FORECASTING THE DEMAND FOR HEALTH TOURISM IN ASIAN COUNTRIES USING A GM(1,1)-ALPHA MODEL

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Abstract
The purpose – Accurately forecasting the demand for international health tourism is important to newly-emerging markets in the world. The aim of this study was presents a more suitable and accurate model for forecasting the demand for health tourism that should be more theoretically useful.
Design – Applying GM(1,1) with adaptive levels of α (hereafter GM(1,1)-α model) to provide a concise prediction model that will improve the ability to forecast the demand for health tourism in Asian countries.
Methodology – In order to verify the feasibility of the proposed approach, using available secondary and primary data covering the period from 2002 through 2009 obtained from the RNCOS "Opportunities in Asian Health tourism" report. Based on a unique and characteristics database for the health tourism industry, this study applies the adaptive α in a Grey forecasting model (GM(1,1)-α) to predict the demand for health tourism in Asian countries.
Approach – Implementation of demand forecasting in health tourism is examined on the short-term and limited dataset, due to importance of a minimum the predicated error on underlying basis for the econometric model for health tourism markets.
Findings – Key findings present that the optimal value of α in GM(1,1) can minimize the predicted error. Finally, in the case of the demand for health tourism in Asian countries, using GM(1,1)-α to predict error is clearly better than the use of the original GM(1,1) and time series models.
The originality of this research – The originality comes from the analysis of the demand forecasting in health tourism of Asian countries, which provides an easy and accurate method to predict the demand for health medical tourism and ideas for further improvements in the sector of health tourism.
Keywords Health Tourism, Health tourism Demand, Grey Forecasting, GM(1,1)-Alpha

INTRODUCTION

The health tourism industry contributes significantly to the economies of certain countries. Various Asian countries such as India, Thailand and Singapore have become the major destinations for medical treatment. The rising costs of medical treatment in western countries are causing many people to rely on health tourism treatment, as they look for high-quality yet low-priced health care in foreign clinics. Therefore, the health tourism market has been growing rapidly and is playing an increasingly important role in international tourism trade. While the demand for medical services on the part of international visitors strongly influences administrative decision-making in tourism, predicting demand remains an extremely challenging task. Management's judgment is widely used to adjust statistical forecasts in order to take into account special events (Lee et al., 2007).

The changes that take place in the demand for health tourism are influenced by many unpredictable factors, thus greatly increasing operational risk and uncertainty. A good ability to forecast demand is thus an essential prerequisite of a new tourism destination that not only aims at cost-efficient investments in the planning of capacity expansion, but also plays an effective role in monitoring environmental issues as well as setting tariffs and relevant plans in place for demand-side management studies. RNCOS (2009) pointed out that more than 3 million health tourists visited Asian destinations in 2008, there by generating combined revenues of more than US$5 billion in 2008. Both tourist arrivals as well as revenues are expected to register significant growth. This situation shows that health tourism in Asia is going through a process of dynamic change, and indicates that the forecasting of demand is significantly important for health tourism industry long-term decision making related to investment in hospitals. Unfortunately, a review of the literature has revealed that research on health tourism forecasting has been quite scant.

Countries thus wish to better understand their international visitors and tourism revenues, to help rapidly formulate appropriate tourism policies. Furthermore, the tourism industry is characterized by variability, creating a need for accurate short and long term tourism demand forecasts. Previous studies on tourism demand forecasting often deal with multiple forecasting methods (Song and Li, 2007; Triantafyllopoulos, 2007), but applying the analytical methods presented above is complex and challenging (Wong et al., 2007; Lee et al., 2007). However, accurate forecasting of international medical tourism demand is important in medical tourism planning by both the public and business sectors owing to the limit resource of employ and investment. Namely, investigations of this area have concluded that econometric models can help policymakers establish appropriate economic strategies to stimulate tourism demand and generate accurate demand forecasts. This shows that the forecasting methodology is most relevant and most easily applicable in management, and that demand forecasting is the key objective of management (Hua, et al., 2007; Pedregal and Young, 2007). Moreover, health tourism is a new and developing industry that indicates that it is difficult to accurately forecast performance. In practice, most studies dealing with the forecasting of the demand for tourism are econometric, (e.g., they adopt spatial models, time-sequence models and ARIMA models) and they frequently achieve good forecasting results (Huang and Lin, 2011). Despite the importance of econometric models, however, there has been relatively little empirical research conducted to develop an accurate understanding using a short-term and limited dataset as the underlying basis for the econometric model for health tourism markets.

According to the above discussion, there is little empirical evidence concerned with how a health tourism demand forecasting model can give rise to a high degree of accuracy given the availability of only a short-term dataset, and thus there is a need to respond to the dearth of research in the health tourism forecasting field. In relation to short-term forecasting, the Grey forecasting model (GM(1,1)) is one of the essential aspects of Grey system theory and GM(1,1) displays its advantages. The principle of the GM model is that it provides forecasting data for decision- and policy-makers and helps the decision-makers achieve a high level of performance in forecasting the short-term dataset (Deng, 1982; Deng, 1989). GM(1,1) has been successfully applied to many fields, i.e., tourism demand forecasting (Lin et al., 2009; Huang and Lin, 2011), the prediction of output in the high technology industry (Hsu, 2009; Wang and Hsu, 2008; Lin and Yang, 2003), the prediction of top executive turnover in the electronics industry (Lin et al., 2008), forecasting in relation to dental clinics (Lin et al., 2007), and predicting electric power (Huang et al., 2007). The Grey forecasting model forms the core of Grey system theory, and Grey forecasting always results in highly accurate measurements. Although these early and recent endorsement studies provide useful information, however, there are few studies that examine the specific issues addressed in how GM(1,1) gives rise to different predicted errors that are directly induced by different levels of α in predicted operations (Hung et al., 2009; Hsu et al., 2006; Wen et al., 2000; Yeh and Lu, 1996; Yang, 1994).

Existing studies on analyzing predicted error have been exclusively devoted to the use of GM(1,1) (e.g., Hung et al., 2009; Hsu et al., 2006; Wen et al., 2000). By contrast, there are no studies that have explored the topic from the viewpoint of health tourism. For tourism researchers, developing a feasible and efficient demand prediction procedure for estimating market size and managerial strategy making is of practical relevance and methodological value. After reviewing the existing research evidence, this study presents a more suitable and accurate model for forecasting the demand for health tourism that should be more theoretically useful. The α=0.5 of the GM(1,1) model is not agreeable with all situations. Thus, this paper used an optimal α of GM(1,1) model to result to a minimum the predicated error. Therefore, the purpose of this study is to apply GM(1,1) with adaptive levels of α (hereafter GM(1,1)-α model) to provide a concise prediction model that will improve the ability to forecast the demand for health tourism in Asian countries.

1. DATA AND METHODOLOGY

Based on the above purpose, this study focuses on the demand for international health tourism in Asian countries, and analyzes and forecasts the demand generated by health tourism passengers visiting India, Singapore, and Thailand. In order to verify the feasibility of the proposed approach, we analyze data covering a period from 2002 through 2009 that are obtained from RNCOS health tourism reports (RNCOS, 2007; RNCOS, 2009).

The Grey model GM(1,1) is a time series and frequently used Grey forecasting model (Deng, 1982). Traditional forecasting methods typically require a large amount of data to construct their respective models (Lin and Yang, 2003). However, production forecasting depends more on a limited amount of current data than on large amounts of historical data. In other words, only a few cogent observations are required in production forecasting. Grey forecasting is thus an appropriate forecasting method because it does not require many observations. According to the Grey forecasting method (GM), having only four observations is sufficient to characterize an unknown system.

The model adopted in this paper is the GM(1,1) model, which involves the creation of a sequence of first-order linear moves. When the model was constructed, we applied a first-order accumulated generating operation to the primitive sequence to provide the basis for building a model and to lessen the tendency toward variation. According to the principles of the GM(1,1) model, it is assumed that α equals 0.5 (Deng, 1982). However, the accumulated evidence from earlier studies has shown that when α equals 0.5, this can lead to higher predicted error (Wen et al., 2000). Moreover, Wen et al. (2000) found that deciding the optimal value of α in GM(1,1) can minimize the predicted error and Hsu et al. (2006) demonstrated that α should not be a fixed value since 0.5. Thus, GM(1,1)-α is processed using the following six steps:

Step 1. Assume the original sequence to be x_0,

$$x_0 = \left(x_0(1), x_0(2), \cdots, x_0(n)\right) \tag{1}$$

Step 2. x_1 is defined as x_0's first-order accumulated generating operation (hereafter AGO) sequence. That is,

$$\begin{aligned} x_1 &= \left(x_1(1), x_1(2), \cdots, x_1(n)\right) \\ &= \left(\sum_{k=1}^{1} x_0(k), \sum_{k=1}^{2} x_0(k), \cdots, \sum_{k=1}^{n} x_0(k)\right) \end{aligned} \tag{2}$$

Step 3. The first-order differential equation of the GM(1,1) model is

$$\frac{dx_1(t)}{dt} + ax_1(t) = b \tag{3}$$

where t denotes the independent variables in the system, a represents the developed coefficient, b is the Grey controlled variable, and a and b denote the model parameters requiring determination.

Step 4. The values of a and b are obtained using the ordinary least-squares method (OLS) as

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_N \tag{4}$$

Furthermore, the accumulated matrix B is

$$B = \begin{bmatrix} -\left[\alpha x_1(1) + (1-\alpha)x_1(2)\right] & 1 \\ -\left[\alpha x_1(2) + (1-\alpha)x_1(3)\right] & 1 \\ \cdots & \cdots \\ -\left[\alpha x_1(n-1) + (1-\alpha)x_1(n)\right] & 1 \end{bmatrix} \tag{5}$$

where α is in the range of [0,1]. The estimated α yields the lowest residual of squares (RSS). If α = 0.5, GM(1,1)-α will reduce to a GM(1,1). Meanwhile, the constant vector $\mathrm{Y_N}$ is

$$Y_N = [x_0(2), x_0(3), \cdots, x_0(n)]^T \tag{6}$$

Step 5. The approximate relationship can be obtained as follows by substituting what is obtained in the differential equation, and solving for the raw data sequence.

$$\hat{x}_1(k+1) = (x_0(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}, \quad k > 0 \tag{7}$$

Step 6. When $\hat{x}_1(1) = \hat{x}_0(1)$, the sequence of the first-order inverse-accumulated generating operation (hereafter IAGO) of reduction is obtained as:

$$\hat{x}_0(k+1) = \hat{x}_1(k+1) - \hat{x}_1(k), \quad k > 0 \tag{8}$$

Given $k = 1,2\cdots,n$, the sequence of reduction is obtained as follows:

$$\hat{x}_0 = \left(\hat{x}_0(2), \hat{x}_0(3), \cdots, \hat{x}_0(n)\right) \tag{9}$$

The forecasting performance of the competing model is evaluated using the mean absolute percentage error (MAPE), defined as follows:

$$\text{MAPE} = \text{N}^{-1}\sum_{t=1}^{N}\left|\frac{X_t - \hat{X}_{k,t}}{X_t}\right| \tag{10}$$

where X_t and $\hat{X}_{k,t}$, respectively, denote the number of tourists demanding medical services as well as the number of tourists demanding medical services in Asian countries generated by model *k* for year *t*.

2. RESULTS

2.1. Data description

Table 1 lists the descriptive statistics on the numbers of tourists demanding medical services in Asian countries. The means of the numbers of tourists demanding medical services in India, Singapore, and Thailand are 170.10, 331.44, and 1,084.29, respectively. This indicates that Thailand has the biggest market in Asia. Moreover, the standard error of the numbers of tourists demanding medical services in Asian countries are 63.62, 55.23, and 146.85, respectively, indicating that the variations in the demand for health tourism in Thailand are clearly larger than in India and Singapore.[1]

[1] The demand for medical tourism in Thailand in creased quite substantially from 2005 to 2006 (RNCOS, 2009).

Table 1: **Descriptive statistics**

Items	India	Singapore	Thailand
Mean	170.10	331.44	1,084.29
Median	72.99	283.00	1,000.00
Maximum	510.00	600.00	1,540.00
Minimum	10.00	150.00	630.00
Standard Error	63.62	55.231	146.85

Note: Numbers of health tourists in thousands.

2.2. Forecasting health tourism demand for Asian countries

Table 2 shows that the true values and forecasting result by GM(1,1)-α model for Asian health tourism demand for 5 years. According to the forecasting result that the 10 years later the health tourists demand to India is 3103, Singapore is 1516, Thailand is 3198, and Malaysia is 774 in 2013.

Table 2: **True values and forecasting result of health tourism demand**

Country	India		Singapore		Thailand		Malaysia	
Item	Tourism Demand	GM(1,1)-α F.V.	Tourism Demand	GM(1,1)-α F.V.	Tourism Demand	GM(1,1)-α F.V.	Tourism Demand	GM(1,1)-α F.V.
2000	-	-	150.00	150.00	-	-	-	-
2001	16.44	33.20	178.00	163.86	-	-	-	-
2002	27.02	48.46	211.00	197.24	630.00	630.00	-	-
2003	44.41	70.73	230.00	237.42	730.00	730.00	-	-
2004	72.99	103.23	283.00	285.79	790.00	846.22	174.20	174.20
2005	180.00	150.67	350.00	344.02	1,000.00	980.94	232.20	241.80
2006	220.00	219.91	410.00	414.10	1,400.00	1,137.12	296.70	279.66
2007	450.00	320.97	571.00	498.47	1,540.00	1,318.15	341.30	323.46
2008	510.00	468.47	600.00	600.02	1,500.00	1,528.02	374.10	374.11
2009	-	683.76	-	722.27	-	1,771.29	-	432.69
2010	-	997.98	-	869.41	-	2,053.29	-	500.44
2011	-	1,456.61	-	1,046.54	-	2,380.19	-	578.81
2012	-	2,126.00	-	1,259.75	-	2,759.14	-	669.44
2013	-	3,103.03	-	1,516.40	-	3,198.42	-	774.27

Note: 1. GM(1,1)-α F.V.=GM(1,1)-α forecast value
2. The number is count by thousand.

Table 3 presents, based on a comparison of the forecasting error for the time series, the GM(1,1) and GM(1,1)-α models for Asian health tourism demand.[2] The alpha values for the GM(1,1)-α model are 0.246, 0.432 and 0.217 for India, Singapore, and Thailand respectively. The results include values of the MAPE of 0.291, 0.043, and 0.063 for India, Singapore, and Thailand, respectively, using the GM(1,1)-α model, which are found to be better than applying the time series model and GM(1,1). Therefore, the empirical results point out that the prediction error for health tourism demand in Asian countries has been reduced by GM(1,1)-α. That is, the GM(1,1)-α model resulted in an improvement in average forecasting performance in relation to the estimated demand for health tourism in India, Singapore, and Thailand.

Table 3: **Forecasting error of health tourism demand**

Country	India			Singapore			Thailand		
Model	**Time Series**	**GM(1,1)**	**GM(1,1)-α**	**Time Series**	**GM(1,1)**	**GM(1,1)-α**	**Time Series**	**GM(1,1)**	**GM(1,1)-α**
Alpha	-	0.500	0.246	-	0.500	0.432	-	0.500	0.217
Year	**PE**	**PE**	**PE**	**PE**	**PE**	**PE**	**PE**	**PE**	**PE**
2000	-	-	-	34.5%	0.0%	0.0%	-	-	-
2001	516.0%	0.0%	0.0%	12.0%	6.6%	7.9%	-	-	-
2002	79.7%	106.9%	79.4%	1.8%	5.0%	6.5%	10.2%	0.0%	0.0%
2003	78.6%	90.8%	59.3%	18.8%	5.2%	3.2%	1.2%	5.1%	0.0%
2004	109.9%	76.0%	41.4%	17.1%	3.2%	1.0%	15.4%	13.2%	7.1%
2005	26.1%	8.2%	16.3%	11.4%	0.6%	1.7%	8.4%	4.2%	1.9%
2006	36.8%	34.1%	0.0%	9.3%	3.6%	1.0%	10.2%	13.2%	18.8%
2007	16.7%	0.6%	28.7%	11.3%	10.2%	12.7%	7.1%	8.1%	14.4%
2008	12.0%	32.9%	8.1%	5.9%	3.1%	0.0%	6.9%	10.0%	1.9%
MAPE	109.5%	43.7%	29.1%	11.0%	4.7%	4.3%	8.5%	7.7%	6.3%

Note: Percentage Error (PE); Mean Absolute Percentage Error (MAPE)

Moreover, Figures 1 to 3 present the real tourism demand, time series model and GM(1,1)-α model used to forecast the values of the demand for health tourism in Asian countries. The results predict that the demand for health tourism will be 0.68 million in India, 0.72 million in Singapore, and 1.77 million in Thailand in 2009 using GM(1,1)-α separately. This noteworthy fact indicates that the demand for health tourism was -0.0068 million in India in 2001 when applying the time series model. This situation suggests that there is a serious inaccuracy in terms of the actual demand for health tourism in India. This information can be useful in supporting the view that the GM(1,1)-α model is much better than the other two methods, and that the GM(1,1)-α model is suited to the forecasting of the demand for health tourism.

[2] The time series model is $y = \beta_0 + \beta_1 time + \varepsilon$, y and time are the real tourism demand and time trend term. ε is error term.

Figure 1: **Forecasting the health tourism demand in India**

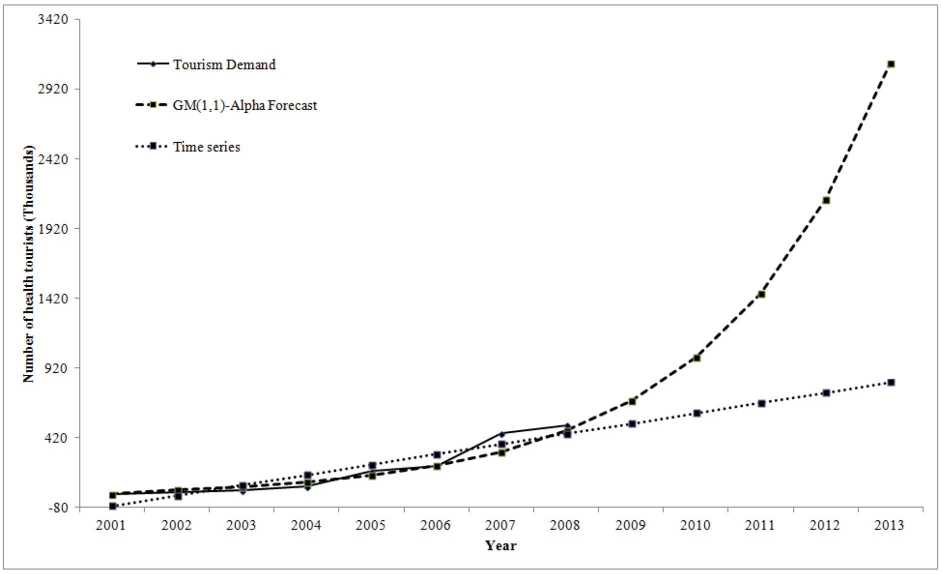


Figure 2: **Forecasting the health tourism demand in Singapore**

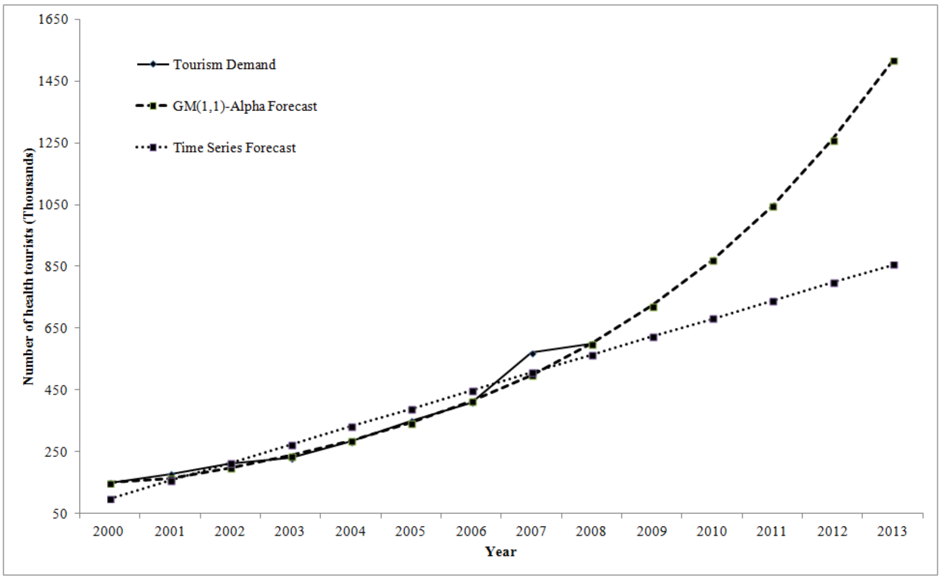
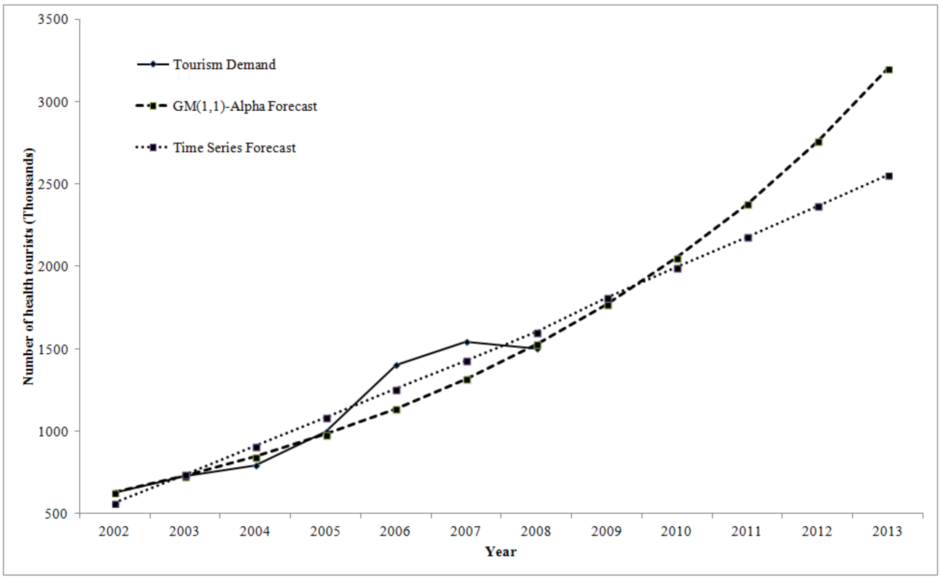


Figure 3: **Forecasting the health tourism demand in Thailand**



CONCLUSIONS AND DISCUSSIONS

Health tourism makes a significant contribution to the economy in a number of countries and health tourism market is also most rapidly growing in the world (Cortez, 2007; Bennett et al., 2004). With the current trend towards the globalization of medicine industry, individuals or insurance companies prefer to seek medical care overseas for lower costs and better service quality, which has led to the emergence of international medical services and related tour arrangements. As for Asian countries, due to the increase demand of old age medical care (e.g. Japan) or rapid economic development (e.g. China and India), the demand for overseas tour plus medical treatment is also on the increase.

In practice, previous studies on tourism demand suffer complex conceptual and methodological problems, thus casting doubt on their validity and interpretability. The methods available for forecasting tourism demand are limited. Most studies dealing with tourism demand forecasting are econometric and often deal with multiple forecasting methods, but applying the analytical methods presented above is complex and challenging (Huang and Lin, 2011). Thus the purpose of this study is developing an easy and accurate method to predict the demand for health medical tourism. This study used an optimal α of GM(1,1) model to result to a minimum the predicated error.

This study has applied the GM(1,1)-α model to forecast the demand for health tourism in Asian countries, and may lead to more accurate forecasts of the effects of administrative decision-making schemes. The results of this study have several practical implications. First, this investigation consists of providing an effective method for forecasting the numbers of health tourists in India, Singapore, and Thailand.

Secondly, in the case of the demand for health tourism in Asian countries, an implementation predicts the error using the GM(1,1) model with an adaptive α model that is evidently better than the original GM(1,1) and time series models. In practical terms, the GM(1,1) is better than the time series model in forecasting performance based on the demand for health tourism. Furthermore, the adaptive α in GM(1,1) is a credible way of improving the accuracy of health tourism demand forecasting. Thirdly, the results indicate that the accurate and efficiently predicted values based on the optimal α value in GM(1,1) is used by researchers, managers and administrators in developing manpower, finance, marketing, and administrative decision-making schemes. Consequently, this study contributes to the body of knowledge concerning the potential that health tourism has in international tourist markets in the tourism industry. Finally, the result pointed that the health tourism demand and industry is growth rapidly, therefore the governments are develop health tourism industry must to enhance relative fundamental construction for health tourism markets.

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