neutral."

(2) Comparing Rule 4 and Rule 9, F9 (information and tourist services) received "barely acceptable" and F10 (tourist safety) received "good" in both rules; at this time F7 (level of prices, living costs) would play a crucial role in deciding the overall evaluations. For example, when F7 received "good" in Rule 4, the overall evaluation would be "satisfied" while, in Rule 9, F7 received "barely acceptable" and the overall evaluation was then "neutral."

(3) Comparing Rule 1, Rule 8, and Rule 9, both of F7 (level of prices, living costs) and F9 (information and tourist services) received "barely acceptable" in each of the rules. In this situation, F10 (tourist safety) would be a key for the overall evaluations. In Rule 1, F10 (tourist safety) received "very good" and the overall evaluation was "satisfied," while, in Rule 8, F10 (tourist safety) received "poor"; and in Rule 9, F10 (tourist safety) received "good" and the overall evaluations of both of Rule 8 and Rule 9 were "neutral."

(4) Comparing Rule 8 and Rule 13, F7 (level of prices, living costs) received "barely acceptable" and F10 (tourist safety) received "poor" in both rules; at this time F9 (information and tourist services) would play an influential role in deciding the overall evaluations. For example, when F9 received "barely acceptable" in Rule 8, the overall evaluation would be "neutral," while, in Rule 13, F9 received "poor" and the overall evaluation was then "dissatisfied."

According to the results of fuzzy analysis, for tourists of 30 years old and below, three (F7, level of prices, living costs, F9, information and tourist services, and F10, tourist safety) of the 10 attributes were strongly influential attributes. Compared with the results in the previous section, there was

Table 6: Levels of attributes (tourists above 30 years old).

Attributes	Numbers of levels	Fuzzy linguistic terms of levels (form high level to low level)
F7: level of prices, living costs	4 levels	"Very good," "good," "poor," and "very poor."
F9: information and tourist services	4 levels	"Very good," "good," "poor," and "very poor."
F10: tourist safety	4 levels	"Very good," "good," "poor," and "very poor."

an extra influential attribute, namely, information and tourist services (F9). In order to analyze the relationship among these three attributes, 3 figures based on three different levels (good, barely acceptable, and poor) of information and tourist services were generated.

Figure 3(a) shows the rule base of tourists of 30 years old and below when information and tourist services of the destinations are good. Only four rules were generated in the upper right corner of Figure 3(a). These 4 rules are all evaluated as "satisfied" with very good or good in safety and good or barely acceptable in living cost. On the other hand, there were no rules created in other areas in Figure 3(a). In the condition of sufficient information, tourists would try their best to avoid going to destinations with poor safety or poor level of prices. Similar to the condition in Figure 2, no rules were found in the upper left corner and the lower right corner.

Figure 3(b) shows the rule base of tourists of 30 years old and below when information and tourist services of the destinations are barely acceptable. Comparing Figure 3(b) with Figure 3(a), Rule 9 in Figure 3(b) is in the same position as Rule 2 in Figure 3(a). However, the overall evaluation of Rule 9 in Figure 3(b) is neutral and that of Rule 2 in Figure 3(a) is satisfied; the authors therefore inferred that good information and tourist services of the destinations may promote the image of a tourist site.

Figure 3(c) shows the rule base of tourists of 30 years old and below when information and tourist services of the destinations are poor. Comparing Figure 3(c) with Figure 3(b), Rule 12 in Figure 3(c) is in the same position as Rule 8 in Figure 3(b). Nevertheless, the overall evaluation of Rule 12 in Figure 3(c) is dissatisfied and that of Rule 8 in Figure 3(b) is neutral; it is therefore inferred that poor information and tourist services of a tourist site may degrade the overall evaluation of a destination. On the other hand, there were no rules generated in other areas in Figure 3(c). Actually, very few people know destinations with poor information. Besides, it is supposed that a tourist site with good safety and living cost condition will soon be popular in this Internet era, and then those cases will be transferred into the section of sufficient information such as the cases in Figures 3(a) and 3(b).

4.3.2. Results from Tourists above 30 Years Old. In the group of tourists above 30 years old, there are pieces of 34 data collected from these tourists. After programming with fuzzy set theory, three of the attributes were found to be crucial, namely, "level of prices, living costs" (F7), "information and tourist services" (F9), and "tourist safety" (F10). The evaluation of all the attributes "level of prices, living costs," "information and tourist services," and "tourist safety" was shown as four fuzzy linguistic terms of levels ("very good," "good," "poor," and "very poor") as shown in Table 6. Fourteen fuzzy rules were derived from fuzzy computing as shown in Table 7.

According to the fuzzy rules obtained from the data of tourists above 30 years old, the following results can be obtained.

(1) Comparing Rule 8 and Rule 14, F7 (level of prices, living costs) received "good" and F10 (tourist safety) received "very poor" in both rules; at this time F9 (information and tourist services) would play a crucial role in deciding the overall evaluations. For example, when F9 received "good" in Rule 8, the overall evaluation would be "neutral," while, in Rule 14, F9 received "very poor" and the overall evaluation was then "dissatisfied."

(2) Comparing Rule 4 and Rule 11, F9 (information and tourist services) received "very good" and F10 (tourist safety) received "good" in both rules; at this time F7 (level of prices, living costs) would be a key for the overall evaluations. In Rule 4, F7 (level of prices, living costs) received "very good" and the overall evaluation was "satisfied," while, in Rule 11, F7 (level of prices, living costs) received "good" and the overall evaluation of Rule 11 was then "neutral."

According to the results of fuzzy analysis, for tourists above 30 years old, three (F7, level of prices, living costs, F9, information and tourist services, and F10, tourist safety) of the 10 attributes were strongly influential attributes. Besides, there are four levels in each of the three attributes as shown in Table 6. In order to analyze the relationship among these three attributes, 4 figures based on four different levels (very good, good, poor, and very poor) of information and tourist services were generated.

Figure 4(a) shows the rule base of tourists above 30 years old when information and tourist services of the destinations are very good. Seven rules were generated: four rules of satisfied were in the upper right corner of Figure 4(a) and the other three rules are of neutral. Comparing Figure 4(a) with Figure 4(b), Rule 7 in Figure 4(a) is in the same position as Rule 13 in Figure 4(b). However, the overall evaluation of Rule 7 in Figure 4(a) is neutral and that of Rule 13 in Figure 4(b) is dissatisfied; it is therefore inferred that better information

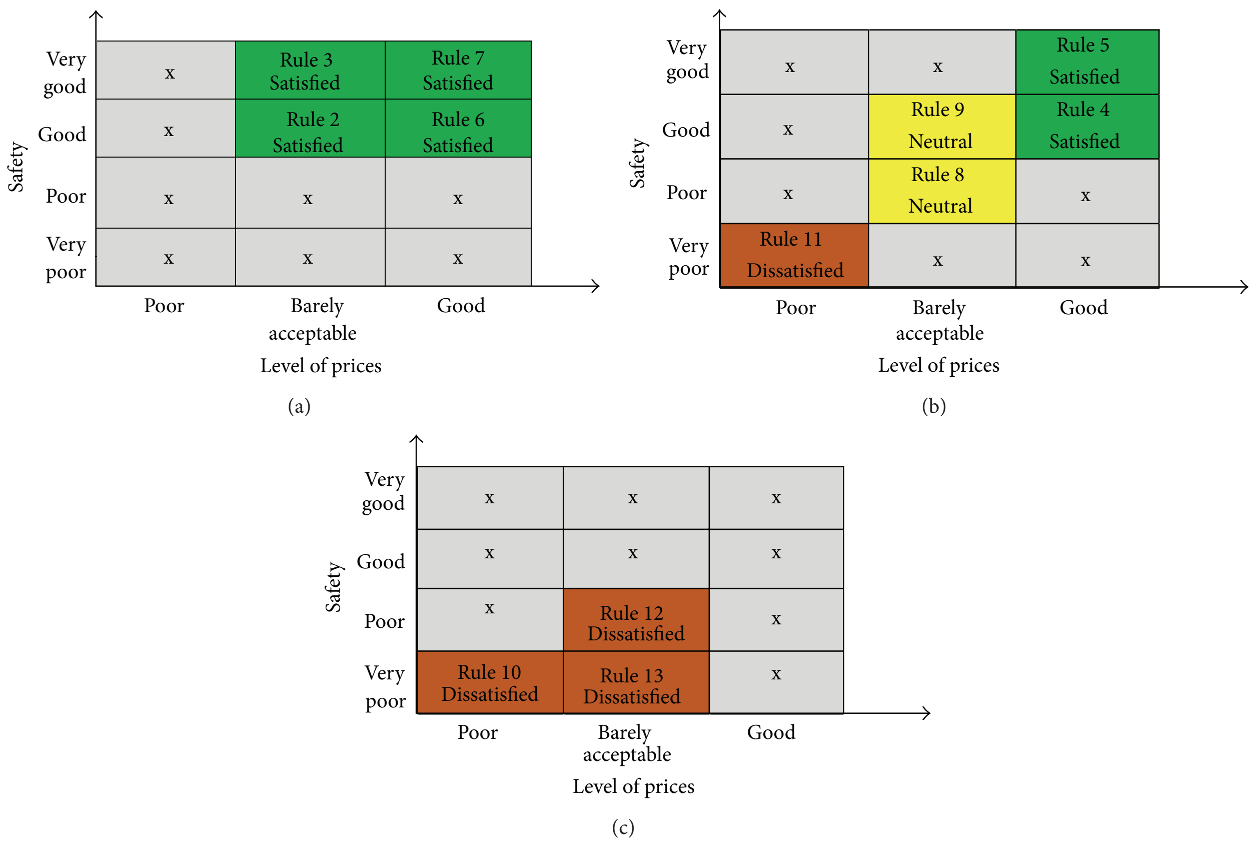

FIGURE 3: (a) Tourists of 30 years old and below/information and tourist services are good. (b) Tourists of 30 years old and below/information and tourist services are barely acceptable. (c) Tourists of 30 years old and below/information and tourist services are poor.

TABLE 7: The 14 rules derived from fuzzy analysis (tourists above 30 years old).

	F7 level of prices, living costs	F9 information and tourist services	F10 tourist safety	Evaluation
Rule 1	Poor	Very good	Very good	Satisfied
Rule 2	Good	Very good	Very good	Satisfied
Rule 3	Very good	Poor	Very good	Satisfied
Rule 4	Very good	Very good	Good	Satisfied
Rule 5	Very good	Very good	Very good	Satisfied
Rule 6	Very poor	Very good	Poor	Neutral
Rule 7	Poor	Very good	Poor	Neutral
Rule 8	Good	Good	Very poor	Neutral
Rule 9	Good	Good	Poor	Neutral
Rule 10	Good	Good	Good	Neutral
Rule 11	Good	Very good	Good	Neutral
Rule 12	Very good	Good	Poor	Neutral
Rule 13	Poor	Good	Poor	Dissatisfied
Rule 14	Good	Very poor	Very poor	Dissatisfied

and tourist services of a tourist site may promote the overall evaluation of a destination.

It is found that very few rules are in Figures 4(c) and 4(d). Similarly, there are few rules found in Figure 3(c) (three rules). The authors inferred that destinations with poor information and tourist services have fewer tourists. There is only one rule especially in each of Figures 4(c) and 4(d) because of lack of data from tourists above 30 years old. It is therefore concluded that tourists in this group (tourists above 30 years old) seldom travel to destinations with poor

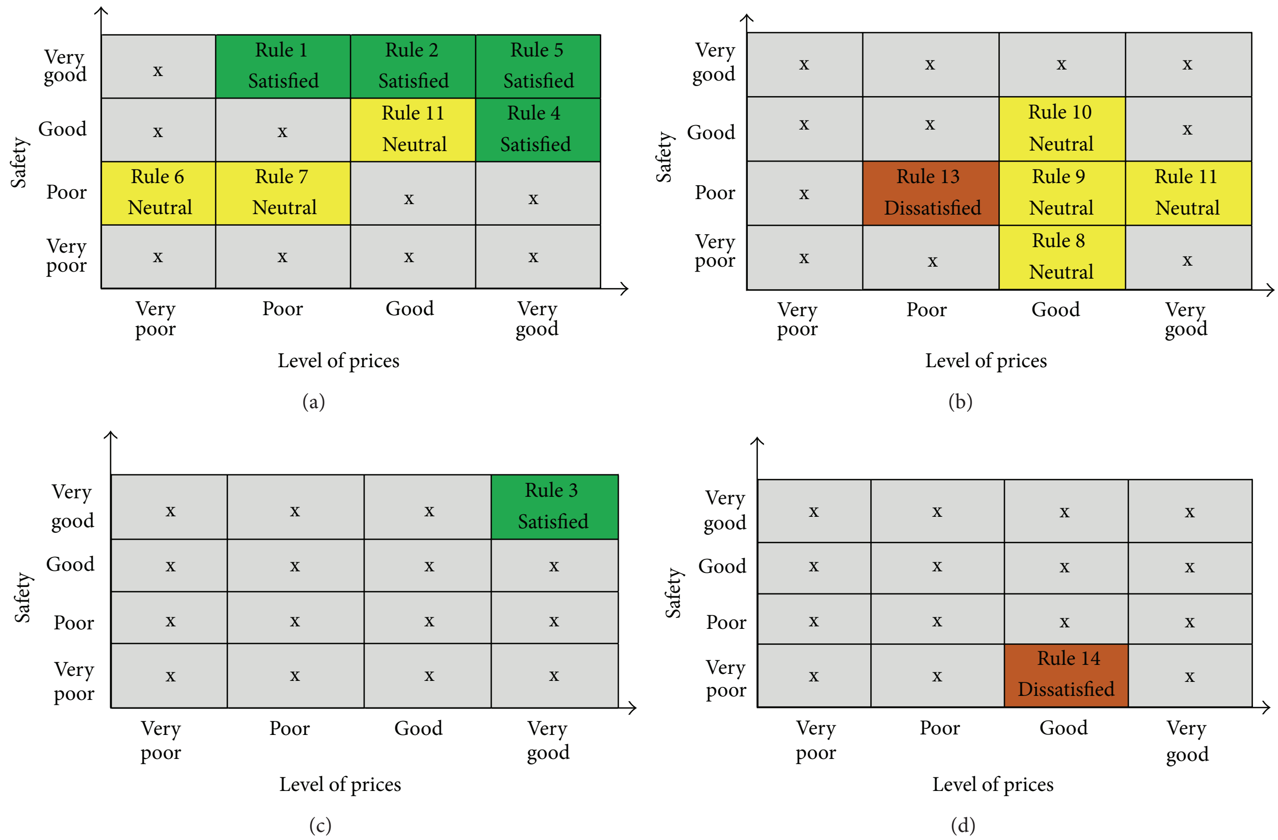

FIGURE 4: (a) Tourists above 30 years old/information and tourist services are very good. (b) Tourists above 30 years old/information and tourist services are good. (c) Tourists above 30 years old/information and tourist services are poor. (d) Tourists above 30 years old/information and tourist services are very poor.

information and tourist services. In other words, tourists above 30 years old need good information and tourist services when they select destinations for tour.

5. Conclusion

In this study, F7 (level of prices, living costs) and F10 (tourist safety) were found influential factors through fuzzy algorithm analysis [20]. From this research, a fuzzy rule database of tourism destinations is established to provide a fuzzy system inference decision-making model. This decision-making rule model can be provided to the tourism managers as a reference to establish tourism management. Tourism planners can use the ten attributes as a reference.

However, the budgets of some tourism destinations are often limited. This research simplified the ten constituent elements into two; in other words, two key attributes were found. While the budgets are limited, the tourism destinations could use the resource in the most crucial attributes to create comparatively large benefit.

From the rule analysis, it can be speculated that when tourists visit a tourism destination, they value "level of prices, living costs" (F7) and "tourist safety" (F10) of this area.

In order to investigate the tourist preference of different ages, the authors divided the data of tourists into two groups: one group is of tourists above 30 years old and the other group is of tourists of 30 years old and below. It was found that tourists of different ages showed their different preferences in three fields, namely, "level of prices, living costs" (F7), "information and tourist services" (F9), and "tourist safety" (F10). In other words, if the tourism industry would satisfy tourists' demands and preferences, especially for tourists of different ages, they have to focus on information and tourist services as well.

On the basis of the results of this study, it is shown that top management of tourism destinations should put resources in these fields first, in order to allow limited resources to perform to maximum effectiveness for the positive evaluations by tourists.

Lastly, this study still has parts that can be further researched or improved. In terms of the fuzzy linguistics, attribute F7 (level of prices, living costs) is of 3 levels, while attribute F10 (tourist safety) is of 4 levels, and 8 rules were produced. If other attributes such as tourists' age or gender are further considered, more focused rules will be obtained, which will assist in providing management of tourism destinations with more precise reference rules. At the same time, this can help decision-makers to make future development plans for tourism destinations that they manage, so as to cater to the preferences of different groups.

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Modelling the Accommodation Preferences of Tourists by Combining Fuzzy-AHP and GIS Methods

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Finding the place of accommodation is one of the most crucial issues during a journey. This study aims to support the decision-making of tourists for choosing the optimal accommodation by combining fuzzy analytic hierarchy process (FAHP) and geographic information system (GIS) techniques. The adopted criteria are the cost per room, the distance from the center, the level of security, the place rating, and the availability of free cancellation and breakfast. Due to some uncertainty and diversity of criteria, the FAHP approach is applied to consolidate tourists' decisions by applying criteria weighting, while the GIS is used to overlay the weighted criteria and to visualize the ranked places of accommodation on a map. The combined technique is applied on a case study in Budapest City, where the analysis is conducted on 364 places of accommodation. The results show that half of the places are recommended for tourists, and more than fifth of the accommodations are highly recommended. Furthermore, it can be concluded that the cost per room was the highest influential criterion with 0.233 importance weight, followed by the security level with 0.205. The lowest factor affecting the choice of accommodation was the free cancellation service. It was demonstrated that the rating weight importance was 0.182, while the breakfast and the distance from the center had approximately the same importance. As a recommendation, some improvements on the accommodation, such as decreasing the cost per room, enhancing the services, or developing the quality of the places, would increase their attractiveness for tourists.

1. Introduction

For several countries, tourism is one of the most important industries in terms of the gross domestic product (GDP) [1]. Data collection about the cities is a relevant issue, where several parameters have to be considered [2]. According to the Hungarian Central Statistical Office, tourism industry is around the fifth of the country's economic activities. The direct and indirect economic influence of tourism in Hungary was about 9.4% in 2015 where more than 20 million tourists arrived in Hungary [3]. Tourism can be defined as the tourists' travelling for leisure or other goals and staying outside their common environment for a specific period, not exceeding one continuous year. Tourism industry involves entertainment destinations (recreation, culture, sports activities, etc.), food establishments (restaurants, cafes, taverns, etc.), places of accommodation (hotels, motels, campgrounds, etc.), transportation (airplane, rail, bus, auto, etc.), shopping facilities, and others [4]. Accommodation is the most important sector in tourism industry, where more than two fifths of tourists' daily expenditures are allocated to this sector [5]. The places of accommodation represent the locations, where tourists can rest and plan their activities [6].

In major touristic cities, there is a lot of uncertainty about choosing the optimal places of accommodation. Finding an optimal accommodation is one of the most important decisions in the tourists' journeys [7]. Despite the availability of online websites and applications for booking accommodation, the issue is still complex due to the extensive number of available options in this sector and the numerous factors that affect the decision-making. Although there is heterogeneity of the characteristics of the tourists themselves, such as the sociodemographic (gender, age, marital status, educational level, and income), the questions seem to be the same: where can I sleep safely and secure? How much is the cost per night? Does accommodation provide services such as breakfast or free cancellation? [8].

In case of a spatial problem, such as the accommodation search, where several criteria have to be considered, multicriteria decision-making (MCDM) methods can be applied. More specifically, in case of uncertainty and fuzzy conditions, the fuzzy analytic hierarchy process (FAHP) method, which is a specific type of an analytic hierarchy process (AHP) and belongs to the MCDM methods, can be used. For example, a study mentioned that tourists face difficulties when choosing the optimal restaurant in a foreign city, which choice includes some subjective elements. Dewi et al. [9] performed a comparison among the AHP, FAHP, and TOPSIS methods using a mobile-based culinary recommendation system. The outcomes proved that FAHP had the highest accuracy compared to the other methods. The concept of FAHP can be also used for evaluating the criteria that affect the accommodation choice, while it would be difficult to use the traditional method (i.e., AHP) because of dealing with a fuzzy environment. Based on the reasons stated above, the FAHP method combined with geographic information system (GIS) technique could offer well-established choices for tourists. Thus, the main objective of this study is to develop a comprehensive model, which supports tourists in choosing the optimal accommodation according to their preferences and constraints.

This paper is organized as follows: after the introduction, Section 2 reviews previous studies which use GIS and MCDM methods. The theoretical methods and the proposed methodology are explained in Section 3. The results and the study area are explained in Section 4, followed by the discussion in Section 5. Finally, the main conclusions are demonstrated in Section 6.

2. Literature Review

Accommodation facilities vary in size and services, but their primary purpose is to provide customer service, where hotels, motels, guesthouses, and apartments are examples of places of accommodation [10]. Tourists choose the place according to their preferences and constraints, where cost, location, and services represent the basic elements of the consideration [11]. Many studies examine the factors that affect the tourists' choices of accommodation. Psychological and nonpsychological factors influence the decision-making process, especially in the field of tourism due to the variety and the competition among the alternatives [12]. Losada et al. [13] conducted a study on the types of accommodation chosen by senior tourists in Spain. An interview survey through telephone was used to obtain data, such as sociodemographic and self-perceived variables as well as factors linked to pull motivation. A multinomial logit model was applied to analyze the collected data. The study found that seven out of ten senior tourists preferred hotels. Additionally, the outcomes indicated that the staying's length highly correlates to the type of accommodation. Another study by [14] considered the global economic crisis's impact on the accommodation of tourists in the Netherlands. The researchers mentioned that affordable hotels play a significant role in tourists' choices. Ananth et al. [15] examined a sample of tourists to evaluate the factors affecting hotel selection. The results demonstrated that the price and the hotel quality were the most influential factors. Another research was carried out by [16], who found that the cost, the location, the cleanliness, and the services are the most persuasive factors in the tourists' accommodation choices. In another study, it was found that factors related to the hotels, such as the size of the room or the provision of breakfast, have a significant effect on tourists' choices [17].

For the location selection process of the accommodation, the decision-maker tries to choose the facility that could fulfil his/her requirements, where several factors for the optimal selection have to be considered. MCDM technique is applied to evaluate and rank the multicriteria problems [18]. Chou et al.[19] applied MCDM (more specifically a fuzzy method) for selecting international hotel locations in Taiwan. The findings proved that the security level, accessibility, and the surrounding cultures are the most important criteria for hotel location selection. Similarly, Sohrabi et al. [20] applied the fuzzy model to analyze the factors that affect hotel selection in Iran. They divided the factors into two main groups: hotel comfort factors and hotel compensatory factors. The first group involved hotel staff, promenade and comfort, pleasure, car parking, network services, and rooms' cleanliness. Security, expenditure, and recreational information refer to the second main group. The main results revealed that the high importance criteria were the expenditure and car parking since most tourists come from poorer cities of Iran. Hsu et al. [21] combined the fuzzy method and TOPSIS to identify the prioritizing factors that affect the destination choice of tourists. The scholars evaluated eight touristic destinations in Taiwan. The final result showed that safety and visiting friends significantly influenced the tourists' destinations, while the cost had the least effect. Ngai and Wat [22] developed a fuzzy expert system called the hotel advisory system (HAS) to help tourists in choosing their hotels. The final evaluation of experts and users revealed the benefit of the system and positive feedback from the questionnaires survey. Thus, MCDM can be applied in order to consider all the influential factors concerning the choice of the optimal place. The most appropriate approach to evaluate the alternative is MCDM, especially for the site selection problems [23].

During the last few years, GIS plays a significant role in assisting the decision-making process by dealing with spatial data and generating the suitability maps [24]. According to [25] definition, GIS is a tool used to capture, store, check, integrate, manipulate, analyze, and display spatial data. Due to the capabilities of GIS, it has been applied in different disciplines for a variety of complex spatial problems. Moreover, several studies applied this tool in tourism. For example, García-Palomares et al. [26] investigated the role of GIS in tourism planning, where tourists' hot spots are identified in eight major European cities, and the distribution pattern is analyzed based on spatial GIS techniques. Another comprehensive study discussed the role of the GIS in tourism [27]. The study aimed to explain the importance of the GIS in tourism through the analysis of data, modelling, and forecasting in the tourism field.

In order to find the suitability of an area, GIS techniques based on MCDM could be used. The combination of MCDM and GIS could improve the capabilities of handling variety and the amount of spatial data [28]. Ibraheem et al. [29] used GIS-AHP combination to explore car parking's optimal location in the CBD of Al Ramadi City, Iraq. The AHP method generated the weight of the criteria, and GIS techniques were applied for the final suitability map. Similarly, Mishra et al. [30] applied GIS and AHP to identify the suitable locations of organic farming. The scholars mentioned that rural tourism and economics could be promoted by developing organic farming in rural regions. The weights of the adopted criteria were calculated with the AHP method. Then, the overlaying tool of GIS was used to generate the map. GIS-based MCDM is a suitable method for dealing with multicriteria spatial problems as shown by [31]. They applied this approach to the northern touristic areas of Iran. Analytical network process (ANP) has been used with GIS-MCDM. The results showed the highest potential tourists area based on the natural environmental features. With the same approach, Sahin et al. [32] evaluated air pollution problems in Turkey. Alam [33] combined AHP and GIS to select the optimal accommodation for living in Chittagong City, Bangladesh. He mentioned that using this combination (i.e., GIS and MCDM) is a useful approach that facilitates the users to evaluate the numerous alternatives. The study helped the clients easily to choose the optimal location for accommodation. The combination of GIS-MCDM is an excellent approach to simplify a complex problem, as mentioned by [34]. However, only a few studies applied this framework in the tourism sector.

Several studies in various disciplines applied a similar methodology to solve an MCDM problem. Table 1 provides a detailed overview of the applied methodology in previous studies taking into account the decision goal, the method approach, the type of the problem, the relevance to tourism sector, and the studied criteria. It can be stated that none of these papers consider the accommodation choice in tourism as an MCDM-spatial problem.

The decision-making for selecting the optimal accommodation becomes complicated due to the multiple criteria that affect the process, as a variety of places can be found based on quality, service availability, rating, accessibility, cost, and location. Thus, FAHP could be used to tackle the fuzziness related to the criteria evaluation, as it can reflect the way of decision-makers' thinking as they can express their judgment in an interval rather than using a single value [35]. Moreover, FAHP is a method that deals with uncertainty to generate decisions [36]. All these advantages make FAHP the appropriate method for the complex decision of choosing the optimal accommodation place. The combination of FAHP and GIS would produce the final suitability map of accommodations for tourists in Budapest.

3. Methodology

3.1. Structure and Criteria. This study was performed in two main phases: the first phase applied FAHP to find the criteria's weight. After collecting the relevant data and preparing the study area's layers using the GIS, the second phase conducted that represents the combination of the outcomes of the first phase and overlay GIS tool to generate the final map. Through two phases, classification process of the alternatives is performed, see Figure 1.

The combination of FAHP and GIS techniques is applied to analyze the locations of accommodations. A crucial step of this approach is the identification of the relevant criteria that can be found in the majority of the online accommodation reservation applications and websites, such as booking.com. The suitable criteria have been chosen based on the literature review and discussions with transport experts and researchers. Figure 2 shows the hierarchical structure that involves the goal, the criteria, and the alternatives considered in this study.

The data have been collected from [37] website. Meanwhile, the number of crimes per district for Budapest City was collected from [38]. These data are utilized to identify the level of security in the study area. Then, the spatial analysis and classification of accommodation places according to the security level criterion was achieved. The criteria can be detailed as follows:

Place rating: the reviews of the customers are used to represent the rating of each accommodation. In case of a missing rating, it is assumed to be equal to the lowest value.

Cost per room: the cost of a single room for one night is calculated.

Distance from the center: the distance from the city center in km is used as an indicator of this criterion.

Breakfast included: if the places do not offer this service, 0 value is assumed. Otherwise, the value is equal to 1.

Level of security: the value of this criterion is obtained based on the number of crimes per each district and the coordination of the places.

Free cancellation: if the accommodations do not offer this service, 0 value is assumed. Otherwise, the value is equal to 1.

Booking.com is one of the biggest websites for accommodations and used for gathering the related data. Octoparse.8 software is applied to scrape the accommodation places of Budapest City in a CSV-file. Then, Excel software used to organise, filter, and summarise the collected attribute data, especially with scraping a website where repeated data might be found. The spatial data of the study area are collected by using Open Street Map (OSM) based on QGIS software (version 3.10.9). The clip tool of ArcGIS 10.5 software is applied to identify the study area of Budapest City. Then, the spatial data are connected with the attribute data to prepare the layers to be used for spatial analysis and classification and as an input layer in the overlay weighted step.

Table 1: Comparison of the applied methodology in this study and previous studies.

Reference	Decision goal	MCDM approach	MCDM-spatial problem	MCDM-GIS	Tourism sector	Studied criteria
[19]	Hotel location building choice	FAHP	Yes	No	Yes	Proximity to public facilities, cost, distance to existing competitors, security, natural resources, rest facilities, distances, parking area, convenience, leisure facilities, diversity of restaurants, local culture, quality of manpower, and regulation restrictions
[29]	Car parking location	AHP	Yes	Yes	No	Accessibility, land-use, location, and cost
[31]	Potential touristic area	ANP	Yes	Yes	Yes	Water attractions, scenic spots, mountain attractions, and forest attractions
[30]	Optimal locations for organic farming	AHP	Yes	Yes	No	Road, drainage, soil, slope, geology, and land-use/land cover
[32]	Optimal region for installing air pollution	AHP	Yes	Yes	No	Topographic and weather parameters
[33]	Optimal accommodation place	MCS	Yes	Yes	No	Road, market, hospital, university, office, beach, school, police station, playground, park, and airport
Proposed study	Optimal accommodation place for tourists	FAHP	Yes	Yes	Yes	Cost per room, distance from the center, level of security, place rating, and availability of free cancellation and breakfast

3.2. FAHP. Choosing a place of accommodation involves an uncertainty circumstances. Thus, the application of a simple AHP method may be not efficient and might lead to inaccurate results [39]. A combination of AHP and fuzzy approach helps to select the optimal place. A pairwise comparison is conducted based on the criteria. The comparison is performed by using the AHP scale from 1 to 9. A survey has to be conducted with a group of experts to evaluate the relevant criteria. It is common to use a limited number of experts. Various research studies reported outcomes using MCDM with a small number of experts, such as the studies [40, 41] utilized only 5 participants, the study [42] worked with 7 participants, and the study [43] used input from 17 participants.

The consistency ratio (CR) of the pairwise comparison matrices is calculated according to [44]. Equations (1) and (2) are used for checking CR, which value should be below 10%:

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

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \leq 0.1, \tag{2}$$

where CI represents the consistency index, $\lambda_{\max}$ is the maximum eigenvalue, n refers to the number of rows in a matrix, and RI is the random index, which values can be seen in Table 2.

Each expert assigns a term according to the AHP scale. Then, the extented FAHP version is applied to calculate the overall weights. The AHP scale is converted to fuzzy numbers by using the triangular fuzzy number (TFN). The membership function of the fuzzy theory indicates a new scale ranging from 0 to 1. Thus, new terms can be used to obtain a range of numerical numbers. Letters l, m, and u are used to identify the triangular fuzzy numbers (TFN), where l, m, and u denote the lower, medium, and upper numbers of TFN, respectively. Equation (3) and Figure 3 illustrate the membership function of a TFN [45]:

$$\mu M(x) = \begin{cases} \dfrac{x}{m-l} - \dfrac{l}{m-l}\,(\text{Placeholder1}), & x \in [l\,m], \\[2ex] \dfrac{x}{m-u} - \dfrac{u}{m-u}, & x \in [m\,u], \\[2ex] 0, & \text{otherwise}. \end{cases} \tag{3}$$

The AHP scale is converted to fuzzy numbers (as shown in Table 3) by using the triangular fuzzy number (TFN).

The calculation of the weights of the criteria by using the extended version of FAHP can be summarized as follows.

Step 1. After checking the consistency ratio of the experts' opinions, the pairwise comparison matrices are converted into fuzzy numbers. Equations (4)–(6) are used to obtain the individual judgment matrix based on the studies of [46], [47], and [48]:

$$l_{ij} = \min_{k=1,2,\ldots,k}\left(l_{ijk}\right), \tag{4}$$

$$m_{ij} = \sqrt[k]{\prod_{k=1}^{k} m_{ijk}}, \tag{5}$$

$$u_{ij} = \max_{k=1,2,\ldots,k}\left(u_{ijk}\right), \tag{6}$$

where i and j refer to the preference or relative importance for each criterion, as assigned by expert k.

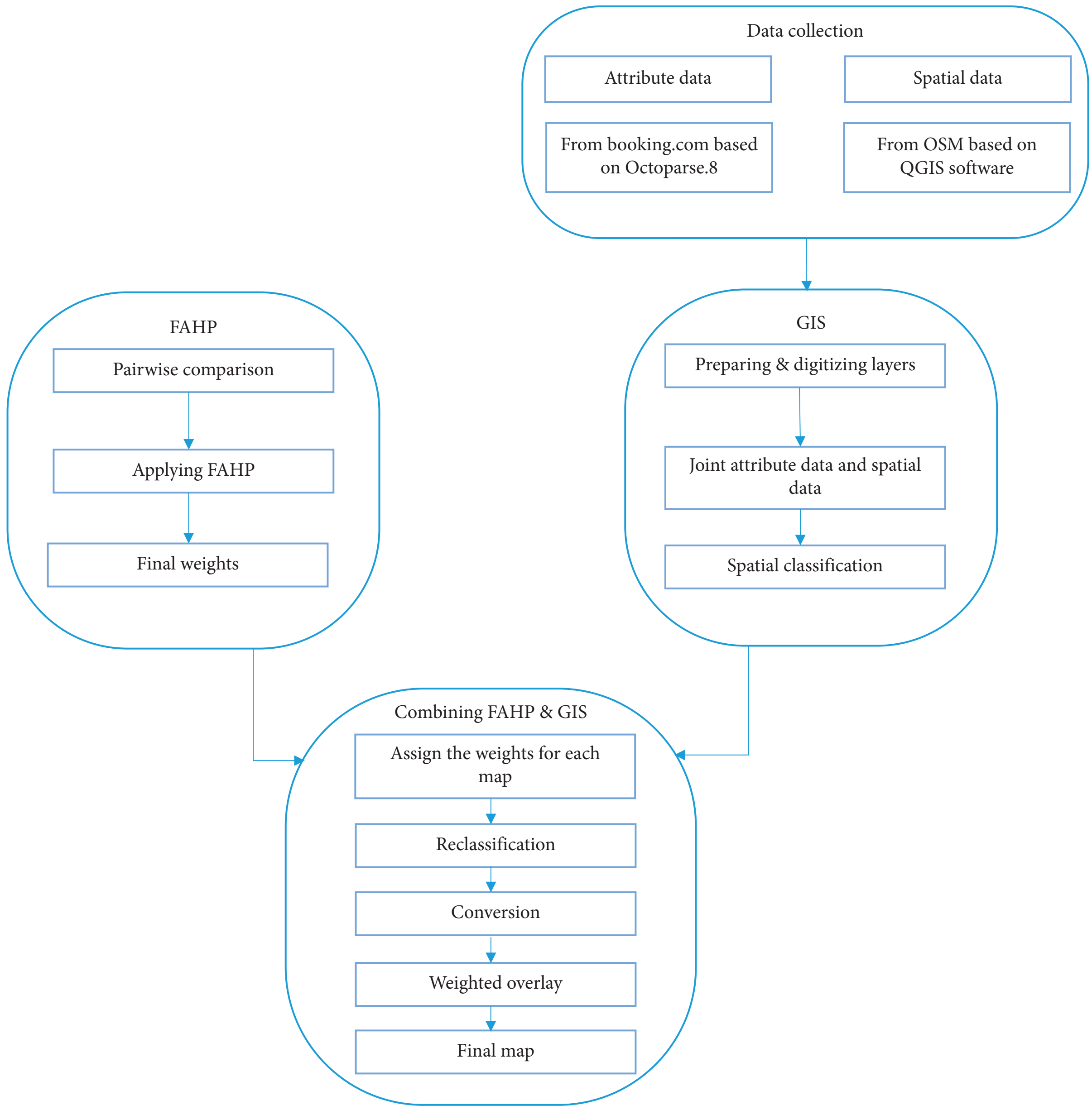


Figure 1: The representation of the methodology.

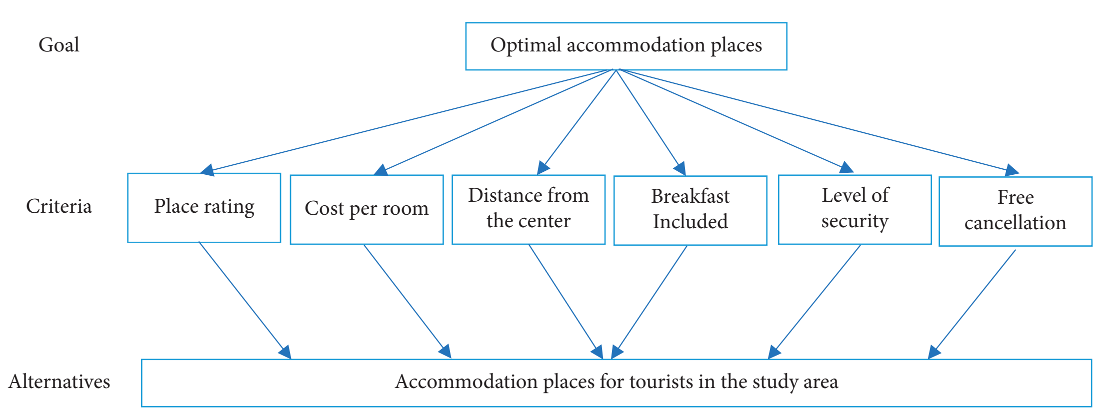


Figure 2: The hierarchical structure of the method to find a place of accommodation.

Table 2: Random index of a matrix.

n	3	4	5	6	7	8	9
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45

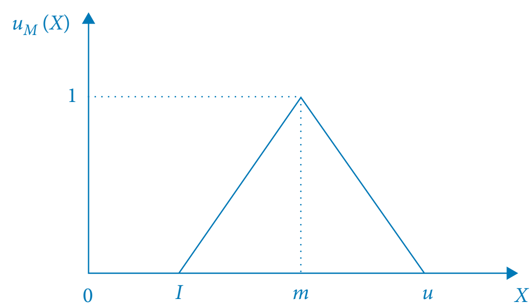


Figure 3: Triangular fuzzy number (TEN) [45].

Step 2. Let the object and the goal set be denoted by $x = \{x_1, x_2, \ldots, x_n\}$ and $G = \{g_1, g_2, \ldots, g_n\}$, respectively. Then, the extent analysis for each goal g_1 is performed. Moreover, the extent analysis is applied for each object:

$$M_{gi}^1, M_{gi}^2, \ldots, M_{gi}^m, \quad i = 1, 2, \ldots\ldots.., n. \tag{7}$$

Thus, the calculation of the fuzzy value synthetic can be obtained for each object as shown in the following equations:

$$S_i = \sum_{j=1}^{m} M_{gi}^j \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1}, \tag{8}$$

where

$$\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{j=1}^{m} l_i, \sum_{j=1}^{m} m_i, \sum_{j=1}^{m} u_i\right), \tag{9}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{j=1}^{m} l_i, \sum_{j=1}^{m} m_i, \sum_{j=1}^{m} u_i\right), \tag{10}$$

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} = \left(\frac{1}{\sum_{j=1}^{m} u_i}, \frac{1}{\sum_{j=1}^{m} m_i}, \frac{1}{\sum_{j=1}^{m} l_i},\right). \tag{11}$$

Step 3. In this step, the degree of possibility of two fuzzy numbers M_1 (l_1, m_1, and u_1) and M_2 (l_2, m_2, and u_2) is determined as shown in the following equation:

$$V(M_1 \geq M_2) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } M_2 \geq M_1, \\ 0, & \text{if } l_1 \geq u_1 \\ \dfrac{l_1 - u_2}{(m_1 - u_2) - (m_1 - l_1)}, & \text{otherwise}, \end{cases} \tag{12}$$

where d denotes the highest intersection point D between μ_{M_1} and μ_{M_2}. In addition, the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are relevant to comparing M_1 and M_2.

Step 4. As illustrated in Figure 4, the degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers is determined as shown in the following equation:

$$\begin{aligned} V(M \geq M_1, M_2, \ldots, M_k) &= V[(M \geq M_1)\text{and}(M \geq M_k)] \\ &= \min V\left(M \geq M_j\right), \quad i = 1, 2, \ldots, k. \end{aligned} \tag{13}$$

Assuming that $\omega_i' = \min V(M_i \geq M_k)$, the weight vector is given based on the following equation:

$$W' = \omega_1', \omega_2', \ldots, \omega_{in}^{'}. \tag{14}$$

Step 5. The final weight vectors are computed via a normalization step, and the nonfuzzy numbers W are given by

$$W = \left(\omega_1', \omega_2', \ldots, \omega_{in}^{'}\right)^T. \tag{15}$$

The arithmetic operations can be summarized as follows [49]:

$$\begin{aligned} \text{Addition}: (l_1 m_1 u_1) + (l_2 m_2 u_2) &= (l_1 + l_2, m_1 + m_2, u_1 + u_2), \\ \text{Subtraction}: (l_1 m_1 u_1) + (l_2 m_2 u_2) &= (l_1 - l_2, m_1 - m_2, u_1 - u_2), \\ \text{Multiplication}: (l_1 m_1 u_1) \times (l_2 m_2 u_2) &= (l_1 \cdot l_2, m_1 \cdot m_2, u_1 \cdot u_2), \\ \text{Inverse}: (l_1 m_1 u_1)^{-1} &= \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right). \end{aligned} \tag{16}$$

Table 3: The definition of AHP terms, the AHP ratio scale, and the associated fuzzy numbers.

definition	AHP scale	Fuzzy number
Equal importance	1	(1, 1, 1)
Somewhat more important	3	(2, 3, 4)
Much more important	5	(4, 5, 6)
Very much more important	7	(6, 7, 8)
Absolutely more important	9	(9, 9, 9)
Intermediate values	2	(1, 2, 3)
	4	(3, 4, 5)
	6	(5, 6, 7)
	8	(7, 8, 9)

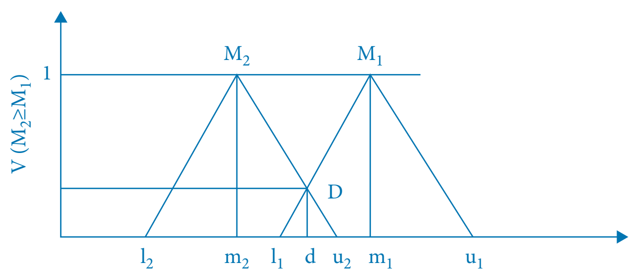


Figure 4: The degree of possibility [45].

3.3. GIS Techniques with FAHP. ArcGIS 10.7 software is used to analyze the accommodations of tourists. The relevant layers are prepared and digitized as vector layers. Calculation processes are conducted on each alternative to standardize all the values on a unified scale. After linking the attribute data (i.e., collected data from booking.com website) with the prepared layers, a classification process is performed. For classification purposes, this study assumes the use of ten classes to formulate all the collected values except for the free cancellation and the breakfast availability, where the number of classes is two. This classification is based on the range of the maximum and minimum values of the collected data.

Then, the reclassification with the GIS tool is carried out to provide integer values instead of ranges. Thus, these values can be combined with FAHP results. The reclassified classes are based on the range of 1 to 10. For example, in case of the cost per room criterion, 10 is assigned for the lowest cost, while 1 is assigned for the highest cost. For the exception criteria, the classes are between 0 and 1, where 0 represents the unavailability of the services of breakfast or free cancellation, and 1 represents availability of these services. Then, the conversion of all reclassified layers from vector to raster is done by using the GIS tools. The converted layers represent the input data for the overlay step. This step includes the combination of FAHP outcomes and the integer values, which can be conducted using the GIS overlay tool. This process can be expressed as

$$S_{(i,j)} = V_{(i)} \times W_{(j)}, \tag{17}$$

where $S_{(i,j)}$ = the final score of each alternative, V_i = the score of each alternative i, and W_j = the weight of each criterion j.

By using the overlaying tool within ArcGIS software, the final map (FM) can be produced. This step represents the summation of the final scores of each alternative. The produced map groups the alternatives into five classes. These classes include a range of recommended places from "highly recommended" to "not recommended." The final step can be expressed as

$$\mathrm{FM} = \sum S_{(i,j)}. \tag{18}$$

4. Results

4.1. Case Study. Budapest is chosen as the location of the case study to analyze the places of accommodation for tourists. Rátz et al. [50] mentioned that Budapest is a major tourism destination in Hungary, and more than four-fifths of the tourists spent a night in the city. The city is the center of cultural and business tourism in Hungary, and it is rich in thermal baths, which makes the country the leader of health tourism in Europe [51]. Budapest consists of 23 districts, and most of the attractions, services, and facilities are located in the central part of the city [52]. Since the places of accommodation and the destinations of attractions are concentrated in the center of the city, only the inner area with 12 districts is selected as a case study. Pinke-Sziva et al. [53] mentioned that tourists prefer their accommodation in the central districts of Budapest City due to the concentration and variety of accommodation places (Figure 5). Thus, there is a high spatial concentration of the accommodation's demand in the city. This study collected the relevant data on accommodation places through searching for one room for one adult per only one night on 2 November was requested on booking.com website. The number of accommodation places was ca 525 places. However, 364 places of accommodation were considered and representing the most visited destinations for accommodation purpose in the city.

4.2. FAHP. The extended version of the FAHP is performed. In this phase of the study, the linguistic expressions are converted into numeric values according to FAHP concept. A survey was distributed to 21 experts and researchers in relevant fields of tourism and transportation, but only a total of 15 respondents completed it. As mentioned in the literature review section, having a relatively small sample size is not a critical issue from the MCDM methodology perspective. The consistency ratio of the 15 experts' preferences is checked using equations (1) and (2). Table 4 demonstrates the CR values of the experts, which do not exceed 10% in any of the cases. This means that the judgments were consistent, and the pairwise comparison matrices can be accepted.

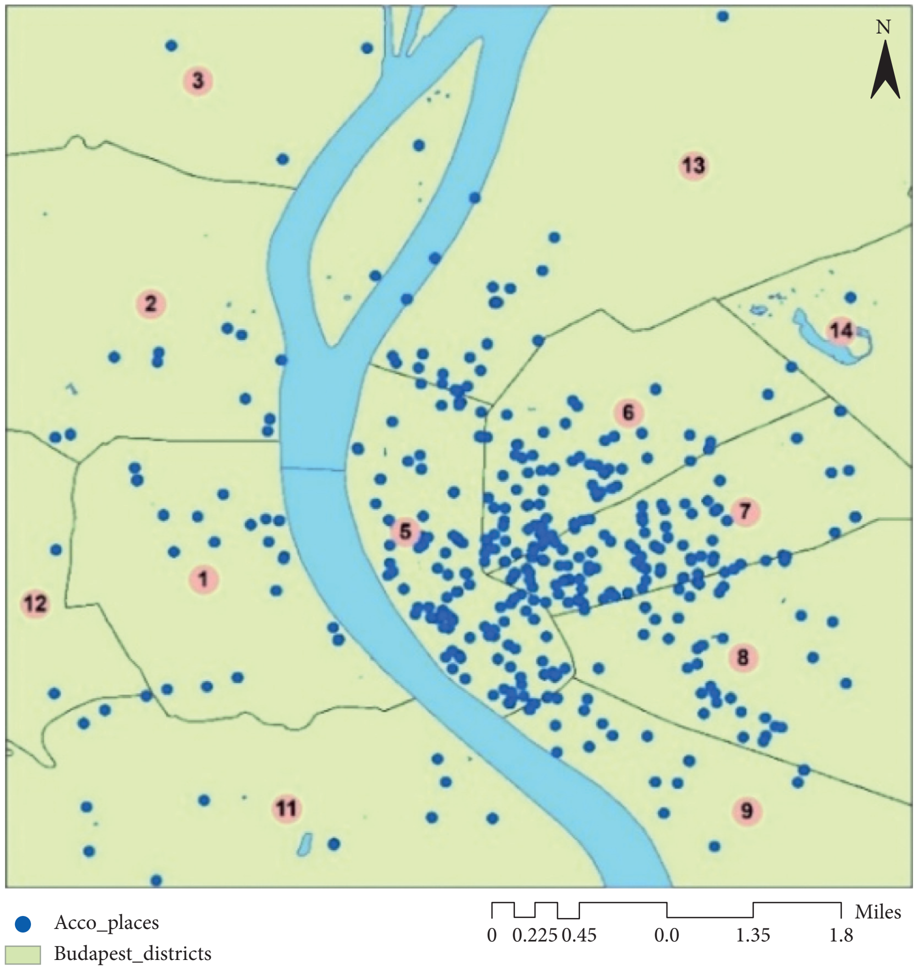


Figure 5: Places of accommodation in the study area.

Table 4: Results of consistency ratio ($n = 6$, RI = 1.24).

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
$\lambda_{\max}$	6.52	6.58	6.45	6.36	6.50	6.55	6.54	6.56	6.58	6.53	6.63	6.49	6.64	6.63	5.57
CI	0.10	0.12	0.09	0.07	0.10	0.11	0.11	0.11	0.12	0.11	0.13	0.10	0.13	0.13	0.11
CR	0.08	0.09	0.07	0.06	0.08	0.09	0.09	0.09	0.09	0.09	0.10	0.08	0.10	0.10	0.09

A pairwise comparison matrix is obtained by applying equations (4)–(6) (Table 5). Thus, Chang's extended version of AHP can be used to calculate the overall weights of criteria.

The values of the fuzzy synthetic can be computed by using equations (8)–(11). Equation (12) is used for the comparison and the calculation of the degree of two fuzzy numbers' possibility as follows:

Table 5: FAHP preference comparison matrix.

	C1	C2	C3	C4	C5	C6
C1	(1, 1, 1)	(0.13, 0.21, 0.5)	(0.17, 1, 6)	(0.17, 2.35, 9)	(0.13, 0.33, 4)	(2, 4.90, 9)
C2	(2, 4.83, 8)	(1, 1, 1)	(4, 5.35, 8)	(2, 6.11, 9)	(0.25, 1.72, 6)	(6, 8.36, 9)
C3	(0.17, 1, 6)	(0.13, 0.19, 0.25)	(1, 1, 1)	(0.25, 2.21, 8)	(0.17, 0.34, 1)	(2, 4.51, 6)
C4	(0.11, 0.43, 6)	(0.11, 0.16, 0.5)	(0.13, 0.45, 3)	(1, 1, 1)	(0.11, 0.30, 3)	(0.25, 1.43, 7)
C5	(0.25, 3, 8)	(0.17, 0.58, 4)	(1, 2.95, 6)	(0.33, 3.35, 9)	(1, 1, 1)	(1, 5.36, 9)
C6	(0.13, 0.21, 0.5)	(0.11, 0.12, 0.17)	(0.17, 0.24, 0.5)	(0.14, 0.55, 4)	(0.13, 0.24, 1)	(1, 1, 1)

Table 6: Weight vectors and the normalized final weights of criteria.

Explanation	Criteria	Weight vector (W')	Final weight (W)
Place rating	C1	0.778	0.182
Cost per room	C2	1.000	0.233
Distance from the center	C3	0.713	0.166
Breakfast included	C4	0.634	0.148
Level of security	C5	0.877	0.205
Free cancellation	C6	0.285	0.066

$$
\begin{aligned}
SC1 &= (3.58, 9.80, 29.50) \times \left(\frac{1}{157.41}, \frac{1}{68.78}, \frac{1}{29.67}\right) = (0.023, 0.142, 0.994),\\
SC2 &= (15.25, 27.36, 41) \times \left(\frac{1}{157.41}, \frac{1}{68.78}, \frac{1}{29.67}\right) = (0.097, 00.398, 1.382),\\
SC3 &= (3.71, 9.25, 22.25) \times \left(\frac{1}{157.41}, \frac{1}{68.78}, \frac{1}{29.67}\right) = (0.024, 0.134, 0.750),\\
SC4 &= (1.71, 3.77, 20.50) \times \left(\frac{1}{157.41}, \frac{1}{68.78}, \frac{1}{29.67}\right) = (0.011, 0.055, 0.691),\\
SC5 &= (3.75, 16.24, 37) \times \left(\frac{1}{157.41}, \frac{1}{68.78}, \frac{1}{29.67}\right) = (0.024, 0.236, 1.247),\\
SC6 &= (1.67, 2.36, 7.17) \times \left(\frac{1}{157.41}, \frac{1}{68.78}, \frac{1}{29.67}\right) = (0.011, 0.034, 0.994).
\end{aligned} \tag{19}
$$

The weight vector is determined by applying equations (13) and (14). Subsequently, equation (15) was used to obtain the final weights for each criterion. Table 6 shows the weight vectors and the final normalized weights.

The fuzzy-AHP results show that the cost per room has the highest weight when choosing the places of accommodation which is 0.233. It is followed by the security level at 0.205. Free cancellation is the lowest influential criterion with the value 0.066. Furthermore, the results demonstrate the importance of the rating, where several tourists check out this factor before decision-making. The distance from the center approximately has the same importance as the breakfast availability for choosing places.

4.3. GIS-FAHP Combination. Based on the GIS techniques, the reclassification process is conducted on the criterion maps. This step is essential to figure out the new values based on the new scale from 1 to 10, except for the free cancellation and breakfast availability where the new scale is 0 or 1. Figure 6 illustrates the places' spatial distribution in the study area according to the adopted criteria and collected data. The output of the reclassification step handles as the input data of the weighted overlay that deals with raster maps solely. However, the outcomes of the reclassification are vector maps. Therefore, these vector maps were converted into raster by using conversion tools within ArcGIS software. Consequently, FAHP outcomes are combined with the raster maps by using the weighted overlaying tool in GIS to generate the final suitability map as shown in Figure 7.

The final suitability map is generated after conducting the weighted overlay for the case study. The map contains five classes (i.e., "not recommended," "less recommended," "neutral," "recommended," and "highly recommended"). The final map (Figure 7) and the statistical descriptive figure (Figure 8) show realistic results, where the majority of the places are located on Pest side because it is the cultural center of Budapest, and most of the tourist attractions and activities are found in that zone [50]. In addition, the touristic activities and nightlife occurs in the center of Budapest (i.e., district 5, district 6, and district 7). The red pixels in Figure 7 indicate that those places of accommodation are "not recommended" for tourists.

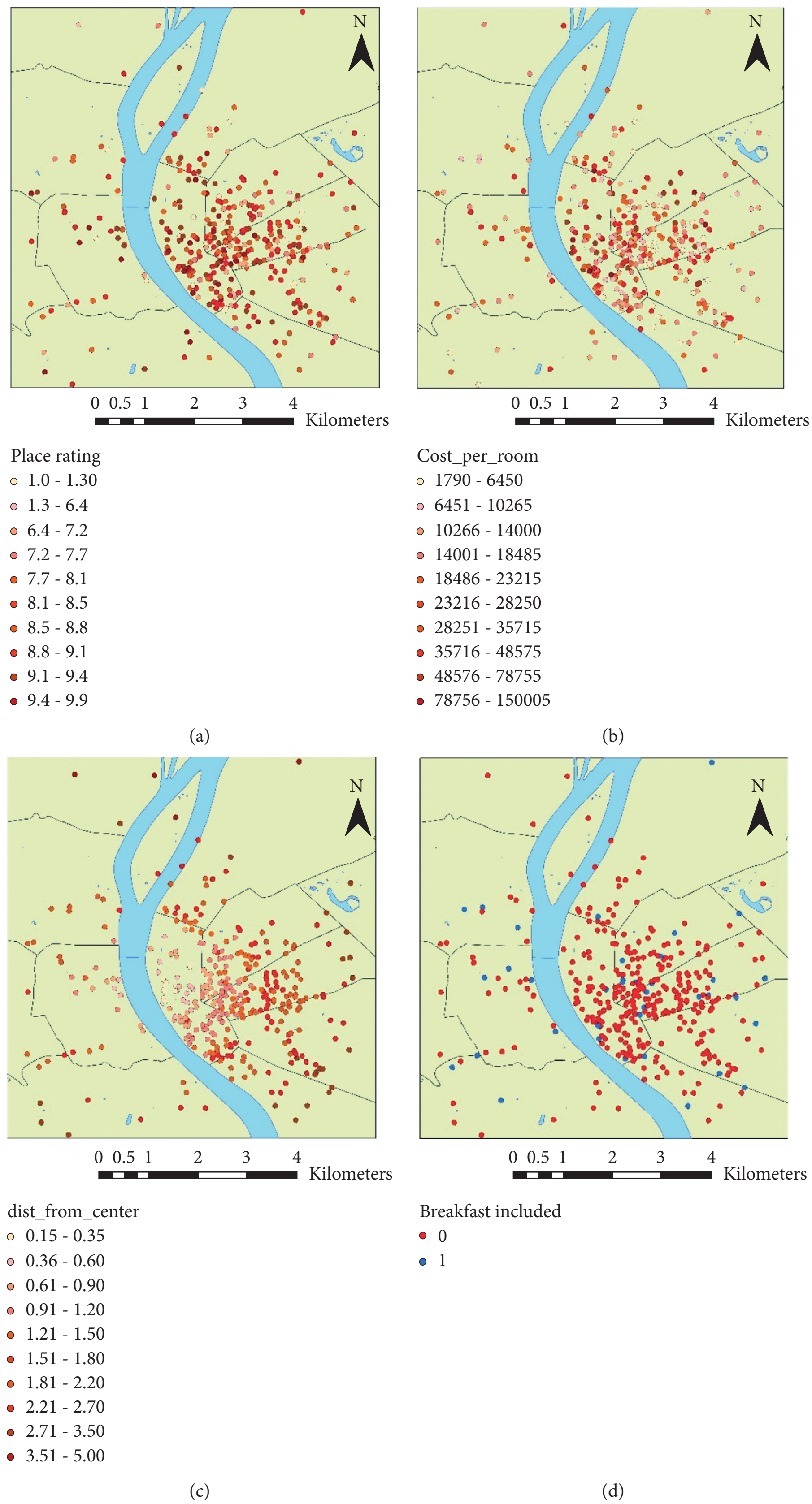
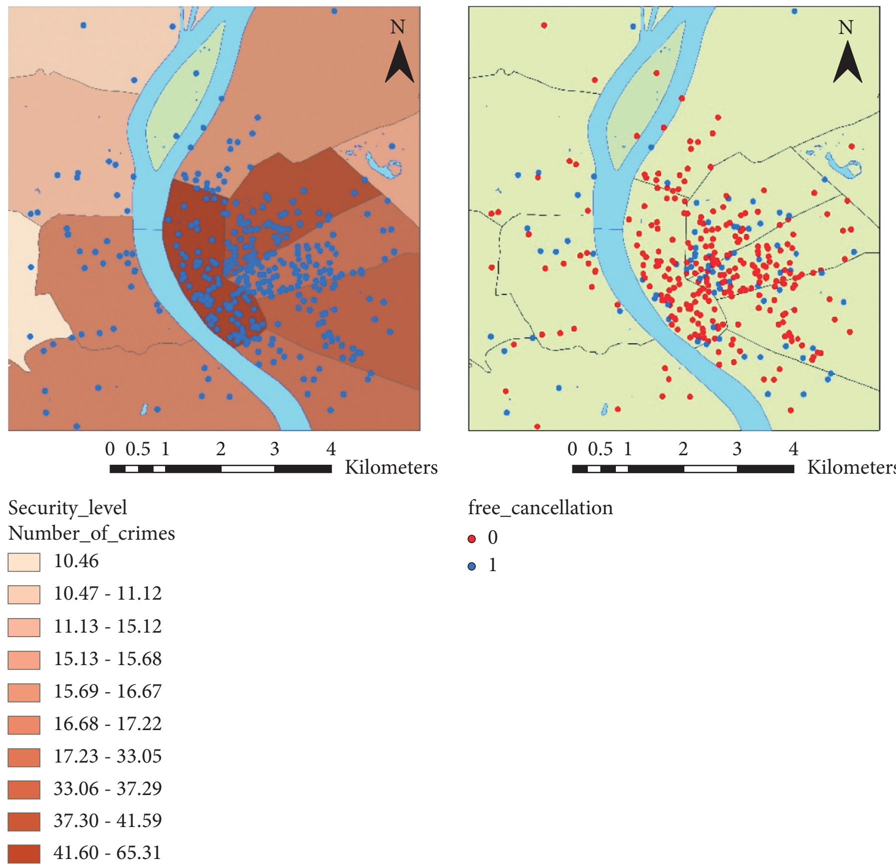


Figure 6: Continued.



(e) (f)

FIGURE 6: The classification of the alternatives in the study area. (a) Place rating. (b) Cost per room. (c) Distance from center result map. (d) Breakfast availability. (e) Level of security. (f) Free cancellation availability.

However, only two places are with red pixel, which was found in district 5 on Pest side because it has the lowest security level compared to other districts. However, only two places are with red pixel, which was found in district 5 on Pest side because it has the lowest security level, high cost, and the unavailability of the necessary services compared to other places, such as free cancellation and breakfast. Furthermore, it is observed that the "less recommended" places of accommodation with orange pixels are primarily on the side of Pest. Two places with orange color are located on Buda side in district 11, due to the fact that these places are so far from the center of the city, as a result they are "less recommended." The number of accommodation places within the "neutral" category with yellow pixels on the Pest side is more than the Buda side (Figure 8). Several "neutral" places are located mainly in district 6, district 7, and district 8 because of the security level and the low rating, and the cost per room. Most of the accommodations on the side of Buda are either "highly recommended" (indicated by dark green color on the map) or "recommended" (marked by green color on the map). However, the number of "highly recommended" places on the side of Pest is more than double compared to Buda side due to the concentration of the accommodation places on this side. A considerable proportion of "recommended" places are located on Pest side, while less than one in ten can be found in the Buda region.

5. Discussion

The findings showed the majority of the accommodation places were recommended or highly recommended for tourist, while the not recommended places were very small portion. The study carried out on the most attractive part of tourist's accommodation. Pinke-Sziva et al. [53] illustrated in their study that tourists preferred the accommodation places located in the city center. This could be easily confirmed from our results, where the spatial distribution of the accommodation places concentrated in the center in Budapest City with more than 65% of the places falling in the districts 5, 6, and 7.

Due to the uncertain conditions and the complex decision-making process of tourists, FAHP has been used to weight the criteria. Similar to [15], our results showed that the cost per room was the highest affected criterion for choosing the accommodation place. In contrast to the results of [21], who used the fuzzy method for prioritizing the criteria that influence the tourists' destination, it was found that cost has the least influence. According to [17], it was found that breakfast availability had a significant effect on tourists' choices. There was a difference with our results, where the most affected criteria were the cost, security level, and place rating, followed by the breakfast availability

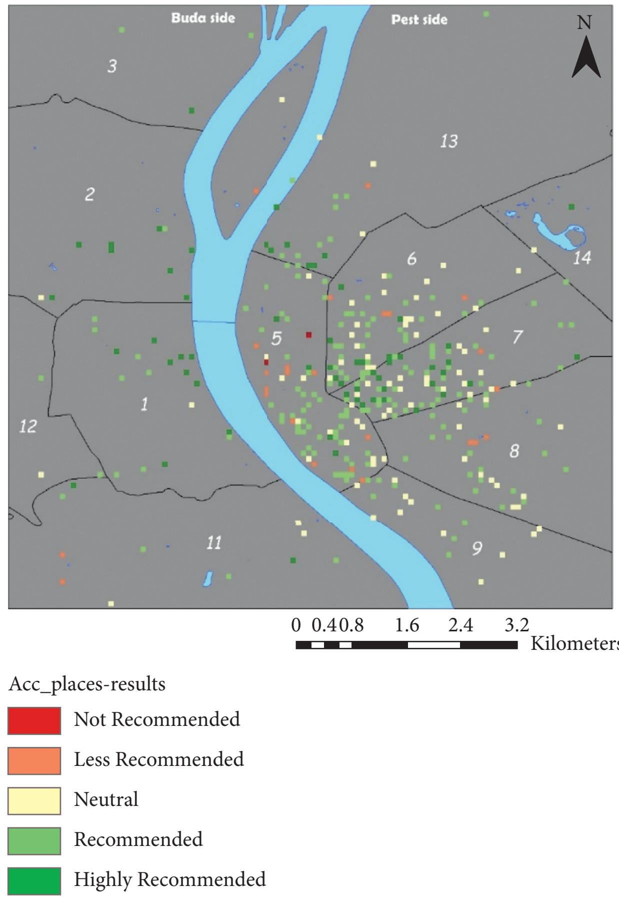
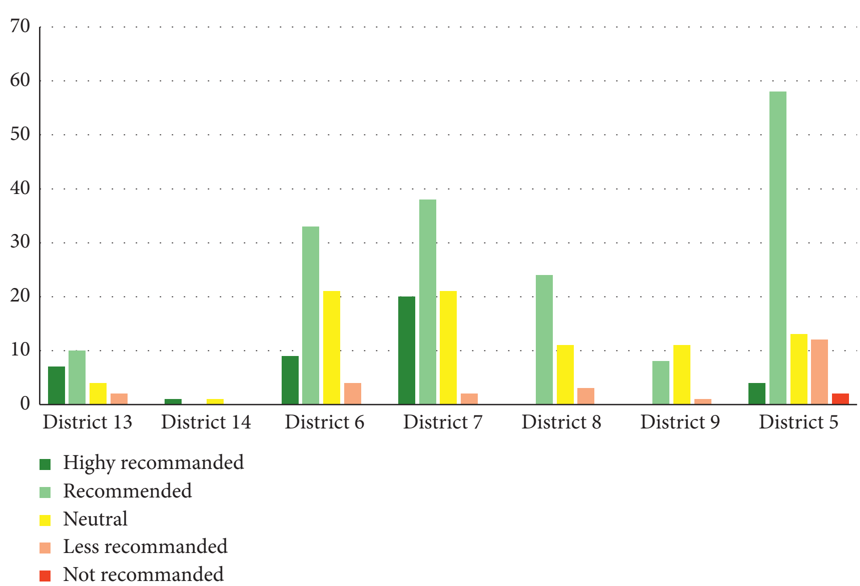
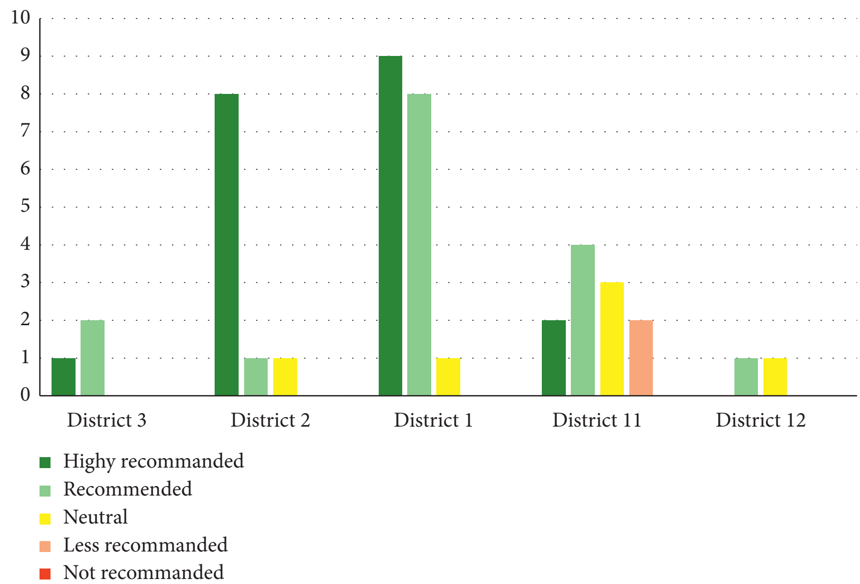


FIGURE 7: The final map of accommodations in Budapest City.



(a)

FIGURE 8: Continued.



(b)

Figure 8: The places of accommodation per district in both sides of Budapest City. (a) Pest side. (b) Buda side.

criterion. However, this study involved realistic criteria for choosing the optimal accommodation places; thus, it could reflect well the preferences of tourists.

GIS systems were utilized in two main phases. Firstly, the spatial classification of the study area according to the chosen criteria was realized. Based on Figure 6, the accommodation places appeared mainly in the city center represented by districts 5, 6, and 7, and that is clearly obvious that it is because they are close to the touristic attractions, services, and facilities. The spatial classification results demonstrated that the accommodations located in this area had the highest-ranking considering location (i.e., distance from center) criterion. However, the classification findings also showed the lowest level of security in the city center, especially in district 5, which represents the general issues with accommodations in city centers. Generally, it was observed that the level of security in Buda is higher than the Pest side. Meanwhile, there was a diversity of the rating, the cost, and the availability of services observed in the study area. At the second phase, GIS was combined with FAHP to produce the final suitability map of accommodation places. The final map in Figure 7 shows realistic findings. The majority of accommodations on the side of Buda are "recommended" or "highly recommended" with more than 80%, while three-fifths have the same class on the Pest side. The reason for this result might be the difference in the security level, or the accommodations' quality.

This study presented a novel idea of applying the GIS system by overcoming the limitations found in previous studies by the using the overlay tool. Other studies divided the study area into regular square grid cells and linked the weight for each cell. Then, they applied the overlay analysis for the entire study area. Our study considered only the relevant point feature classes (i.e., the accommodation places) and not grid cells. The adopted accommodation place had a unique ID, and each point linked with the FAHP outcomes. Consequently, the number of used cells has been decreased, and a large volume of data was analyzed.

A main limitation of this paper was the survey, which can be extended to involve more criteria affecting the choice of the optimal accommodations. It is recommended to use other methods such as structural equation model (SEM) to reveal unobserved variables. Furthermore, more criteria, such as the accessibility of cultural destinations, might enrich future studies.

6. Conclusions

This study aimed to identify the optimal accommodation places in Budapest by combining the fuzzy-AHP method and GIS technique. First, a ranking with the adopted criteria was realized using the FAHP approach. Then, the GIS was applied to develop the final suitability map, which indicates the accommodations according to the five categories from highly recommended to not recommended places. Thus, the proposed model facilitates the decision-making of tourists for selecting the optimal accommodation places in Budapest City.

Realistic criteria represented the tourists' preferences and constraints for choosing an optimal accommodation. Security level, cost per room, distance from the center, place rating, and the availability of breakfast and free cancellation services were the adopted criteria in this study. On both sides of Budapest, altogether 12 districts with 364 places of accommodation were chosen to be examined. Unlike other studies conducted in the same field, this study applied the FAHP-based GIS to eliminate the fuzziness and the uncertainty of selecting the optimal place for accommodation. The importance weight of each criterion was calculated by using FAHP. Then, GIS techniques were used for preparing and digitizing the alternatives (i.e., accommodation places) on the maps and to produce the final suitability map. The classification process was performed on the developing maps to formulate the collected data on a unique scale. The considered scale was 1 to 10 on all criteria except for breakfast and free cancellation as these criteria were either 1 or 0 for availability or unavailability, respectively. GIS techniques were used to combine the classified maps with FAHP outcomes to generate the final suitability map.

Based on FAHP results, it was concluded that the cost per room was the highest influential criterion with 0.233 importance weight, followed by the security level with 0.205. The lowest factor affecting the choice of accommodation was the free cancellation service. Furthermore, it was demonstrated that the place's rating weight importance was 0.182, while the breakfast and the distance from the center had approximately the same importance. The combination of FAHP and GIS results made the presentation of the places' final suitability map, which contained five classes (i.e., "not recommended," "less recommended," "neutral," "recommended," and "highly recommended") possible. It can be concluded that the majority of the accommodations on Buda side were within the classes of "recommended" or "highly recommended." However, the number of places on Pest side exceeded the four-fifths of the number on the other side. The "recommended" or "highly recommended" places were about 60% of the total number. A very small number of "not recommended" places not exceeding 1% were found on Pest side.

Based on the results, the FAHP-GIS combination was found very useful for solving the MCDM-spatial problem. The final suitability map can be adopted for the tourist's decision-making process for finding the optimal accommodation. Furthermore, this comprehensive model provides insights on the hotels' competitiveness, which gives a clear direction for the accommodation managers and investors to identify the weaknesses of the existing services and make appropriate enhancements to further strengthen the service quality.

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Research on Spatial Pattern Dynamic Evolution Algorithm and Optimization Model Construction and Driving Mechanism of Provincial Tourism Eco-Efficiency in China under the Background of Cloud Computing

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Based on the research of spatial pattern dynamic evolution algorithm and optimization model construction and driving mechanism of provincial tourism eco-efficiency in China under the background of cloud computing, this paper takes 30 provinces in mainland China (excluding Tibet, Hong Kong, Macao, and Taiwan) as the research object and scientifically constructs the measurement index system of tourism eco-efficiency. The Super-SBM-Undesirable model is used to measure the tourism eco-efficiency of each province from 2004 to 2017, and the algorithm and model are optimized. This paper explores the spatial evolution trajectory and path of tourism eco-efficiency by using the barycentric standard deviation ellipse method and constructs a dynamic panel model to identify the factors affecting the evolution trajectory and their driving mechanisms by using the SYS-GMM method. The results show that China's tourism eco-efficiency is at a high level and the eastern region is higher than the central and western regions. From the moving track of the center of gravity, the center of gravity of China's tourism eco-efficiency is located in Henan province, which has experienced a process of moving from southeast to northwest. From the standard deviation ellipse, the spatial distribution direction of China's tourism eco-efficiency presents a "northeast-southwest" pattern, and there is a further strengthening trend of deviation. There is a significant positive correlation between tourism eco-efficiency and tourism industrial structure upgrading, tourism industrial structure rationalization, tourism technology level, and tourism human capital, as well as a significant negative correlation between tourism eco-efficiency and tourism economic development level, environmental regulation intensity, and the degree of opening to the outside world, while the relationship between urbanization and tourism eco-efficiency is relatively vague.

1. Introduction

With the advent of the era of artificial intelligence and cloud computing, the future development of tourism service industry is closely related to artificial intelligence and cloud technology. Since the reform and opening up, the development of China's tourism industry has attracted worldwide attention and created tremendous economic and social value. At the same time, the tourism industry is also suffering from the huge impact of the rapid growth of regional economy. The impact of resource consumption and environmental pollution is prominent, which seriously hinders the transformation of China's tourism industry from high-speed growth to high-quality development stage [1]. During the period of the 13th Five-Year plan, Green Development has become the main theme of China's economic growth. How to seek the balance between tourism economic growth and environmental impact is the current focus of attention [2]. At the Second International Conference on Climate Change and Tourism, the Chinese government called on tourism-related departments in all regions of the world to actively take measures to save energy and reduce emissions. At the same time, the report of the 19th National Congress of the Communist Party of China raised the construction of ecological civilization to an unprecedented level, emphasizing that "the construction of ecological civilization can be considered as a millennium plan related to the sustainable development of the Chinese nation"; therefore, it is necessary to integrate the concept of Green Development into the whole process of tourism economic activities, optimize the structure of tourism industry, change the mode of tourism development, and realize the sustainable improvement of tourism economic growth and tourism environment. Visible, the impact of tourism on the ecological environment has attracted more and more attention. The tourism eco-efficiency is an important judgment index which reflects the two-way effect of the economic value of tourism and environmental impact and can objectively represent how to realize the efficient development of tourism under the background of Green Development, and it provides a new way to measure the level of tourism ecologicalization. Therefore, it is of great theoretical and practical significance to scientifically measure China's provincial tourism eco-efficiency and analyze its spatial pattern dynamic evolution characteristics and driving mechanism for formulating reasonable tourism development policies and promoting the coordinated development of tourism economy and ecological environment.

The idea of eco-efficiency dates back to the 1970s; German scholars Schaltegger and Sturm formally put forward the concept of eco-efficiency in 1990, which is defined as the ratio of economic value added to environmental impact [3]. Subsequently, a number of organizations have developed definitions, analyses, and extensions of eco-efficiency [4, 5], most notably the World Business Council for Sustainable Development (WBCSD), which proposes "creating maximum value with minimal environmental impact." With the development of research on tourism environmental impact, Gössling et al. derived tourism eco-efficiency from the idea of eco-efficiency and defined it as the amount of CO_2 consumed per unit tourism economic value [6]. Since then, tourism eco-efficiency has attracted extensive attention of scholars and has made a wealth of effective research results. From the perspective of the research object, the research object of tourism eco-efficiency is gradually extended from various sectors and different tourism activities to the region, and more and more scholars study the tourism eco-efficiency from the regional perspective [7–9]. From the perspective of measuring methods, the method of measuring tourism eco-efficiency has been extended from single ratio method to DEA and its improved model method, and the methods and models of measuring tourism eco-efficiency have gradually matured and perfected [10]. From the research content, scholars gradually began to pay attention to the time series evolution, spatial pattern, and correlation change of tourism eco-efficiency [11] and, on this basis, use data model to analyze the formation mechanism and influencing factors of spatial-temporal differences of tourism eco-efficiency [12]. Generally speaking, although scholars have carried out in-depth discussion in the field of tourism eco-efficiency, a reference is provided for this paper. However, there are still some problems that need to be further developed: When using DEA and its improved model to measure tourism eco-efficiency, the treatment of undesired output does not conform to the process of tourism economy, and most of the nonexpected output indicators are based on tourism carbon emissions or tourism ecological footprint [13], and some are based on tourism "three wastes" emissions. At the same time, in the empirical analysis of the spatial-temporal evolution of regional tourism eco-efficiency at different scales, the existing literature explored its dynamic characteristics, failed to effectively reflect the spatial evolution characteristics and laws of tourism eco-efficiency, and revealed the influencing factors and mechanism of the evolution process. In view of this, this paper takes China's 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) as the research object and scientifically constructs the index system of tourism eco-efficiency, using Super-SBM-Undesirable model to measure the eco-efficiency of tourism in various provinces from 2004 to 2017, and, on this basis, by means of the method of logarithmic deviation and gravity standard ellipse, to explore the spatial evolution track and path of tourism eco-efficiency, a dynamic panel model is constructed to identify the factors that influence the evolutionary track and its driving mechanism using SYS-GMM.

2. Research Methods

2.1. Models

2.1.1. Super-SBM-Undesirable Model. Common tourism eco-efficiency measurement models are mainly divided into parametric method and nonparametric analysis method. Compared with the parametric method, the nonparametric analysis method does not require a specific function form and residual distribution to explain the deterministic frontier production function. It is easy to apply and has many applications. The nonparametric deterministic frontier production function uses data envelopment analysis (DEA) as the basis. The DEA method is a "data-oriented" analysis method proposed by Charnes in 1978 to measure the relative efficiency of multiple inputs and multiple outputs. Because of the limitation of radial and angle, the traditional DEA model has deviation in efficiency Measure. Tone adds slack variable to the objective function and proposes a nonradial and nonangular SBM model, and the influence of radial and angle selection on efficiency measurement is effectively solved. At the same time, SBM model can also deal with the undesired output according to the production reality. Therefore, Tone extends the SBM model further and proposes an SBM model with undesired outputs [14]. In addition, the traditional DEA model cannot distinguish the differences among multiple DMUs (Decision Making Units) when the efficiency value is 1. In view of this deficiency, Andersen and Petersen put forward the Super Efficiency DEA model which can distinguish the efficient DMUs [15]. The inefficiency of the measure is consistent with the traditional DEA, and the effective value is more than 1, so that the efficient DMUs can be distinguished. SBM model also has problems similar to those of the traditional DEA model. So, Tone extended SBM model, defined it as Super Efficient SBM model, and compared and evaluated DMU which is in the front of production [16]. The model is constructed as follows:

$$\rho^* = \min \frac{1 + (1/m)\sum_{i=1}^{m} s_i^- / x_{ik}}{1 - (1/(q_1 + q_2))\left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{t=1}^{q_2} s_t^{b-} / b_{tk}\right)},$$

$$\text{s.t.} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik}, \quad i = 1, 2, \ldots, m,$$

$$\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \leq y_{rk}, \quad r - 1, 2, \ldots, q_1, \tag{1}$$

$$\sum_{j=1, j\neq k}^{n} b_{tj}\lambda_j - s_t^- \leq b_{rk}, \quad k = 1, 2, \ldots, q_2,$$

$$1 - \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_2} \frac{s_t^{b-}}{b_{tk}}\right) > 0, \quad s^- \geq 0, s^+ \geq 0, \lambda \geq 0, j = 1, 2, \ldots, n(j \neq k),$$

where ρ^* indicates the value of tourism eco-efficiency; λ refers to the Weight Matrix; and s^-, s^+, and s^{b-} represent the slack of input, expected output, and unexpected output, respectively.

2.1.2. Standard Deviation Ellipse. Standard deviational ellipse (SDE) is a spatial pattern statistical method, mainly used to analyze the global characteristics of the spatial distribution of geographic elements. The standard deviation ellipse is a statistical method of spatial pattern, which is mainly used to analyze the global characteristics of spatial distribution of geographical elements [17]. The gravity center, area, standard deviation of x-axis, standard deviation of y-axis, and rotation angle are the basic parameters of this method.

Gravity center is as follows:

$$X = \frac{\sum_{i=1}^{n} R_i X_i}{\sum_{i=1}^{n} R_i};$$
$$Y = \frac{\sum_{i=1}^{n} R_i Y_i}{\sum_{i=1}^{n} R_i}. \tag{2}$$

Rotation angle is as follows:

$$\tan\theta = \frac{\left(\sum_{i=1}^{n} R_i^2 X_i^{*2} - \sum_{i=1}^{n} R_i^2 Y_i^{*2}\right) + \sqrt{\left(\sum_{i=1}^{n} R_i^2 X_i^{*2} - \sum_{i=1}^{n} R_i^2 Y_i^{*2}\right)^2 - 4\sum_{i=1}^{n} R_i^2 X_i^{*2} Y_i^{*2}}}{2\sum_{i=1}^{n} R_i^2 X_i^{*2} Y_i^{*2}}. \tag{3}$$

Standard deviation of x-axis is as follows:

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} \left(R_i X_i^* \cos\theta - R_i Y_i^* \sin\theta\right)^2}{\sum_{i=1}^{n} R_i^2}}. \tag{4}$$

Standard deviation of y-axis is as follows:

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n} \left(R_i X_i^* \sin\theta - R_i Y_i^* \cos\theta\right)^2}{\sum_{i=1}^{n} R_i^2}}, \tag{5}$$

where (X, Y) is the gravity center of tourism eco-efficiency; (X_i, Y_i) is the geographical center coordinate of province i; R_i is the attribute value of province i; (X_i^*, Y_i^*) is the deviation of (X_i, Y_i) from the ellipse center of province i; (σ_x, σ_y) are the standard deviations of x-axis and y-axis; and the values of the major and minor axes of the ellipse.

2.1.3. Dynamic Panel Metering Model. Panel data has both cross-sectional dimension and time dimension, which can reflect heterogeneous factors (non-time-varying unobservable) and homogeneous factors (time-varying unobservable). Considering the economic inertia, the past economic behavior may have an impact on the current economic behavior. This paper chooses the dynamic panel econometric model. First, it can control the fixed effect; second, it can overcome the omission of variables; and, third, it can overcome the reverse causality problem. The general form of dynamic panel data model is as follows:

$$\mathrm{Ln}Y_{i,t} = \alpha + \beta Y_{i,t-1} + \gamma X_{i,t} + \varepsilon, \quad (6)$$

where $\beta Y_{i,t-1}$ is lag tool variable and γ is the regression coefficient that explains the variable.

2.2. Index System Construction

2.2.1. Index System of Tourism Eco-Efficiency Measurement. Referring to the existing research [18–20] and combining the tourism sustainable development theory and ecosystem theory, this paper constructs the index system of tourism eco-efficiency in China from three aspects of resources, economy, and environment. The input variables include tourism energy consumption, water resource consumption, tourism resource endowment, the number of tourism employees, and tourism capital input. The total tourism consumption and the number of tourism receptions are selected as the expected output, and tourism wastewater, COD, ammonia nitrogen, SO_2, smoke (powder) dust, CO_2 emissions, and the amount of tourism garbage removal were used as undesired outputs. Among them, the tourism capital input is obtained by the method of perpetual inventory and the method of tourism capital stock estimation modified by Wu [21]; tourism resource endowment is determined by Zuo's scenic area weighting method [22]; the consumption of tourism water resources is calculated by using the regional input-output table and "tourism consumption stripping coefficient" [23]; by using the data of domestic and foreign tourists' consumption composition as well as the relevant data of regional input and output, the tourism energy consumption is separated from the specific industry by the "tourism consumption stripping coefficient" [24], and tourism CO_2 emissions are then converted using the IPCC greenhouse gas emission inventory method. It should be noted that the various environmental impact assessments are not homogeneous in the tourism industry, so the entropy method is chosen to integrate the index.

2.2.2. Index of Influencing Factors. Integrating existing research and combining the particularity of tourism and the accessibility of tourism statistics, this paper identifies and analyzes the factors affecting the spatial dynamic evolution of tourism eco-efficiency by seven factors: the level of tourism economic development, the structure of tourism industrial, the technical level of tourism, the intensity of environmental regulation, the human capital of tourism, the degree of opening to the outside world, and urbanization. Specific indicators are shown in Table 1.

2.3. Data Source. All data come from "China Statistical Yearbook" (2005–2018), "China Tourism Statistical Yearbook (Original and Copy)" (2005–2017), "China Tourism Statistical Yearbook 2018," "Tourism Sampling Survey Data" (2006–2018), "China Energy Statistical Yearbook" (2005–2018), "China Population and Employment Statistical Yearbook" (2005–2018), "China Regional Economic Statistics Yearbook" (2005–2018), "China Water Resources Bulletin" (2005–2018)), "China Real Estate Statistical Yearbook" (2005–2018), and the statistical bulletins of national economic and social development of various provinces, statistical bulletins of tourism industry, and statistical bulletins of tourism development from 2004 to 2017. For missing data in some provinces, the average growth rate method is used to fill in.

3. Empirical Study

3.1. Results of Tourism Eco-Efficiency Measurement. Based on the input-output data of tourism eco-efficiency in 30 provinces from 2004 to 2017, using the scale-return constant model of Super-SBM-Undesirable and using MaxDEA Ultra 8.1.2 to measure the tourism eco-efficiency of 30 provinces in the Chinese mainland, the results are shown in Table 2. The MaxDEA Ultra 8.20 software comes from Beijing Revomed Software Co., Ltd.

3.2. Spatial Distribution Characteristics of Tourism Eco-Efficiency. In order to explore the spatial differentiation characteristics of tourism eco-efficiency in different provinces of China, this paper selects four pieces of time-section data of tourism eco-efficiency in 2004, 2009, 2013, and 2017 and uses the software of ArcGIS 10.2 and draws the spatial distribution figure of China's tourism eco-efficiency (as shown in Figure 1). Based on the classification of eco-efficiency and tourism efficiency by Willard and Lu et al. [25] and combining with the research practice, the tourism eco-efficiency can be divided into five grades: high efficiency level (i.e., fully effective) (≥1), near-high efficiency level (0.801–0.999), medium efficiency level (0.601–0.800), near-low efficiency level (0.401–0.600), and low efficiency level (0.101–0.400).

By analyzing the spatial distribution figure of tourism eco-efficiency, it is found that, in 2004, the tourism eco-efficiency of Beijing, Tianjin, Hebei, Shanxi, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Chongqing, Sichuan, Guizhou, Yunnan, and Qinghai is in a completely effective state, accounting for 56.67% of all provinces; it is mainly distributed in the eastern coastal areas and southwest regions, while the rest of the provinces are at a higher level only in Hunan; Xinjiang and Gansu are at a very low level, and China's overall tourism eco-efficiency is at a higher level of efficiency. In 2009, 11 provinces, Tianjin, Hebei, Shanxi, Heilongjiang, Jiangsu, Anhui, Fujian, Shandong, Henan, Chongqing, and Guizhou, achieved full efficiency in terms of tourism eco-efficiency, accounting for 36.67% of all provinces, the high-value areas gradually showed a clear distribution of the eastern coastal areas, and tourism eco-efficiency of China in 2013 was relatively stable compared to that in 2009, and the overall situation did not improve; the tourism eco-efficiency in Liaoning rose from a relatively low level in 2009 to a fully effective level, the medium level in Jiangxi and Shaanxi rose to a fully effective level, and Shanxi, Jiangsu, Anhui, and Henan dropped from a completely effective level to a relatively low level. In 2017, the four provinces of Hebei, Liaoning, Heilongjiang, and Shaanxi showed different degrees of decline in tourism

Table 1: Index system of influencing factors.

Influencing factors	Variable selection	Abbreviations
Level of tourism economic development	Per capita income from tourism	ECON
Structure of tourism industry	Rationalization and optimization of tourism industry structure	SR, SO
Technical level of tourism industry	Energy consumption per unit of tourism income	TECH
Intensity of environmental regulation	Environmental Regulatory Strength Index	GR
Human capital of tourism	Average years of education	HUM
Degree of opening to the outside world	Operating income of foreign-funded star hotels/star hotels	OPEN
Urbanization	Urbanization rate	UR

Table 2: Measurement results of tourism eco-efficiency.

Provinces	Year										
	2004	2006	2008	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.098	1.098	0.367	1.002	0.373	0.335	0.410	0.378	0.336	0.338	0.372
Tianjin	1.959	1.299	1.230	1.273	1.454	1.546	1.301	1.323	1.392	1.380	1.254
Hebei	1.019	1.042	1.052	1.117	1.112	1.083	1.019	0.462	0.404	0.422	0.503
Shanxi	1.090	1.076	0.450	0.617	0.435	0.413	0.531	0.574	1.005	1.075	1.168
Neimenggu	0.470	0.527	0.408	0.297	0.266	0.239	0.265	0.286	0.255	0.327	0.345
Liaoning	0.481	0.568	0.476	0.508	0.683	0.559	1.019	1.014	0.541	0.495	0.461
Jilin	0.633	0.493	0.380	0.395	0.394	0.378	0.388	0.402	0.375	0.427	1.016
Heilongjiang	0.678	0.732	0.729	1.122	1.086	1.130	1.132	0.252	0.290	0.272	0.331
Shanghai	1.147	1.174	0.510	1.057	1.003	0.564	1.071	1.044	1.009	1.025	1.035
Jiangsu	1.032	1.138	1.045	0.709	1.046	1.036	0.638	0.581	0.524	1.001	1.006
Zhejiang	1.125	0.689	0.483	0.551	0.482	0.410	0.463	0.455	0.428	0.451	0.486
Anhui	1.249	1.070	1.018	1.085	1.039	1.023	0.679	0.648	0.722	0.652	0.826
Fujian	1.058	1.083	1.794	0.635	0.497	0.396	0.504	0.479	0.444	0.484	0.609
Jiangxi	1.081	1.119	0.479	0.545	0.762	0.726	1.026	0.667	1.021	1.010	1.084
Shandong	1.143	1.207	1.059	1.740	1.724	1.368	1.489	1.377	1.381	1.550	2.283
Henan	1.059	1.230	1.333	1.106	1.073	1.024	1.071	1.084	1.063	1.108	1.119
Hubei	0.616	0.598	0.439	1.019	0.540	0.485	0.629	0.576	0.524	0.558	0.648
Hunan	0.853	0.555	0.501	0.527	0.482	0.454	0.540	0.460	0.484	0.461	0.742
Guangdong	0.537	1.033	0.426	1.003	0.280	0.265	0.459	0.448	0.435	0.340	0.323
Guangxi	0.517	0.508	0.360	0.408	0.439	0.425	0.541	0.484	0.460	0.541	0.653
Hainan	0.399	0.314	0.200	0.063	0.205	0.189	0.177	0.169	0.181	0.285	0.293
Chongqing	1.063	1.024	0.584	1.041	1.109	1.152	1.059	1.113	1.091	1.070	1.117
Sichuan	1.024	1.070	0.485	0.517	0.642	0.453	0.592	0.707	0.519	0.474	0.474
Guizhou	1.028	1.225	1.101	1.002	1.066	1.044	1.064	1.062	1.111	1.169	1.210
Yunnan	1.444	1.040	0.376	0.321	0.306	0.284	0.351	0.366	1.371	0.466	1.023
Shaanxi	0.411	0.717	0.469	0.693	1.056	1.030	1.010	0.755	0.542	0.595	0.770
Gansu	0.360	0.339	0.226	0.288	0.281	0.281	0.294	0.306	0.309	0.332	0.417
Qinghai	1.112	1.018	0.385	0.247	0.235	0.216	0.225	0.205	0.194	0.201	0.201
Ningxia	0.513	0.384	0.290	0.350	0.304	0.329	0.281	0.231	0.193	0.242	0.435
Xinjiang	0.370	0.255	0.153	0.191	0.165	0.157	0.164	0.156	0.145	0.153	1.284
The National	0.886	0.854	0.627	0.714	0.685	0.633	0.680	0.602	0.625	0.630	0.783
Eastern China	1.000	0.968	0.786	0.878	0.805	0.705	0.777	0.703	0.643	0.706	0.784
Central China	0.907	0.859	0.666	0.802	0.726	0.704	0.750	0.583	0.685	0.695	0.867
Western China	0.756	0.737	0.440	0.487	0.534	0.510	0.531	0.516	0.563	0.506	0.721

Note. Not fully listed due to space limitation.

eco-efficiency, while Jiangsu and Yunnan returned to the state of full efficiency, and the overall level of China's tourism eco-efficiency has increased slightly. The regions with higher levels of tourism eco-efficiency are scattered in the three regions, and the differences among the regions are obvious.

3.3. Characteristics of the Spatial Dynamic Pattern of Tourism Eco-Efficiency. After defining the spatial distribution characteristics of China's tourism eco-efficiency, in order to understand the spatial dynamic pattern of China's tourism eco-efficiency, this paper analyzes its spatial pattern evolution by using gravity center and standard deviation ellipse. From the whole distribution of gravity center (as shown in Table 3), the moving path of the of gravity center of tourism eco-efficiency in China experienced the change of "southeast-northeast-north-west-southwest-northwest" during 2004 to 2017. From the three selected characteristic time points of 2004, 2009, 2013, and 2017, the gravity center is in Henan province. In the east-west direction, the tourism eco-efficiency of the western

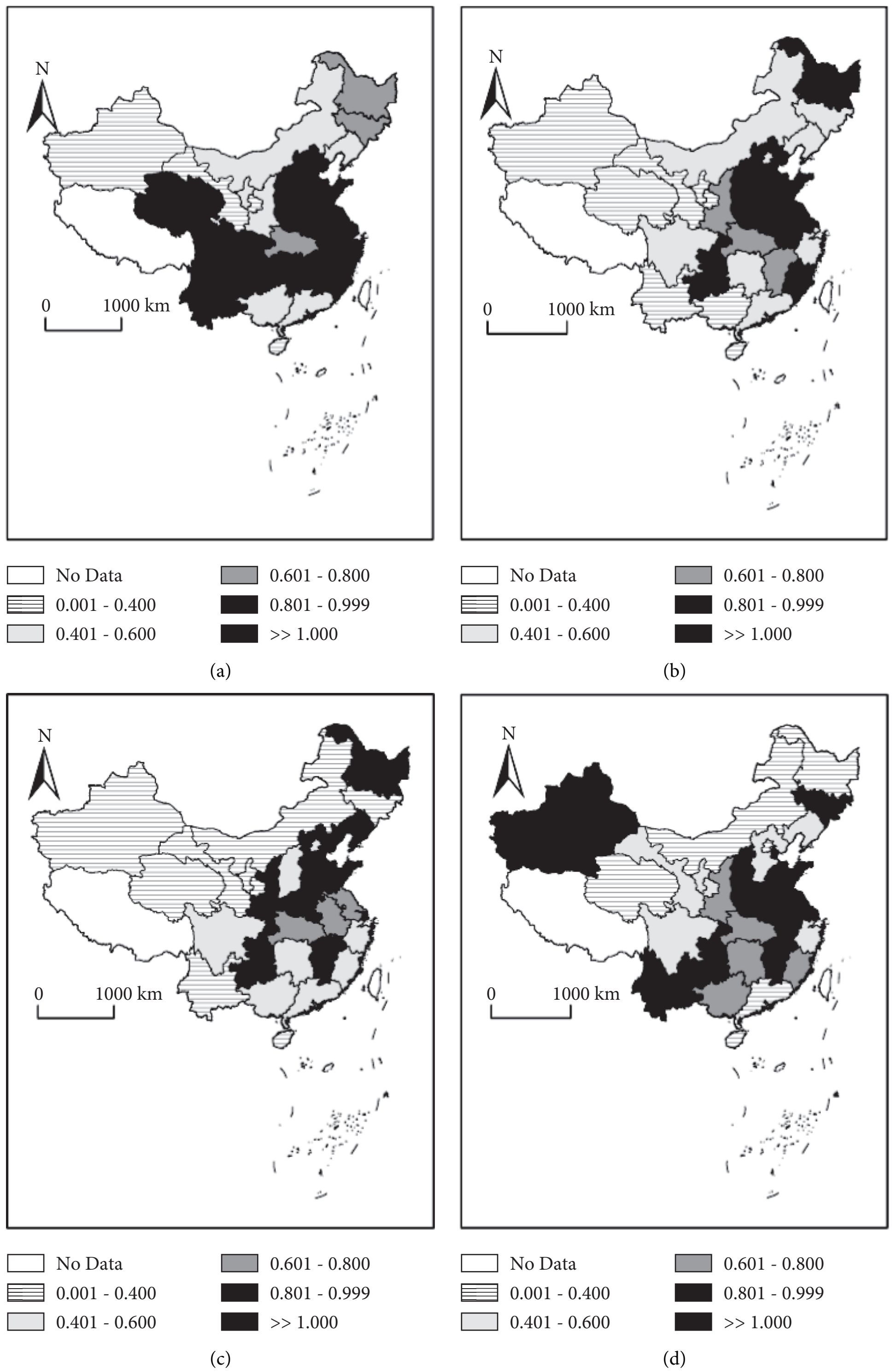

Figure 1: Spatial distribution of tourism eco-efficiency.

provinces is higher than that of other regional provinces. From the perspective of the moving direction of the gravity center, the gravity center of tourism eco-efficiency was near Nanzhao county, Nanyang, Henan province, in 2004. From 2004 to 2009, the gravity center gradually moved to the southeast, with a direction of 54.25° southeast, the gravity center moved from Nanzhao county to Fangcheng county, and the gravity center of tourism eco-efficiency moved to the vicinity of Shangcai county, Zhumadian, with a shift direction of 6.13° southeast in 2009–2013. Thus, the tourism eco-efficiency showed a trend of migration to the southeast from 2004 to 2013, indicating that the tourism eco-efficiency of the provinces in the southeast of China improved greatly during this period, which caused the gravity center to move to the southeast. After 2013, the gravity

Table 3: Direction and distance of the gravity center of tourism eco-efficiency.

Year	Gravity center	Direction	Moving distance (km)	East-west distance (km)	North-south distance (km)	Speed (km/a)	East-west (km/a)	North-south (km/a)
2004	112.76°E, 33.52°N							
2009	112.87°E,33.37°N	Southeast 54.25°	20.54	12.00	16.67	4.11	2.40	8.33
2013	114.15°E,33.23°N	Southeast 6.13°	143.62	142.80	15.34	28.72	35.70	3.84
2017	112.27°E,33.94°N	Northwest 20.54°	222.39	208.26	78.01	55.60	52.07	19.50

center of tourism eco-efficiency began to move to the northwest and moved to Ruyang county of Luoyang, with a direction of 20.54° northwest, which shows that the tourism eco-efficiency of the western region has improved greatly compared with the eastern and central regions during 2013 to 2017. From the perspective of distance and speed of gravity center movement, the distance and speed of gravity center movement of tourism eco-efficiency from 2004 to 2009 are the smallest, which are 20.54 km and 4.11 km/a, respectively. In 2009–2013, the speed of gravity center moving suddenly accelerated, the speed of east-west direction is 35.7 km/a, the speed of north-south direction is 3.84/a, and the speed of gravity center moving eastward is equivalent to the speed of gravity center moving as a whole (28.27 km/a), which indicates that the gravity center of tourism ecological efficiency mainly moves eastward in 2009–2013, and the moving distance is 143.62 km. From 2013 to 2017, the speed and distance of gravity center movement increased again, which were 4.11 km/a and 222.39 km, respectively. This is mainly due to the significant increase of the speed and distance of westward movement in the east-west direction, reaching 52.07 km/a and 208.26 km, respectively. On the whole, the moving speed of the center of gravity of tourism eco-efficiency continues to accelerate.

From the standard deviation ellipse of 4 years (as shown in Figure 2 and Table 4), the range of coverage from 2004 to 2017 is shrinking as a result of expansion. From 2004 to 2013, the standard deviation ellipse scope of tourism eco-efficiency showed a downward trend, and the area decreased from $300.45 \times 10^4\,km^2$ in 2004 to $253.00 \times 10^4\,km^2$ in 2013, reaching the minimum value. Compared with 2004, the space scope continuously reduced, the spatial agglomeration effect of tourism eco-efficiency of provinces in the interior of the standard deviation ellipse increases, but the spatial spillover effect is not obvious. In 2013–2017, the area of standard deviation ellipse increased from $253.00 \times 10^4\,km^2$ in 2013 to $341.83 \times 10^4\,km^2$ in 2017. The area of standard deviation ellipse expanded in all directions, and the overall spatial distribution of tourism eco-efficiency tends to be scattered.

In the spatial direction (as shown in Table 4), the spatial direction of tourism eco-efficiency has two evolutional trends with 2009 as the cut-off point. From 2003 to 2009, the rotation angle θ decreased from 41.39° to 26.83°, indicating that the space direction changed from "northeast-southwest" to "north-south". From 2009 to 2017, the rotation angle θ increased from 26.83° to 72.95°, indicating that the space direction changed from "north-south" to "northeast-southwest." On the whole, the spatial distribution of tourism eco-efficiency in China presents a pattern of "northeast-southwest," and this pattern has a tendency of further strengthening.

3.4. Driving Mechanism Analysis

3.4.1. Panel Data Unit Root and Cointegration Test. The stationary and white noise of variables is the premise of panel data regression estimation; otherwise, it may lead to false regression or spurious regression, and the unit root test must be carried out for variable data. In order to prevent the error caused by the single test method, LLC Test, Breitung Test (for same root), IPS Test, Fisher-ADF Test, and Fisher-PP Test (for different root) are used in this paper. The results are shown in Table 5. LnTE, LnECON, LnSO, LnSR, LnTECH, LnGR, and LnOPEN all reject the null hypothesis of unit root at the 1% level in the 5 test methods, indicating that these 7 variables are all "integrated of order zero," while the sequence of LnHUM and LnUR is stationary after first-order difference, indicating that these two variables are "integrated of order one." All variables are stationary after first-order difference. Therefore, all variables are "integrated of order one."

Variables must be of the same order, so that the panel data can pass the cointegration test. Therefore, the same order is the necessary condition of the panel data cointegration. On the premise of the same-order single integration after difference, it is possible to test whether there is a long-term cointegration relationship between panel data. In order to guarantee the reliability and robustness of cointegration test results, Modified Dickey–Fuller t-test, Dickey–Fuller t-test, Augmented Dickey–Fuller t-test, Unadjusted Modified Dickey–Fuller t-test, and Unadjusted Dickey–Fuller t-test in Kao test are used to test the cointegration of regression equations. It can be seen from Table 6 that all the statistical variables of the equations reject the original assumption that there is no cointegration relationship under the condition of 1%; that is, there is a significant long-term stationary equilibrium relationship between the explanatory variables and the explanatory variables of the equations.

3.4.2. Selection of the Measurement Estimation Method. In terms of model regression for influencing factors, the model identified in this article has lags in the explained variables so as to avoid omitting the dynamics of the model and leading to biased results. At the same time, the explained

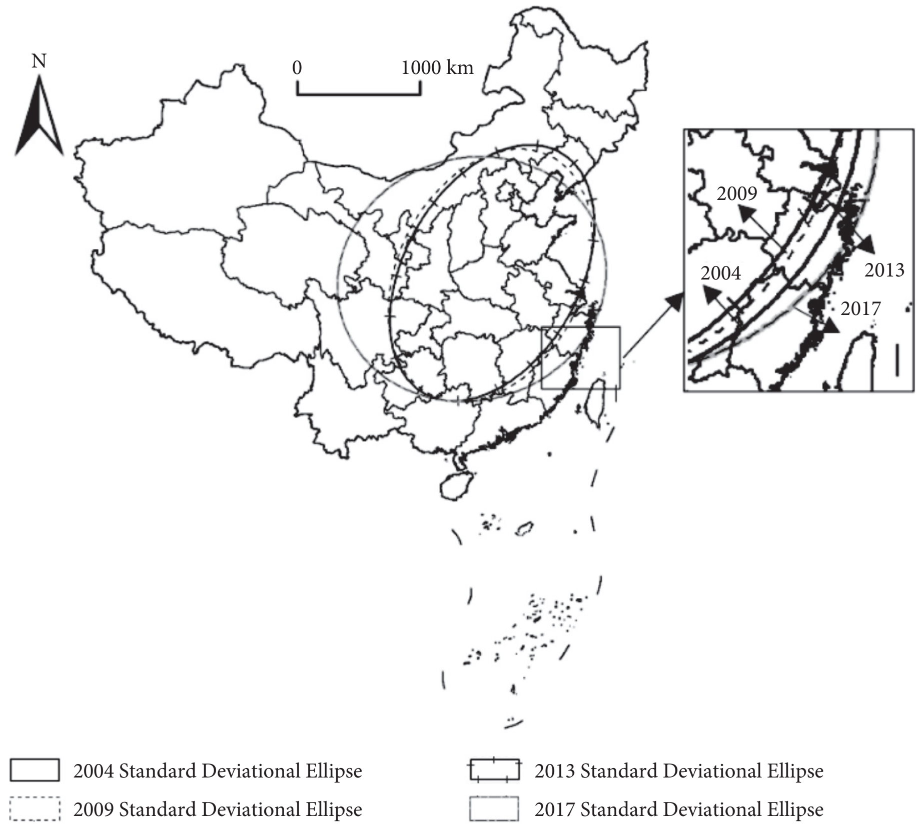

Figure 2: Standard deviation ellipse of tourism eco-efficiency.

Table 4: Standard deviation ellipse parameter of tourism eco-efficiency.

Year	2004	2009	2013	2017
Rotation angle θ (°)	41.39	26.83	29.47	72.95
Standard deviation of x-axis (km)	873.23	752.23	715.06	985.04
Standard deviation of y-axis (km)	1095.25	1085.63	1126.33	1104.67
Area (km^2)	300.45×10^4	256.54×10^4	253.00×10^4	341.83×10^4

Table 5: Unit root test for panel variables.

Variable	LLC Test	IPS Test	Breitung Test	Fisher-ADF Test	Fisher-PP Test
LnTE	-3.260^{***}(0.000)	-2.816^{***}(0.002)	-2.888^{***}(0.001)	180.637^{***} (0.000)	124.832^{***}(0.000)
LnECON	-2.701^{***}(0.003)	2.471^{***}(0.000)	8.990^{***}(0.000)	124.674^{***} (0.000)	117.620^{***}(0.000)
LnSO	-3.983^{***}(0.000)	-0.147^{***}(0.004)	3.191^{***}(0.000)	130.885^{***} (0.000)	53.779^{***}(0.000)
LnSR	-8.066^{***}(0.000)	-3.663^{***}(0.000)	-2.785^{***}(0.002)	217.317^{***} (0.000)	195.529^{***}(0.000)
LnTECH	-5.749^{***}(0.000)	0.237^{*}(0.057)	0.108^{***}(0.000)	161.372^{***} (0.000)	60.725^{***}(0.000)
LnGR	-7.342^{***}(0.000)	-7.856^{***}(0.000)	-10.635^{***}(0.000)	223.499^{***} (0.000)	265.733^{***}(0.000)
D.LnHUM	-8.093^{***}(0.000)	-9.718^{***}(0.000)	-12.054^{***}(0.000)	183.122^{***} (0.000)	474.034^{***}(0.000)
LnOPEN	-22.938^{***}(0.000)	-7.650^{***}(0.000)	-7.586^{***}(0.000)	281.887^{***} (0.000)	263.000^{***}(0.000)
D.LnUR	-2.833^{***}(0.002)	-8.458^{***}(0.000)	-3.199^{***}(0.007)	139.882^{***} (0.000)	478.798^{***}(0.000)

Note. *, **, and ***are significant at the levels of 10%, 5%, and 1%, respectively.

variables and the explanatory variables of the model have a causal relationship with each other, and there are endogenous problems. In dealing with endogenous problems, Manuel Arellano and Stephen Bond believe that the use of ordinary panel regression in the model will lead to deviations in the estimation results, which can be achieved through instrumental variable (IV) and generalized method of moments (GMM) to be eliminated. In the selection of instrumental variables, Anderson and Cheng rely on traditional methods to select instrumental variables that are not related to interference items and then first-order difference, selecting items lagging more than two orders as the instrumental variables of their difference items. Combined with the proposal of dynamic panel theory, differential

Table 6: Panel cointegration test results.

Test method	Value	P value
Modified t	−9.278	0.001
Dickey–Fuller t	−13.71	0.001
Augmented t	−9.392	0.001
Unadjusted Modified t	−17.32	0.001
Unadjusted t	−15.88	0.001

generalized moment estimation (Diff-GMM) and system generalized moment estimation (SYS-GMM) methods have become the mainstream of research. Diff-GMM uses difference to eliminate fixed effects and builds instrumental variables on the basis of difference equations, but the problem of weak instrumental variables cannot be solved. Furthermore, Arellano and Richard proposed the SYS-GMM method, which starts with the information of difference and level equations to select instrumental variables. Compared with other methods, it can better solve the problem of endogeneity, and the model estimation results are also more effective. Based on the above analysis, this paper chooses the SYS-GMM estimation method to estimate the relevant factors of tourism eco-efficiency.

3.4.3. Model Estimates. Considering that SYS-GMM method selects instrumental variables from the information of difference and level equation, it can solve the endogeneity problem better than other methods, and the model estimation results are more effective. Therefore, SYS-GMM method was used for regression analysis in this paper, and the regression results are shown in Table 7. As can be seen from Ward test, the set model is very significant. The Sargan test shows that the setting of the tool variable set is valid.

The regression results of Table 7 show that the tourism economic development level, which is expressed by per capita tourism income, has a negative effect on tourism eco-efficiency, and it is significant at 1% level. The rapid development of tourism economy has not brought about the rational allocation and utilization of resources and energy as well as the scale effect but inhibited the promotion of tourism eco-efficiency. The possible reason is that China's tourism economy is in a transitional stage, and the annual growth rate of tourism income is far higher than the average growth rate of China's GDP in the same period. With the rapid development of the tourism economy, unreasonable low-cost extensive development and operation mode gradually emerged.

The coefficient of tourism industry optimization (SO) passed the test on the level of 5% significance, which shows that the optimization of tourism industry structure has a positive and significant impact on tourism eco-efficiency. In view of the reality of the development of China's tourism industry, in recent years, driven by endogenous technology, the internal and external integration of the tourism industry ("tourism +") and other patterns have achieved a breakthrough in the innovation of tourism products, and its industrial added value has maintained long-term and steady growth; this technology upgrading and value-added growth

Table 7: Regression results of influencing factors.

Independent variable	LnTE
L1.	0.440***(0.000)
LnECON	−0.219***(0.000)
LnSO	0.012**(0.013)
LnSR	0.070**(0.005)
LnTECH	−0.603***(0.000)
Wald test	247.72***(0.000)
Sargan test	0.127
LnGR	−0.057***(0.000)
LnHUM	0.0394***(0.002)
LnOPEN	−0.002***(0.008)
LnUR	−0.150(0.667)
Cons	1.196***(0.000)

Note. *, **, and ***are significant at the levels of 10%, 5%, and 1%, respectively.

is the external performance of the structural adjustment of the tourism industry, which is beneficial to the energy-saving and emission reduction and environmental protection of tourism. The coefficient of tourism industry rationalization (SR) also passed the test at the significant level of 5%, indicating that the rationalization of industrial structure has effectively promoted the eco-efficiency of tourism in China. It can be seen that the flow and reconfiguration of factors of production such as labor and capital among different economic sectors of tourism can effectively utilize all factors and bring about economic growth of tourism, but they do not cause resource depletion and ecological environment deterioration.

The technical level of tourism industry represented by the energy consumption per unit tourism income is a negative indicator. The higher the energy consumption per unit tourism income, the lower the technical level of tourism industry. Its coefficient is obviously negative, which fully shows that enhancing the technical level of tourism is an important way to improve the eco-efficiency of tourism. On the one hand, technological progress can be conducive to the promotion of advanced ecological production and the improvement of energy and resource efficiency of tourism enterprises; on the other hand, technological progress can promote pollution reduction and treatment technologies so as to improve the end of pollution control capacity and further promote the generation of clean energy.

The impact of environmental regulation intensity on tourism eco-efficiency is negative, and it has passed the significance test. The possible reasons for the failure of the government's environmental regulation are as follows: Firstly, the relevant environmental policies and measures formulated by the government have not been effectively implemented, there is a lack of supervision, and it cannot effectively correct the negative externalities of environmental pollution in various sectors related to tourism. Secondly, the cost of effective implementation of environmental regulation is too large and the government intervention is difficult to grasp, which leads to the decrease of the coordination between the economic growth of tourism and the development of ecological environment. Thirdly, due to the traditional development concept, the extensive development mode of China's tourism industry has not changed in essence. Compared with developed countries, the intensity of environmental regulation is still relatively low, and the innovation effect of environmental regulation has not been effectively triggered.

The effect of tourism human capital on tourism eco-efficiency is positive at the significance level of 1%. The main reason is that the education level can, to a certain extent, reflect the social environmental protection consciousness, and environmental protection consciousness enhancement helps consciously perform the obligation of environmental protection; at the same time, tourism practitioners are the higher level of education, and professional skills and technical innovation ability are higher, which is good for energy saving and "three wastes" emissions.

The impact coefficient of the degree of opening to the outside world on tourism eco-efficiency is negative and significant. The amount of foreign investment in tourism reflects the region's ability to attract foreign investment in some aspects, but it is not conducive to improving the regional tourism eco-efficiency. The following are the possible reasons: Firstly, the foreign investment to consider more for tourism is China's rich tourism resources, vast market and its cheap labor supply, foreign investment in the process of actual operation, and the development of tourism resources using a double standard only for the purpose of economic interests of predatory development brought about great pressure to the ecological environment. Secondly, the purpose of China's introduction of foreign capital is to consider the structural and technological effects of foreign investment and the "spillover effect" of management experience and eco-production techniques as well as the "demonstration effect" of high standards of environmental protection brought about in the process of promoting employment and economic development in the region, thus promoting the structural transformation and upgrading of local tourism industry; however, the ecological damage and environmental pollution caused by pollution-intensive foreign capital inflow offset the benefits to some extent. Finally, some local governments relax environmental regulation in order to attract foreign investment in tourism and promote the development of tourism economy at the expense of the environment, thus restraining the promotion of tourism eco-efficiency.

4. Conclusion and Discussion

4.1. Conclusion. In this paper, the Super-SBM-Undesirable model is used to measure the tourism eco-efficiency of 30 provinces in China from 2004 to 2017. On the basis of clarifying the spatial distribution characteristics of tourism eco-efficiency, this paper explores the spatial evolution track and path of tourism eco-efficiency with the help of the the method of gravity center and standard deviation ellipse, constructs a dynamic panel model, and uses SYS-GMM to identify the factors influencing the evolution track and its driving mechanism. The results are as follows: Firstly, during the study period, the overall eco-efficiency of tourism in China is at a high level, and the eastern region is higher than the central and western regions. The provinces with higher tourism eco-efficiency are scattered in three regions, with obvious differences in each region. Secondly, from 2004 to 2017, the gravity center of China's tourism eco-efficiency is distributed in Henan province, and its movement track is "Nanyang (Nanzhao county)-Nanyang (Fangcheng county)-Zhumadian (Shangcai county)-Luoyang (Ruyang county)," the change pattern of the gravity center is first to the southeast and then to the northwest, and the moving speed of the center of gravity is continuously accelerating. Thirdly, from the perspective of the standard deviation ellipse, the overall spatial distribution pattern of China's tourism eco-efficiency tends to disperse, and the rotation angle shows a process of "shrinking a little, increasing a little, then increasing"; the result shows that the spatial distribution of China's tourism eco-efficiency shows a pattern inclined northeast-southwest and has the trend of further strengthening. Fourthly, the optimization of tourism industry structure, the rationalization of tourism industry structure, the technical level of tourism industry, and tourism human capital are positively correlated to tourism eco-efficiency; the development level of tourism economy, the intensity of environmental regulation, and the degree of opening to the outside world are negatively related to tourism eco-efficiency, while the relationship between urbanization and tourism eco-efficiency is ambiguous.

4.2. Policy Implications. In order to promote the sound and coordinated development of China's provincial tourism industry and ecological environment and promote the high-quality development of tourism economy, the following policy recommendations are put forward: First, we should put the protection of tourism ecological environment in a prominent position in combination with the current big data analysis and research and promote the process of nationalization of ecological civilization theory education, as well as change the evaluation index system of tourism development only based on total tourism revenue and tourist receptions. Second, we should combine big data artificial intelligence technology to promote the precise coordination of the allocation of tourism industry elements and comprehensively weigh the impact of tourism economic growth and ecological environment deterioration brought about by the flow of technology, capital, information, labor, and other factors, increase the proportion of green, circular, and low-carbon economy in the tourism industrial structure, and promote the coordinated development of various economic sectors of tourism, as well as comprehensive use of tourism industry planning and policy means to optimize and integrate tourism production factors from the source, while effectively supplying, to avoid duplication of factors, blind investment, and overcapacity. Thirdly, combined with the development of artificial intelligence technology, precise, informationized, and scientific economic policies such as finance and taxation should be adopted to provide support for tourism enterprises adopting advanced ecological technology, accelerate the pace of popularizing pollution control and prevention technology, gradually establish energy statistics and auditing system for tourism industry, and encourage the development of energy-saving and consumption-reducing tourism enterprises. Moreover, we should improve the access standards of foreign investment in tourism industry, change from attracting investment to selecting investment, and select appropriate technologies consistent with the regional tourism economic development environment so as to improve the utilization efficiency of advanced ecological management and technology. Finally, we will make full use of the strictest eco-environmental protection system in the National New-Type Urbanization Plan (2014–2020) and continue to strengthen the construction of tourism eco-environment and improve the efficiency of tourism eco-environment under the mechanism of green, circular, and low-carbon development. The planning of urbanization should consider the present situation of tourism ecological carrying capacity, enhance the support of Environmental Protection Industry, comprehensively study the change characteristics of regional wind direction and the location of tourism service facilities, and rationally plan and arrange the industrial location. Combining the tourism planning with the urbanization ecological planning and on the basis of the tourism planning, setting out a single ecological control index to guide the development and construction of tourism, it also plans energy-saving and emission reduction targets for water-saving rate, rainwater utilization rate, and carbon emission rate of tourism service facilities. The corresponding indicators of tourism ecological response indicators will be brought into the government performance appraisal, improve tourism infrastructure, fully tap the consumption potential of regional tourism market, and vigorously develop green tourism and ecotourism.

4.3. Discussion. Based on the theory of sustainable tourism development and the theory of ecosystem, this paper attempts to construct an index system for the measurement of China's provincial tourism eco-efficiency in order to comprehensively evaluate China's tourism eco-efficiency and to study the dynamic evolution of the spatial pattern of China's tourism eco-efficiency and its driving mechanism by means of artificial intelligence thinking logic, geographical methods, and dynamic panel model. However, there are still some shortcomings to be further explored: on the one hand, the input-output indicators of tourism industry involved in the measurement index system of tourism eco-efficiency are quantifiable indicators. Some social and environmental indicators that are difficult to quantify are not involved, and it is assumed that environmental pollution is homogeneous and stable in all industries. On the other hand, due to the strong correlation of tourism industry, the influencing factors of the spatial dynamic pattern evolution of tourism eco-efficiency are very complex, and it is difficult to fully cover the selection of indicators, and it is impossible to cover all the influencing factors in the regression model. In this sense, the results of empirical analysis in this paper cannot fully explain the actual situation but only have statistical significance in probability. Therefore, in the future, more variables should be included in the theoretical analysis model in the process of factor analysis.

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