An Integrative Framework for Collaborative Forecasting in Tourism Supply Chains

Xinyan Zhang
School of Professional Education and Executive Development,
The Hong Kong Polytechnic University, Hong Kong SAR
spalina@speed-polyu.edu.hk

Haiyan Song
School of Hotel and Tourism Management,
The Hong Kong Polytechnic University, Hong Kong SAR
haiyan.song@polyu.edu.hk

An Integrative Framework for Collaborative Forecasting in Tourism Supply Chains

Abstract

Tourism practitioners must often rely on each other in a tourism supply chain (TSC). Demand forecasting plays a key role in shaping the activities of TSC practitioners. In the past four decades, researchers have developed many techniques for advanced tourism demand forecasting, but practitioners have had little interest in them. To bridge this gap, we examine the nature of the forecasting tasks of TSC practitioners in Hong Kong and propose a collaborative TSC forecasting framework that not only integrates tourism demand forecasting methods with practitioners' knowledge, but also facilitates information sharing between TSC practitioners to increase industry collaboration and improve forecasting performance.

Keywords: tourism demand; forecasting; tourism supply chain; forecasting support system; collaborative forecasting

Introduction

Tourism is one of the most fragmented service-oriented industries and tourism offerings are often composed of multiple travel services, such as transportation, accommodation and attractions. Thus, tourism practitioners often have to rely on each other in a tourism supply chain (TSC) to achieve sustainable economic value and tourist satisfaction. The performance of individual tourism practitioners affects the overall competitiveness of the entire tourism industry at the destination.

Supply chain management has been widely studied in the manufacturing industry since Houlihan (1985) first introduced the concept. Over the past decade,

TSCs have received increasing attention (e.g., Zhang, Song, & Huang, 2009; Huang, Song, & Zhang, 2010; Zhang, Song, Huang, & Chen, 2010; Zhang & Song, 2012; Guo, Shi, Dong, Guo, & Anderson, 2014; Lee & Fernando, 2015; Jena & Jog, 2016). In a comprehensive review of TSC management, Zhang *et al*. (2009, p. 347) define a TSC as '*a network of tourism organizations supplying different components of tourism products/services such as flights and accommodation for the distribution and marketing of the final tourism products at a specific tourism destination, and involves a wide range of participants in both the private and public sectors*'. This definition indicates that a TSC involves more than the distribution of tourism services. It covers the entire tourism product (formation and delivery) and includes practitioners from service suppliers to end customers or travellers. Therefore, the main TSC business stakeholders include service suppliers (e.g., hotels and airlines), principals (e.g., tour wholesalers/operators) and distributors (e.g., travel agents).

Tourism is a demand-driven and dynamic industry. It is obviously important for industry practitioners to understand tourism demand. Demand forecasting is a key aspect of the planning process in tourism companies. In the past four decades, numerous researchers have developed techniques for tourism demand forecasting. However, it is hypothesised that tourism practitioners have little interest in scholarly journals and thus do not benefit from this research. In addition, tourism practitioners face a number of special challenges that do not exist in other industries in terms of demand forecasting (Frechtling, 2001; Yoeman, 2008). For instance, the tourism industry has higher demand uncertainty and more complex dynamics than its counterparts. A variety of factors can influence tourism demand. For example, as travel is a luxury product, people tend to cut back on holidays when economic conditions are

bad. Unpredictable economic shocks, such as the current global financial turmoil and economic recession, can cause significant demand uncertainty in tourism. Many other factors contribute to market uncertainty and its effect on the demand for tourism products. For example, effective advertising can increase the number of tourist arrivals, whereas negative word-of-mouth publicity can decrease demand.

To bridge the gap between academia and industry and to tackle the effects of demand uncertainty in the tourism industry, we establish a collaborative tourism demand forecasting mechanism for TSC practitioners. We use Hong Kong as the research context for several reasons. First, Hong Kong is an important tourism destination. Often referred to as the Pearl of the Orient, Hong Kong is famous for its beautiful nightlife, its shopping and theme park facilities and its variety of dining choices. As an international hub in the Asia Pacific region, Hong Kong attracts visitors from around the world and consistently ranks among the top destinations in Asia (Li, Song, Cao, & Wu, 2013). Furthermore, tourism has been a pillar industry of the Hong Kong economy for years. Its GDP contribution grew by 161% between 2002 and 2012, the fastest of the four pillar industries (Census and Statistics Department, 2015). This fast growth has largely been due to the launch and extension of the Individual Visit Scheme. However, the tourism industry in Hong Kong, especially inbound tourism, is facing a number of challenges, such as keen competition from its nearby competitors (e.g., Singapore), decreasing enthusiasm among Chinese tourists and public demonstrations in the streets. Whether tourism demand in Hong Kong can continue to grow is uncertain. Given the increasing uncertainty regarding future tourism demand in Hong Kong, more precise tourism demand forecasts are crucial for tourism practitioners in Hong Kong. Therefore, there is a higher incentive for TSC practitioners

in Hong Kong to collaborate. Finally, Hong Kong is a typical island economy. Therefore, findings from this study can be generalised and applied to similar destinations, such as Singapore and Macau.

In recent years many businesses have used collaborative forecasting to improve forecast accuracy (Ramanathan, 2012). The broad exchange of information in collaborative forecasting improves forecasting accuracy, as supply chain members share knowledge about demand forecasts, sales data and pricing strategies (Datta & Christopher, 2011; Hung, Lin, & Ho, 2014). Technologically, collaborative forecasting can be achieved by designing a collaborative forecasting support system (FSS), which is a type of decision support system (DSS). According to Fildes, Goodwin and Lawrence (2006), the key features of FSSs include (1) an historical time series stored in the system, (2) a set of quantitative forecasting methods and (3) forecast adjustment tools. In practice, FSSs are widely used by private and public organisations to prepare forecasts (Fildes *et al*., 2006). The effectiveness of collaborative forecasting is also highly dependent on the people and processes used. Therefore, the objectives of this study are as follows:

- to understand the forecasting processes of various TSC practitioners;
- to understand TSC practitioners' perceptions of FSSs;
- to understand the current information sharing status of TSC practitioners; and
- to propose a collaborative TSC forecasting framework.

We make three contributions. First, we are the first to empirically study TSC practitioners' forecasting and information sharing practices. Our findings provide a valuable reference for future academic research in this area. Second, we propose a collaborative TSC forecasting framework and identify the conditions under which

efficient collaborative forecasting is likely to occur. We argue that under the new idea of collaborative TSC forecasting, forecast accuracy will increase, as the framework we propose includes advanced tourism demand forecasting methods and the practitioners' knowledge and updated information. Third, the proposed collaborative TSC forecasting framework can be developed as part of a smart infrastructure that can increase the competitiveness of the entire tourism industry at a destination.

Literature Review

Tourism Supply Chain

From a macro perspective, a supply chain can be described as a network of related organisations that are engaged in different functions ranging from the supply of raw materials through the production of end products to delivery to target customers. In 1975, the United Nations World Tourism Organization (UNWTO) published a report on the distribution channels of the tourism industry (UNWTO, 1975). A distribution channel can be defined as a type of supply chain focused on distribution and marketing activities.

Tourism is a system in which interdependence is essential (Björk & Virtanen, 2005). Interdependence means that the consequences of an entity's specific strategy depend not only on the strategy, but also on the strategies of other entities. Although the importance of TSCs is obvious, scholarly publications in this area have been scattered and disjointed and no effort has been made to identify the core issues involved in TSC management. Nevertheless, several studies have been conducted on such supply chains, such as those of the UNWTO (1994), Sinclair and Stabler (1997), Buhalis and

Laws (2001), Page (2003) and Zhang *et al*. (2009). Zhang *et al*. (2009) provide a systematic review of current tourism studies from the TSC management perspective. We extend the review conducted by Zhang *et al*. (2009) by proposing a general TSC network for a destination and developing a general research framework for TSC management. To facilitate both theoretical and empirical TSC studies, we identify future research directions for the study of collaborative forecasting, TSC coordination and integrated product and TSC design.

Supply Chain Collaborative Forecasting and Information Sharing

The concept of supply chain collaboration emerged in the mid-1990s in the form of collaborative planning, forecasting and replenishment (VICS, 1998; Barratt, 2004). Various studies have shown that collaborative forecasting (i.e., sharing forecasts and joint forecasting by supply chain companies) is an essential element in improving supply chain performance (e.g.. Lee *et al*., 1997; Helms *et al*., 2000; Barratt & Oliveira, 2001; Ramanathan, 2012). However, studies of collaborative forecasting have mainly modelled manufacturing supply chains (Småros, 2007), focusing on their importance and the extent to which this approach can be used in manufacturing (Mentzer & Kahn, 1997; Fosnaught, 1999; Helms, Ettkin, & Chapman, 2000; Wilson, 2001; Småros, 2003). Empirical studies in this area have been limited and little attention has been paid to how collaborative forecasting should be set up in practice and what methods can be used to achieve collaboration.

Although collaborative demand forecasting has been studied in supply chain management, with a focus on information sharing between the links in the chain (Dong, Zhang, & Xi, 2010), few studies have been conducted on TSC collaboration. TSC

collaboration is critical, as all of the practitioners in a TSC must interact to achieve good business performance. Accordingly, collaborative TSC forecasting must be based on cooperation and information sharing between links in the chain.

In reality, members of a supply chain usually do not share business information, such as demand forecasts, costs, margins and quality (Mukhopadhyay, Zhu, & Yue, 2008). Successful information sharing can be induced by explicit contracting mechanisms between supply chain members. Alternatively, it can be induced by communication known as 'cheap talk', in which parties have long-term relationships and interact repeatedly (Ren *et al*., 2010).

Studies have demonstrated the numerous benefits of information sharing in supply chain networks. For example, sharing demand information with upstream members helps reduce manufacturers' supply chain costs (Raghunathan, 1999; Kulp *et al*., 2004). Bourland *et al*. (1996), Gavirneni *et al*. (1999) and Lee *et al*. (2000) state that knowledge of demand information reduces the inventory costs for both supplier and customer. Other studies have asserted that sharing demand information along with current inventory status facilitates the reduction of inventory costs (Chen, 1998; Cachon & Fisher, 2000). Recent studies have suggested that sharing supply chain information about point of sale, inventory, price, production and delivery improves overall supply chain efficiency (Byrne & Heavey, 2006; Ketzenberg, 2009; Nakano, 2009). Furthermore, information sharing improves forecasts, albeit to different degrees for different supply chain members (Zhu, Mukhopadhyay, & Yue, 2011).

Forecasting Support System

An FSS is a set of computerised procedures that supports forecasting (Armstrong, 2001). A detailed and precise forecast is an essential input in planning or decision-making processes. Armstrong (2001) points out that an FSS also allows a forecaster to incorporate judgments and monitor accuracy.

Many commercial FSSs are on the market. For example, Küsters and Bell (1999) list and review 43 commercial FSSs. However, according to Fildes *et al*. (2006), the use of FSSs in practice is far from ideal. Managers either rely too exclusively on their own judgments or are unable to input their adjustments into the computerised systems. In addition, Küsters, McCullough and Bell (2006) find that few FSSs provide state-of-the-art functionality and that continuing advances in forecasting are not being incorporated into forecasting software in reasonable timeframes. They conclude that closer integration between the information provided by forecasts and the use of this information in decision making is required. Goodwin, Fildes, Lawrence and Nikolopoulos (2007) suggest that FSS designers should consider the ways in which individual forecasters use their systems. We attempt to understand Hong Kong TSC practitioners' forecasting processes and their views on the use of FSSs in the business planning process.

More advanced FSSs can be grouped into two large categories according to their features: general and specific FSSs (Song, Witt, & Zhang, 2009). General FSSs focus on general market research and are often partially automated due to the large number of time series data involved (e.g., Cortez, Machado, & Neves, 1996; Nikolopoulos & Assimakopoulos, 2003). The basic forecasting algorithm embedded in a general FSS is either an artificial intelligence (AI) technique or a combination of

statistical FSS and knowledge-based techniques. In contrast, specific FSSs concentrate on solutions to specific forecasting problems, such as electric load forecasting (Charytoniuk & Chen, 2000; Vilcahuamán, Meléndez, & de la Rosa, 2002), weather forecasting (Nelson & Winter Jr., 1964; Kallos, Kotroni, & Lagouvardos, 1997; Stern, 2002), stock price forecasting (Baba & Kozaki, 1992; Hiemstra, 1994), sales forecasting (Kuo, 2001; Thomassey & Fiordaliso, 2006) and flood forecasting (Kouwen, 2000; Li, Chau, Cheng, & Li, 2006). Research on tourism demand FSSs, however, is rare. A few exceptions are reviewed in the following section.

Tourism Demand Forecasting Methods

Most attention has been directed to the development of advanced statistical forecasting methods (Song & Li, 2008). Witt and Witt (1995) and Li, Song and Witt (2005) review the large body of literature published on tourism demand forecasting using modern econometric techniques. In contrast, qualitative or judgmental forecasting has received relatively little attention from tourism researchers (Croce & Wöber, 2011).

In a review, Song and Li (2008) divide the latest developments in quantitative forecasting approaches into three categories: (1) time-series models, (2) the econometric approach and (3) other emerging AI methods. The final category reflects the influence of advances in information technology on tourism demand forecasting approaches. FSSs and the Internet represent other areas of expansion in the use of information technology in tourism demand forecasting. Petropoulos, Patelis, Metaxiotis, Nikolopoulos and Assimakopoulos (2003) establish a statistical and forecasting tourism information system (SFTIS) for tourism demand forecasting. The

SFTIS is based on a proposed two-step econometric approach: (1) splitting inbound tourism demand for a destination into the outbound tourism flow from a source market and the market share of the source market for the particular destination and (2) using a stepwise forward-with-a-backward-look regression algorithm to decide the best subset of explanatory variables for each of the dependent variables. Judgmental techniques are not included in this system. Patelis, Petropoulos, Nikolopoulos, Lin and Assimakopoulos (2005) propose integrating the SFTIS into an e-government system, namely eSFTIS, so that tourism forecasting can be a component of e-government services. The eSFTIS is supposed to serve end users, such as hoteliers, tour operators, scientists, engineers, researchers and academics, via e-government services, which are citizen-focused and accessible via various modes, including the Internet. In the belief that experts' judgments are valuable inputs to tourism demand forecast accuracy, Song *et al*. (2008) develop a tourism demand forecasting system based on a two-step process: (1) the most advanced econometric forecasting techniques and (2) a Delphi-type revision of the estimates through a panel of 12 experts. The system uses the Internet as the platform for the experts' inputs of judgments via human-machine interactions. More recently, Croce and Wöber (2011) describe a group forecasting system in which base forecasts are produced by simple extrapolation forecasting methods. The system is embedded in TourMIS, which supports collaborative short-term forecasting tasks between tourism managers. Estimates in TourMIS can be made either through pure judgment, one of the two established quantitative methods (i.e., Naive 2 and Winters' exponential smoothing) or a combination of the two approaches.

These studies suggest that a collaborative FSS that can facilitate the sharing of information and knowledge in a TSC and encourage collaboration in tourism demand

forecasting is highly desirable. For tourism practitioners, the methods for generating forecasts and using an FSS may vary. To develop a more successful collaborative FSS for a TSC, system designers must understand the nature of the forecasting task for TSC practitioners and their use of FSSs.

With the rapid growth of online travel retail and review sites, a more recent trend in tourism demand forecasting is forecasting with big data generated by users. Although there is no unified definition, big data is often used to describe massive, complex and real-time data that require special management, analytical and processing techniques to extract value from the information (Beyer & Laney, 2012). There exists a widespread belief that big data can help improve tourism demand forecasts provided that tourism forecasters can analyse and discover hidden patterns (Blal & Sturman, 2014; Song & Liu, 2017). Choi and Varian (2012) use search engine data (i.e., Google Trends) to forecast visitor arrivals in Hong Kong. They find that search engine data can improve the forecasting accuracy of arrivals from several countries. Yang *et al*. (2014) use the web traffic volume data of the Charleston Area Convention and Visitors Bureau to forecast the destination's hotel demand. The results show that incorporating the web traffic data can improve forecasting accuracy. Li *et al*. (2017) adopt search engine query volumes to forecast tourism demand for a destination. Their results suggest that the proposed method improves forecast accuracy more than a traditional time series model and a PCA-based index model. Pantano, Priporas and Stylos (2017) attempt to predict tourists' process of selecting tourist destinations and/or services by transforming large amounts of open data into value propositions. Travellers generate various information on open sources, such as TripAdvisor and social networks (e.g., Facebook and Twitter). Such information affects other travellers' decision-making

processes, such as their selection of a tourist destination, accommodations and attractions to visit (Pantano & Di Pietro, 2013; Hudson, 2014; Filieri, Alguezaui, & McLeay, 2015; Xiang, Magnini, & Fesenmaier, 2015; Pantano *et al*., 2017). Recognising the benefits and challenges of big data analytics to tourism demand forecasters, Song and Liu (2017) propose a tourism demand forecasting framework using big data. They suggest that the potential growth in application of big data in the tourism and hospitality industry is huge.

Conceptual Research Framework

According to Zhang *et al*. (2009), there are six major TSC stakeholders at every destination: the local government (e.g., business associations and research institutions), customers (tourists), travel agents, tour operators, service suppliers and the suppliers' suppliers. For the purpose of this study, we develop a TSC structure that focuses on industry practitioner stakeholders, as shown in Figure 1.

[Figure 1 near here]

In this TSC structure, each position represents a group of TSC practitioners (e.g., airline and tour operator), whereas 'Suppliers', 'Principals' and 'Distributors' are regarded as TSC stakeholders. Note that there is not necessarily a business relationship or commercial agreement between any two TSC practitioners. They may be two companies in the same sectors.

In general, suppliers in a TSC, such as hotels and airlines, use demand forecasts to decide on issues, such as capacity building, resource planning and market prices

(revenue management). Furthermore, demand-supply matching, customer satisfaction and profitability can be significantly improved when forecast accuracy is improved. Principals (tour operators) play a crucial role in TSC networks, as they are the intermediaries who identify customers' (tourists') demands and transfer their requirements to the service suppliers (Piboonrungroj & Disney, 2009). Although all TSC practitioners develop their own forecasts using their own methods, it is hypothesised that shared information may be an essential element in TSCs, due to the dynamic nature of the tourism industry and the high interdependence between practitioners.

Accordingly, we propose a collaborative TSC forecasting framework, shown in Figure 2. The core of a collaborative TSC forecasting system has three features: an FSS that acts as the forecasting platform, a range of tourism demand forecasting methods and TSC information sharing. Each feature facilitates collaborative TSC forecasting.

[Figure 2 near here]

We use the preceding conceptual frameworks to explore TSC practitioners' perceptions of tourism demand forecasting methods and FSSs and their current information sharing practices during their forecasting processes. The results of this empirical study are then used to establish a better collaborative TSC forecasting mechanism.

Research Methodology

In-depth interviews were used for three reasons. First, collaborative TSC forecasting is a new area in tourism studies. The use of in-depth interviews is ideally suited to in-depth explorations of new issues (Boyce & Neale, 2006). Second, tourism practitioners generate forecasts in different ways and possess different views on the use of FSSs. In-depth interviewing is more flexible and adaptable than other qualitative research methods, such as the use of focus groups (Stainback & Stainback, 1988; Bailey, 1994). Interviewees are more likely to share their true individual opinions and experiences in an individual setting. Thus, the in-depth interview approach was an appropriate research method for this study.

The conceptual TSC framework was used during the sampling process. A list of practitioners from different tourism sectors in Hong Kong, such as service suppliers, principals and distributors, was compiled from a variety of sources, such as relevant industry contacts and industry association publications. The final list consisted of 19 key practitioners in Hong Kong's TSC, such as travel agents, tour operators and suppliers (e.g., airlines, hotel chains, catering services and attractions). Managers with relatively high positions in these companies who probably assessed future business trends were our targeted interviewees. Ten managers agreed to be interviewed. The sample profile of the 10 interviewees is provided in Table 1. Seven of the interviewees were suppliers (i.e., one airline, three hotel chains, two attractions and one catering service) and three were principals and/or distributors in the TSC. We combined principals and distributors, as some principals (tour operators) also owned or operated the distributors (travel agents). Therefore, both of these categories combined were defined as 'travel services'.

The conceptual TSC framework was also used during the interviews to explain the concept of a TSC to interviewees and to collect their opinions. It is important to note that some non-business entities, such as local governments, business associations and research institutions, are also involved in the TSC and may play an important role in public and private sector collaboration.

The interviews took place between June 2012 and August 2012 and were all conducted at the interviewees' place of work. An interview guide was prepared with open-ended questions related to the two areas of primary interest, that is, the company's forecasting process and the manager's views on using FSSs. The interviews were conducted in English. Each interview took approximately 1 hour and was subsequently transcribed. We identified and coded the themes and sub-themes that emerged from the data.

[Table 1 near here]

Findings

Forecasting Processes and Methods

When asked, 'Does your company carry out any form of forecasting in your business decision making', all of the respondents were absolutely sure of the importance of demand forecasting in their businesses. They indicated that their companies conducted long- and short-term forecasting to project future demand. Short-term forecasts, typically daily forecasts, were mainly conducted to facilitate labour planning or for sales and revenue management purposes, whereas long-term forecasts were normally

used for budgeting, capacity building or long-term planning. Some examples are presented below:

- ‘Our number one cost of doing business is labour…Thus, forecasting becomes very important, because that’s how you can judge whether you have sufficient labour, or you don’t have sufficient labour and what is sufficient labour to provide the quality and standard of service you are looking for…As a matter of fact, we do forecasting consistently and regularly throughout the year. I can tell you that we are probably doing a major forecast for the development and budget’. (Respondent 1)
- ‘What we use that forecast for is for revenue management purposes’. (Respondent 3)

The respondents indicated that forecasts were conducted frequently. For instance, Respondent 3 stated, ‘*Every day [I] forecast 560 days in advance, in the future per market segment, per length of stay*’. Other companies updated their forecasts every month or every quarter.

It is worth mentioning that Respondent 3 also pointed out that in his/her company, ‘forecast’ meant short-term predictions for revenue management purposes and ‘analysis’, not ‘forecast’, was used for long-term predictions. This discrepancy in terminology between industry practitioners and academics may cause misunderstandings.

The respondents noted that their forecasting process was very complicated. The data analysis suggested that the complexity was in their data collection processes. In addition to collecting information about the historical demand for their services, the

respondents tried to collect every piece of market information, both formally and informally. They purchased various industry reports when their budgets allowed and developed networks with counterparts in other companies to collect information in a casual way. The findings about the information collection process are reported in detail in the Information Sharing section. When asked about their forecasting methods, many of the respondents stated that statistical demand forecasting methods were too complicated.

- 'I wish I could tell you we are half as sophisticated as you are. I am not. We are not anywhere as sophisticated as what you have done…The forecasting that we do here is probably not that similar. It's probably not much different from what you do, except that I don't have much access to the data and perhaps you do…A lot of what we do in forecasting is really through experience'. (Respondent 1)
- 'We don't apply any models. We generate forecasts based on experience and judgments'. (Respondent 2)
- 'We use a revenue management system that helps create a forecast for our hotels…The revenue management system takes into account our own forecast based on history and the competitors' pricing'. (Respondent 3)
- 'We use the system PROS (pricing and revenue optimisation solutions) and seek opinions from analysts'. (Respondent 4)
- 'We don't have very systematic forecasting models…Forecasting or the marking projection is not very systematic'. (Respondent 5)
- 'In the annual plan, we have basic forecasts of our future demand in the next year…Each sector (i.e., business unit) will make their own forecasts for their

market demand next year. That will be our so-called forecasting system…Generating forecasts is based more on experience'. (Respondent 6)

- 'We do judgmental forecasting. We use judgments, experience'. (Respondent 7)
- 'We will retrieve from the (reservation) system what bookings are on book and we will also evaluate how it looks compared to last year…Then, we base on that to retrieve reports that we need in order to make the forecast [manually]…Industry people are not academic people. Academic people try to have so many different things. To us, we only want to look at the summary'. (Respondent 8)
- 'Mostly we use human judgment. Don't like scientific stuff'. (Respondent 9)
- 'Our company has our own data collection website that we can keep for tracking data, like which countries book Hong Kong hotels…Because we keep all the data, that's why we can compare every year…I don't know whether I can use the word "forecast" because our system can capture…For example, today people are booking 2013 (i.e., 1 year after this interview) check ins and our database is already capturing this. For example, for the Dutch people, they like to book hotels half a year before they come to Hong Kong, but for mainland Chinese, maybe they book 1 week or 3 days before they come to Hong Kong. So we capture all these data'. (Respondent 10)

Interestingly, the forecasting process discussed by Respondent 10, who worked for an online travel portal, was distinct. Due to its proximity to the source markets, the company used first-hand information about the actual future tourism demand. Therefore, the respondent was not sure whether the process should be called a forecast.

The preceding comments reveal that none of the respondents were interested in statistical forecasting methods. In their forecasting process, they relied on either human judgment or some kind of specialised system with a forecasting module. This implies that practitioners either make pure judgmental forecasts without any support from forecasting methods or seek support from a statistical forecasting method that is embedded in a specialised computer system.

These findings support our hypothesis that TSC practitioners have little interest in scholarly journals or studies. Thus, they have little or no knowledge of advanced tourism demand forecasting methods. As implied by the respondents, they are not researchers and therefore do not have the competence to make use of such sophisticated methods. Due to these limitations, TSC practitioners cannot incorporate scholarly insights into their forecasting processes. Accordingly, they do not see the value of tourism demand forecasting methods. Thus, there exists an extensive gap between industry practices and academic studies.

Tourism Supply Chain Practitioners' Perceptions of Forecasting Support Systems

Although all of the respondents agreed that forecasting was very important, there was less agreement about FSSs. Half of the respondents indicated that they would not invest in or use an FSS to help generate forecasts. Some of their comments are presented below:

- 'Our forecasting is done with a piece of paper and pencil'. (Respondent 1)
- 'Honestly, I do not look at any forecasting system'. (Respondent 5)

- ‘We have our own forecasting method right now. We don’t see any necessity in having extra resources or budget put into a new system, except that it can add value to the existing system or help generate new income in the market’. (Respondent 6)
- ‘Basically no, no forecasting system…no plan to buy any FSS’. (Respondent 7)
- ‘Mostly we use human judgment’. (Respondent 9)

It is worth noting that the respondents’ answers were consistent with their forecasting processes. They indicated that they did not use systematic forecasting methods, but that they preferred using their experience or judgment. Thus, using an FSS was not deemed necessary. The respondents who used an FSS stressed that human intervention was imperative.

- ‘Many times human intervention is needed, because we can know things that the system can never know’. (Respondent 3)
- ‘The accuracy of the forecasts depends on the people who use the system, not on the system itself. Analysts are more important than the system’. (Respondent 4)
- ‘Forecasts will be manually adjusted’. (Respondent 8)
- ‘If you see our record then you will know every year from September to December, the demand is always high. Then you will expect next year to be the same…But of course we always need to compare, because our own data can only capture the business that comes via our system. So, currently, we only have Hong Kong Tourism Board (forecasting) data to compare…We will always see what will happen in the market…We have also registered with a lot of travel e-magazines’. (Respondent 10)

When we asked further questions about the factors that affected their decision to purchase an FSS, the respondents mentioned five major factors. These are presented in Table 2, which also provides the frequency of the factors and illustrative quotes.

[Table 2 near here]

Due to their varying situations, only five respondents provided answers about the desired attributes of an FSS. Functionality was the most important attribute for TSC practitioners, but ease of use, user friendliness and cost were also major considerations. Interestingly, although two respondents pointed out that accuracy was important, Respondent 5 mentioned that accuracy was not important to them, as '*Nobody is going to use the forecasts from the system for business*'.

Respondents 2, 3 and 4 explained that their company used the revenue management system to do statistical forecasting and that there was no pure FSS. Respondent 2 added, '*In the hotel industry, we don't have a forecasting system*'. In addition, Respondent 8 said that his/her company had a specialised system that generated forecasts and budget plans together like a financial system. This system was connected to the company's reservation system. Finally, Respondent 10 showed an in-house designed system that helped with the analysis of historical booking data. This was not an FSS, as it had no forecasting function.

On the basis of these findings, it can be concluded that TSC practitioners do not consider FSSs or pure FSSs to be very important or necessary. They do not see the value of an FSS and are reluctant to invest in one. Similar to their views on tourism demand forecasting methods, they think FSSs are academic and 'scientific stuff' that

they cannot understand. Although hotel chains and airlines are more likely to use certain specialised computerised systems (i.e., DSSs) to support their decisions or forecasting, these systems are not solely used for forecasting and do not use advanced forecasting methods.

It is important to note that all of the respondents, with or without FSSs, mentioned the importance of human judgment in forecasting processes. This is consistent with the tourism industry often facing higher demand uncertainty. As indicated by Özen, Sošić and Slikker (2012), high forecast errors are common in some service industries (e.g., telecommunications and electronics) where customers can place orders well in advance and it is hard to predict how many orders will materialise. This is especially true for the tourism industry. Therefore, a knowledge of past demand patterns, recent market information and future events that will affect tourism demands and have a strong influence on tourism demand forecast accuracy is important. Managers may possess and make use of so-called 'tacit knowledge', which is often situational, highly personal and difficult to communicate (Wang, 2006). To incorporate this important knowledge into the forecasting process, FSSs must include appropriate interfaces that allow human-machine interaction.

Information Sharing Practices

As mentioned in the Research Methodology section, the respondents were shown the conceptual TSC framework depicted in Figure 1 during the interviews. They were then asked to comment on the following statement: 'Sharing of information in a TSC can improve the forecasting accuracy of TSC members'. All of the respondents agreed that

information sharing was important. Some of their comments are presented below:

- ‘I rely very much on what I hear from hotels, airlines, restaurants, tour operators and travel agents’. (Respondent 1)
- ‘This has to be a synchronised process based on experience, market situations and actual booking of the hotel…Exchange of information is quite important’. (Respondent 2)
- ‘We encourage our revenue managers to seek a network with other revenue managers or sales and marketing professionals in the hotel industry in Hong Kong…We are subscribing to all these third-party reports…Many times, human intervention is needed, because we can know things that the system can never know’. (Respondent 3)
- ‘More information is always useful. Currently our information comes from the sales team and they will get the information from travel agents’. (Respondent 4)
- ‘Our forecasting process starts with our budget. When I do the budget, I will start talking with my customers, with this information (from customers) and the economic data, exchange rate change, I will decide my budget…We use talks to collect information. By casual conversation, you try to extract the information you want’. (Respondent 5)
- ‘We will try to gather as much information as possible from different sources, like from airlines, from hotels, from HKTB, our own records and the performance of the market the year before, to make the forecasts’. (Respondent 6)

- ‘We rely on travel agents for 60% of the sales. There are many inbound travel agents in Hong Kong…We collect information from all sorts of channels’. (Respondent 7)
- ‘Basically, all suppliers should have a platform that allows us to work together to help boost the tourism industry…From time to time, when we hear from (Hong Kong) tourism broad’s presentation, we have some past information on where the tourists came from, their age groups and all that. One day, if there is a more proactive way to look in advance at who are these people coming in and what can be done before their arrival (it will be good)’. (Respondent 8)
- ‘We have been using multiple sources to gauge against the real forecast…We use at least four to five sources to reconcile what we actually believe…We have tried to purchase the data in terms of airline demand…but a lot of mainland Chinese guests do not fly to Hong Kong. So airline data does not tell the whole picture of arrival’. (Respondent 9)
- ‘What we do from time to time is check with the Tourism Board’s report to see what they are doing…We always see what will happen in the market…We have also registered with a lot of travel e-magazines…We really need to read a lot of this kind of newspaper and e-magazine and then we will know what is coming’. (Respondent 10)

These findings support our hypothesis that shared information in a TSC is an essential element of practitioners’ forecasts. We make two major observations. First, TSC practitioners collect all sorts of information to generate forecasts. The information comes from both competitors (e.g., a hotel collects information from a competing hotel) and non-competitors (e.g., a hotel collects information from a non-competing hotel or a

travel agent). Second, information sharing is frequent and happens formally and informally. Often, information sharing happens without complex contracts or reputation-building mechanisms. Instead, informal, costless, nonbinding and non-verifiable communication (or cheap talk) is prevalent. Although some of the respondents admitted that the information collected in this way was not always credible, it seemed that they did not have a better platform for information sharing.

Discussions and Collaborative Tourism Supply Chain Forecasting Framework

We unify the research findings and the features of collaborative TSC forecasting in a framework, as depicted in Figure 3. The following subsections discuss the main components of the framework.

[Figure 3 near here]

Statistical Forecasting

It is desirable to integrate the advantages of tourism demand forecasting methods into the implementation of collaborative TSC forecasting. Tourism demand forecasting studies have used quantitative and qualitative approaches. Most of the quantitative or statistical studies have used one of two major forecasting methods: time series and econometrics. Time-series forecasts project patterns identified in recent time-series observations. Such forecasts can be used to support decisions about investment, human resource planning and infrastructure and capacity planning. Econometrics methods use explanatory variables to predict the future. Established forecasting models also support

a company's pricing and/or marketing decision making. Although econometric methods can provide more meaningful support for decision making, they require intensive historical data resources and data analysis abilities. Due to the high variance in tourism demand forecasting requirements, time-series methods are more suitable for the forecasting process in the tourism field. They are also more flexible and easier to use in various situations.

Judgmental Forecasting and Forecast Combination

The interview results indicate that TSC practitioners, especially small enterprises, sometimes rely on pure judgment to generate forecasts. Such direct judgmental forecasting methods, in contrast with the statistical forecasting methods mentioned previously, are non-scientific methods for eliciting predictions of future demands. The popularity of this approach in TSCs can be explained by its convenience and low requirements in terms of statistical skills. However, evidence shows that direct judgments can be inefficient, biased and inconsistent (Song, Gao, & Lin, 2013). They are only recommended when historical data are unavailable or in particularly dynamic environments. Therefore, a combination of statistical methods and judgmental adjustments is more appropriate. This is also supported by the interviews. The TSC practitioners widely supported the use of judgmental forecast adjustments, based on their belief that forecast accuracy was likely to increase with forecasters' interventions.

In terms of forecasting accuracy, no single method can consistently outperform others in all situations (Song & Li, 2008). It is generally accepted that forecast combinations can help improve forecasting accuracy (Wu, Song, & Shen, 2017). Combinations refer to joining individual forecasts by imposing either simple or

weighted averages, according to the historical performance of the individual methods. The features of judgmental forecasting and forecast combinations make these approaches more practical and objective and improve forecasting accuracy.

Forecasting with Big Data

Tourism is a data-rich industry. For example, travellers generate various information on open sources, such as TripAdvisor and social networks (e.g., Facebook and Twitter). Such information affects other travellers' decision-making processes. However, TSC practitioners save a wealth of information about their clients to better forecast demands and discover new opportunities. In fact, some tourism practitioners have already turned to big data to improve decision-making performance (Irudeen & Samaraweera, 2013). For example, IHG and Hyatt have started using big data to better predict their occupancy levels and room rates. The use of big data in tourism forecasting has only recently gained academic attention. For example, Pantano *et al*. (2017) investigate the extent to which open data analyses can predict tourists' responses to a certain destination and Song and Liu (2017) propose a framework for tourism forecasting with big data.

Big data brings an opportunity to nowcast tourism demands. Compared to traditional forecasting input data, many big data sources are free of charge and in real time, allowing forecasters to generate short-term nowcast betimes. Nowcasting refers to the use of real-time data to make short-term forecasts and produce predictions before official data are available (Song & Liu, 2017). This allows for the high-frequency (e.g., daily) forecasting of tourism demands. TSC practitioners normally conduct both long-term and short-term forecasting, as indicated by the research findings. Adding big data

forecasting into the framework can better fulfil the needs of short-term forecasting and therefore create higher value for TSC practitioners.

Tourism Demand Forecasts and Nowcasts

As mentioned above, TSC practitioners value both long-term and short-term forecasts. Therefore, in collaborative TSC forecasting, tourism demand forecasts should be categorised as long-term forecasts and short-term nowcasts. Long-term forecasts can be generated regularly using advanced forecasting methods and vast historical data. Short-term nowcasts are more based on the current and ad-hoc situations in the tourism industry. For both categories, there can be two levels: a total demand level and an individual demand level.

Total tourism demand forecasts are predictions for an entire destination. Such forecasts are important for all TSC practitioners. From a long-term perspective, tourism investment decisions, especially investment in destination infrastructures and tourism resorts, which require long-term financial commitment, are highly dependent on demand forecasts. The sunk costs can be very high if the investment projects fail to generate demand to match their design capacities. From the short-term perspective, if the number of tourists visiting a particular destination in a given period is predicted to increase, more labour can be hired, more tours/flights/itineraries can be arranged and more facilities/capacity can be added.

Individual demand forecasts are predictions for TSC practitioners regarding their own businesses. TSC practitioners normally save a large amount of enterprise-specific data about their operations and clients. This can be used to generate predictions of future demands and identify opportunities. However, TSC practitioners have little or

no knowledge of advanced demand forecasting approaches and cannot incorporate them into their forecasting processes. Therefore, the collaborative TSC forecasting system needs to provide the support of forecasting methods to individual TSC practitioners.

Databases

Databases are indispensable for any FSS. They provide and store data for the system. The data sources of the collaborative TSC forecasting system are more complex than those of a traditional FSS. In addition to providing data for statistical and judgmental forecasting, TSC practitioners' enterprise-specific information, experience and tacit knowledge must be stored for collaborative forecasting.

In terms of big data forecasting, an increasing amount of online open data sources are available to forecasters. One type of data source is search engine query data, such as Google and Baidu. For example, Yang *et al*. (2015) use Baidu and Google search trend data to predict Chinese tourist flows. Travellers tend to use online communities, such as TripAdvisor, Facebook and Twitter, to obtain and share information. For instance, Pantano *et al*. (2017) predict tourists' responses to a tourist attraction using TripAdvisor data.

Information Sharing

Information sharing is essential for supply chain collaboration. According to the interview respondents, shared information is an essential ingredient in their forecasts. However, information sharing initiatives are based primarily on nonbinding and costless communication (i.e., cheap talk). There is no formal platform for information

sharing. To enable credible information sharing in a long-term TSC collaboration, an information sharing approach outlining information types, update frequency and information sharing methods should be designed.

Information about a wide range of activities can be shared along supply chains. In particular, forecasts developed by various practitioners in the supply chain are an important area of information sharing, as forecast information affects practitioners' fundamental decisions (Özer, Yanchong, & Kay-Yut, 2011). The interview respondents said that they frequently updated their demand forecasts with market signals or observations to achieve more accurate demand forecasts. Due to their proximity to the market, principals (tour operators) and distributors (travel agents and travel portals) can acquire more accurate demand forecasts. TSC suppliers, such as hoteliers, depend on such information from travel agents. Therefore, it is highly likely that sharing forecast information with other members can improve the forecasting accuracy of all TSC practitioners. Information about marketing plans, such as sales promotions and market trends, can also help collaborative partners in a TSC work jointly on business development.

How is information shared between TSC practitioners? Advances in information technology have significantly affected the development of the tourism industry (Buhalis & Laws, 2008). Technological advances, such as electronic data interchange, databases, data warehouses, data mining techniques and the Internet, facilitate the exchange of information between TSC members. Timely, accurate and relevant information sharing, on both routine and non-routine bases, is a key component of effective collaborative forecasting. For instance, regular online surveys

can be a routine component of information sharing. Online forums, posts and blogs can be used as platforms for non-routine information sharing.

The interview respondents mentioned that they would not share information if they felt that the risk of sharing was noticeably high. Some of the respondents also worried that sharing real information would affect their competitiveness. Others pointed out that they were not allowed to share information because their companies were publicly listed. These concerns can be addressed by aggregating information. For example, information collected by online surveys may be shared in aggregate, such that the identities of individual respondents would not be released. On online information sharing platforms, participants' identities would not be shown to each other. The system would only provide relevant business information about the participants (e.g., they work for a 5-star hotel). However, a credibility rating system could be used to ensure the quality of the shared information.

Forecasters

Collaborative TSC forecasting would not happen without the active participation of various forecasters. In line with the definition of a TSC, there are three types of TSC forecasters, namely TSC practitioners, forecasting academics and the government (or the Destination Management Organization [DMO]). Each forecaster is expected to bring special experience and background information and to stay focused on the collaborative forecasting task. TSC practitioners possess different types of information that enhance forecast accuracy, such as price change, inventory and promotional plan information. Forecasting academics contribute to the forecasting process by suggesting

advanced forecasting approaches. The government or DMO can bring historical and current tourism demand data and future promotional plans into the forecasting efforts.

To control and propel the forecasting process, forecasting administrators are required. Administrators register new users and maintain user details for collaborative forecasting. They also collect and distribute needed information during the forecasting process and are responsible for the daily operations and maintenance of the FSS.

Implementation of the Collaborative Tourism Supply Chain Forecasting Framework

Forecasting Process

For total tourism demand, the specific forecasting outputs include different tourism demand measures by major source markets. For example, according to statistics published by the Hong Kong Tourism Board, the major source markets of the Hong Kong tourism industry include mainland China, Taiwan, Japan, the US, Korea and Australia. Tourist arrivals, receipts and hotel room nights are typically used to measure tourism demand. Tourist arrivals in Hong Kong can in turn be categorised by transportation mode, such as air, land and water. Similarly, hotel rooms in Hong Kong can be divided into High Tariff A, High Tariff B and Medium Tariff.

Total tourism demand forecasts can be created and updated on a regular basis. The workflow in each round is as follows:

1. The basic forecasts are generated by system administrators using statistical forecasting and big data forecasting approaches and are shared with TSC practitioners and the government.

2. When sharing basic forecasts, system administrators seek input from TSC practitioners and the government through surveys in the FSS or on online forums.
3. Administrators combine basic and judgmental forecasts and develop the final forecasting results. A forecasting report summarising inputs from various forecasters should anonymously be shared with the members.
4. System administrators generate short-term forecasts by occasionally combining long-term forecasts and real-time big data analytics.

At the individual demand level, eligible TSC practitioners can access and use the forecasting methods embedded in the FSS to generate their own or individual forecasts. This is valuable to and serves as an incentive for practitioners who do not use an FSS to support their forecasting process. As TSC practitioners think human judgments are important, they can use a judgmental adjustment tool to adjust the statistical forecasts generated by the forecasting module according to their own information and tacit knowledge.

System Design

The insights provided by the respondents suggest that a tourism demand FSS should be easy to use and flexible enough to serve different purposes. The cost of the FSS is also a major concern. One way to solve the cost concern is to make the forecasting component of the tourism demand FSS free for registered or qualified users. The FSS design features that are important to industry practitioners are summarised below:

- Functionality: Customise the functions according to the needs of different TSC practitioners and offer a flexible range of appropriate facilities and methods.

- Ease of use: Implement advanced forecasting methods into the system so that users do not have to understand the underlying methods.
- User friendliness: Include different adjustment tools in the system so that users can make adjustments easily.
- Cost: Instead of monetary payment, make access to the system dependent on users agreeing to share information.
- Accuracy: Tourism demand forecasts should be generated by combining statistical forecasts with all of the information input by system users. Better quality real-time information sharing should result in higher forecasting accuracy.

The FSS should also be accessible and should facilitate the transfer of information and knowledge between TSC practitioners. As the Internet has become the most cost-effective communication platform, the FSS should be an Internet-based application. A Web language should be used to develop the system and the interfaces between system users and the external software.

Conclusions and Implications

The past several decades have witnessed great advances in our understanding of tourism demand forecasting. Studies have expanded the research focus and depth of theoretical foundation and have made advances in forecasting methods. However, tourism practitioners typically generate forecasts based on their own experiences and judgments and have not benefitted from research on tourism demand forecasting. A carefully designed tourism demand FSS can reduce this gap. The nature of tourism

products calls for TSC collaboration. One breakthrough point may be collaborative tourism demand forecasting. We aim to implement a tourism demand FSS to facilitate collaborative TSC forecasting in Hong Kong.

To achieve this aim, we use in-depth interviews to explore TSC practitioners' current forecasting practices, views on using FSSs and information sharing practices. Our findings indicate that tourism practitioners frequently conduct both short- and long-term forecasting. Forecasts are important for their business decisions and strategy development, but their forecasting processes do not use modern forecasting methods or FSSs. They have little or no knowledge of advanced forecasting methods. Due to their limited exposure to FSSs, they do not see the value of such systems and are reluctant to invest in them. However, practitioners strongly rely on judgmental forecasts and information collected from TSC members through informal communication (i.e., cheap talk). The credibility of such information is sometimes very low.

Based on these findings, we develop a systematic framework for implementing collaborative TSC forecasting. The framework is composed of three connecting features: tourism demand forecasting methods, TSC information sharing and an FSS. We identify techniques and methods of forecasting, content and approaches to information sharing, design considerations and the modular structure of the FSS. The proposed framework combines advanced tourism demand forecasting methods with practitioners' knowledge and regularly updated information. More importantly, it can be developed as part of a smart infrastructure to incubate broader industry collaboration. Although Hong Kong is the focus of this study, the proposed framework can be generalised to other destinations. We hope that this framework will encourage further

research on best-in-class TSC collaboration. Ultimately, this would lead to higher performance and competitiveness in the tourism industry.

References

Armstrong, J. S. 2001. *Principles of Forecasting: A Handbook for Researchers and Practitioners*. Boston: Kluwer Academic Publishers.

Baba, N., Kozaki, M. 1992. *An intelligent forecasting system of stock price using neural networks*. Proceedings of the International Joint Conference on Neural Networks (IJCNN'92, pp. 371–377).

Bailey, K. D. 1994. *Methods of Social Research* (4th ed.). New York: Macmillan.

Barratt, M. 2004. Understanding the meaning of collaboration in the supply chain. *Supply Chain Management: An International Journal* ***9***(1): 30–42.

Barratt, M., Oliveira, A. 2001. Exploring the experiences of collaborative planning initiatives. *International Journal of Physical Distribution & Logistics Management* ***31***(4): 266–289.

Beyer, M. A., Laney, D. 2012. *The Importance of 'Big Data': A Definition*. Stamford, CT: Gartner.

Björk, P., Virtanen, H. 2005. What tourism project managers need to know about co-operation facilitators. *Scandinavian Journal of Hospitality and Tourism* ***5***(3): 212–230.

Blal, I., Sturman, M. C. 2014. The differential effects of the quality and quantity of online reviews on hotel room sales. *Cornell Hospitality Quarterly* ***55***(4): 365–375.

Boyce, C., Neale, P. 2006. *Conducting in-depth interviews: A guide for designing and conducting in-depth interviews for evaluation input*. Retrieved on 7 June 2012 from http://www2.pathfinder.org/site/DocServer/m_e_tool_series_indepth_interviews.pdf.

Buhalis, D., Law, R. 2008. Progress in information technology and tourism management: 20 years on and 10 years after the Internet – the state of eTourism research. *Tourism Management* ***29***(4): 609–623.Buhalis, D., Laws, E. 2001. *Tourism Distribution Channels: Practices, Issues and Transformations*. London: Continuum International Publishing Group.

Census and Statistics Department. 2015. Retrieved on 6 June 2015 from http://www.censtatd.gov.hk.

Charytoniuk, W., Chen, M.-S. 2000. Very short-term load forecasting using artificial neural networks. *IEEE Transactions on Power Systems* ***15***(1): 263–268.

Cortez, P., Machado, J., Neves, J. 1996. *An evolutionary artificial neural network time series forecasting system*. Proceedings of the International Conference on Artificial Intelligence, Expert Systems AND Neural Networks (IASTED'96, pp. 278–281), Honolulu, Hawaii.

Croce, V., Wöber, K. W. 2011. Judgemental forecasting support systems in tourism. *Tourism Economics* ***17***(4): 709–724.

Datta, P. P., Christopher, M. G. 2011. Information sharing and coordination mechanisms for managing uncertainty in supply chains: A simulation study. *International Journal of Production Research* ***49***(3): 765–803.

Dong, S., Zhang, Z., Xi, B. 2010. Study on mechanisms of collaborative demand forecast in supply chain. *Operations Research and Management Science* ***19***(5): 66–70.

Fildes, R., Goodwin, P., Lawrence, M. 2006. The design features of forecasting support systems and their effectiveness. *Decision Support Systems* ***42***: 351–361.

Fosnaught, K. 1999. The strategic power of consensus forecasting: Setting your organization up to win. *Journal of Business Forecasting Methods & Systems* ***18***(3): 3–7.

Frechtling, D. C. 2001. *Forecasting Tourism Demand: Methods and Strategies*. Oxford: Butterworth-Heinemann.

Goodwin, P., Fildes, R., Lawrence, M., Nikolopoulos, K. 2007. The process of using a forecasting support system. *International Journal of Forecasting* ***23***: 391–404.

Guo, Q., Shi, Y., Dong, J., Guo, X., Anderson, C. K. 2014. Pricing competition and channel coordination in the tourism supply chain with optional tours. *Tourism Economics* ***20***(5): 939–960.

Helms, M. M., Ettkin, L. P., Chapman, S. 2000. Supply chain forecasting — collaborative forecasting supports supply chain management. *Business Process Management Journal* ***6***(5): 392–407.

Hiemstra, Y. 1994. *A stock market forecasting support system based on fuzzy logic*. Proceedings of the 27th Annual Hawaii International Conference on System Sciences (pp. 281–288).

Houlihan, J. B. 1985. International supply chain management. *International Journal of Physical Distribution & Materials Management* ***15***: 22–38.

Huang, G. Q., Haiyan, S., Xinyan, Z. 2010. A comparative analysis of quantity and price competitions in tourism supply chain networks for package holidays. *Service Industries Journal* ***30***(10): 1593–1606.

Hung, W.-H., Lin, C.-P., Ho, C.-F. 2014. Sharing information in a high uncertainty environment: Lessons from the divergent differentiation supply chain. *International Journal of Logistics Research and Applications: A Leading Journal of Supply Chain Management* ***17***(1): 46–63.

Irudeen, R., Samaraweera, S. 2013. *Big data solution for Sri Lankan development: A case study from travel and tourism*. Paper presented at the 2013 International Conference on Advances in ICT for Emerging Regions, ICTer 2, Colombo.

Jena, S. K., Jog, D. 2016. Price competition in a tourism supply chain. *Tourism Economics* (Forthcoming).

Kallos, G., Kotroni, V., Lagouvardos, K. 1997. *The regional weather forecasting system SKIRON: An overview*. Proceedings of the Symposium on Regional Weather Prediction on Parallel Computer Environments (pp. 109–122), University of Athens, Greece.

Kouwen, N. 2000. *WATFLOOD/SPL9: Hydrological Model & Flood Forecasting System*. Retrieved on 8 July 2010 from http://www.watflood.ca/.

Kuo, R. J. 2001. A sales forecasting system based on fuzzy neural network with initial weights generated by genetic algorithm. *European Journal of Operational Research* ***129***: 496–517.

Küsters, U., Bell, M. 1999. *The Forecasting Report: A Comparative Survey of Commercial Forecasting Systems*. Höhenkirchen, Germany: It-Research.

Küsters, U., McCullough, B. D., Bell, M. 2006. Forecasting software: Past, present and future. *International Journal of Forecasting* ***22***: 599–615.

Lee, H. K., Fernando, Y. 2015. The antecedents and outcomes of the medical tourism supply chain. *Tourism Management* ***46***: 148–157.

Lee, H. L., Padmanabhan, V., Whang, S., 1997. The bullwhip effect in supply chains. *Sloan Management Review* ***38***(3): 93–102.

Li, G., Song, H., Cao, Z., Wu, D. C. 2013. How competitive is Hong Kong against its competitors? An econometric study. *Tourism Management* ***36***: 247–256.

Li, G., Song, H., Witt, S. F. 2005. Recent developments in econometric modeling and forecasting. *Journal of Travel Research* ***44***(2): 82–99.

Li, X., Pan, B., Law, R., Huang, X. 2017. Forecasting tourism demand with composite search index. *Tourism Management* ***59***: 57–66.

Li, X.-Y., Chau, K. W., Cheng, C.-T., Li, Y. S. 2006. A Web-based flood forecasting system for Shuangpai region. *Advances in Engineering Software* ***37***: 146–158.

Mentzer, J., Kahn, K. B. 1997. State of sales forecasting systems in corporate America. *Journal of Business Forecasting* ***16***: 6–13.

Mukhopadhyay, S. K., Zhu, X., Yue, X. 2008. Optimal contract design for mixed channels under information asymmetry. *Production and Operations Management* ***17***(6): 641–650.

Nelson, R. R., Winter Jr., S. G. 1964. A case study in the economics of information and coordination: The weather forecasting system. *The Quarterly Journal of Economics* ***78***(2): 420–441.

Nikolopoulos, K., Assimakopoulos, V. 2003. Theta intelligent forecasting information system. *Industrial Management & Data Systems* ***103***(8/9): 711–726.

Özen, U., Sošić, G., Slikker, M. 2012. A collaborative decentralized distribution system with demand forecast updates. *European Journal of Operational Research* ***216***(3): 573–583.

Özer, Ö., Yanchong, Z., Kay-Yut, C. 2011. Trust in forecast information sharing. *Management Science* ***57***(6): 1111–1137.

Page, S. J. 2003. *Tourism Management: Managing for Change*. Oxford: Butterworth-Heinemann.

Pantano, E., Priporas, C.-V., Stylos, N. 2017. 'You will like it!' using open data to predict tourists' response to a tourist attraction. *Tourism Management* ***60***: 430–438.

Patelis, A., Petropoulos, C., Nikolopoulos, K., Lin, B., Assimakopoulos, V. 2005. Tourism planning decision support within an e-government framework. *Electronic Government: An International Journal* ***2***(2): 134–143.

Petropoulos, C., Patelis, A., Metaxiotis, K., Nikolopoulos, K., Assimakopoulos, V. 2003. SFTIS: A decision support system for tourism demand analysis and forecasting. *Journal of Computer Information Systems* ***44***(1): 21–32.

Piboonrungroj, P., Disney, S. M. 2009. *Tourism supply chains: A conceptual framework*. Proceedings of the Ph.D. Network Conference (pp. 132–149), Nottingham, UK.

Ramanathan, U. 2012. Supply chain collaboration for improved forecast accuracy of promotional sales. *International Journal of Operations & Production Management* ***32***(6): 676–695.

Ren, Z., Cohen, M., Ho, T., Terwiesch, C. 2010. Information sharing in a long-term supply chain relationship: The role of customer review strategy. *Operations Research* ***58***(1): 81–93.

Sinclair, M. T., Stabler, M. 1997. *The Economics of Tourism*. London: Routledge.

Småros, J. 2003. Collaborative forecasting: A selection of practical approaches. *International Journal of Logistics: Research and Applications* ***6***(4): 245–258.

Småros, J. 2007. Forecasting collaboration in the European grocery sector: Observations from a case study. *Journal of Operations Management* ***25***(3): 702–716.

Song, H., Li, G. 2008. Tourism demand modelling and forecasting – A review of recent research. *Tourism Management* ***29***(2): 203–220.

Song, H., Liu, H. 2017. Predicting tourism demand using big data. In Z. Xiang & D. R. Fesenmaier (Eds.), *Analytics in Smart Tourism Design*, *Tourism on the Verge*. Switzerland: Springer.

Song, H., Witt, S. F., Zhang, X. 2008. Developing a Web-based tourism demand forecasting system. *Tourism Economics* ***14***(3): 445–468.

Stainback, S., Stainback, W. 1988. *Understanding and Conducting Qualitative Research*. Dubuque, IA: Kendall/Hunt.

Stern, H. 2002. *A knowledge-based system to generate Internet weather forecasts*. Proceedings of the 18th Conference on Interactive Information and Processing Systems, Orlando, Florida, USA.

Thomassey, S., Fiordaliso, A. 2006. A hybrid sales forecasting system based on clustering and decision trees. *Decision Support Systems* ***42***: 408–421.

UNWTO. 1975. *Distribution Channels*. Madrid, Spain: World Tourism Organization.

UNWTO. 1994. *Global Distribution Systems in the Tourism Industry*. Madrid, Spain: World Tourism Organization.

VICS. 1998. *Collaborative planning, forecasting and replenishment (CPFR)*. Retrieved on 7 June 2012 from www.cpfr.org.

Vilcahuamán, R., Meléndez, J., de la Rosa, J. L. 2002. FUTURA: Hybrid system for electric load forecasting by using case-based reasoning and expert system. In M. T. Escrig, F. Toledo, & E. Golobardes (Eds.), *Topics in Artificial Intelligence*, *Series of Lecture Notes in Computer Science*. Berlin: Springer.

Wang, F. K. 2006. Applying case-based reasoning in knowledge management to support organizational performance. *Performance Improvement Quarterly* ***19***(2): 173–188.

Wilson, N. 2001. Game plan for a successful collaborative forecasting process. *The Journal of Business Forecasting Methods & Systems* ***20***(1): 3–6.

Witt, S. F., Witt, C. A. 1995. Forecasting tourism demand: A review of empirical research. *International Journal of Forecasting* ***11***(3): 447–475.

Wu, D. C., Song, H., Shen, S. 2017. New developments in tourism and hotel demand modelling and forecasting. *International Journal of Contemporary Hospitality Management* ***29***(1): 507–529.

Yang, X., Pan, B., Evans, J. A., Lv, B. 2015. Forecasting Chinese tourist volume with search engine data. *Tourism Management* ***46***: 386–397.

Yeoman, I. 2008. *Tomorrow's Tourist: Scenarios & Trends*. Oxford: Elsevier Science.

Zhang, X., Song, H., Huang, G. Q. 2009. Tourism supply chain management: A new research agenda. *Tourism Management* ***30***: 345–358.

Zhang, X., Song, H., Huang, G. Q., Chen, W. 2010. A game-theoretic approach to tourism supply chain coordination under demand uncertainty for package holidays. *Tourism Analysis* ***15***(3): 287–298.

Zhu, X., Mukhopadhyay, S. K., Yue, X. 2011. Role of forecast effort on supply chain profitability under various information sharing scenarios. *International Journal of Production Economics* ***129***(2): 284–291.

Table 1. Interviewee Profiles

Respondent Number	Job Title	Sector
1	Executive Director, Sales and Marketing	Attractions
2	General Manager	Hotel Chains
3	Director of Corporate Revenue Management	Hotel Chains
4	Manager Revenue Management Systems	Airlines
5	Vice President	Travel Services
6	Director & General Manager	Travel Services
7	General Manager	Hotel Chains
8	Sales & Marketing Manager	Catering Services
9	Manager, Forecasting & Planning	Attractions
10	Regional Director, Product Development	Travel Services

Table 2. Forecasting Support System Requirements

Attribute	**Frequency**	**Illustrative Quotes**
Functionality	3	Whether the functions fit our needs. The system should be flexible enough to generate different reports. When there is too much data, the system can help manage it.
Ease of use	2	It should be something that doesn't require something that only PhD's can understand.
User friendliness	2	Most important to users, I think, is user friendliness.
Cost	2	Cost is a major consideration.
Accuracy	2	Accuracy would be one on how close we can get to a number that is workable. Increasing accuracy means increasing productivity and increasing revenue.

Figure 1. Conceptual Tourism Supply Chain Framework

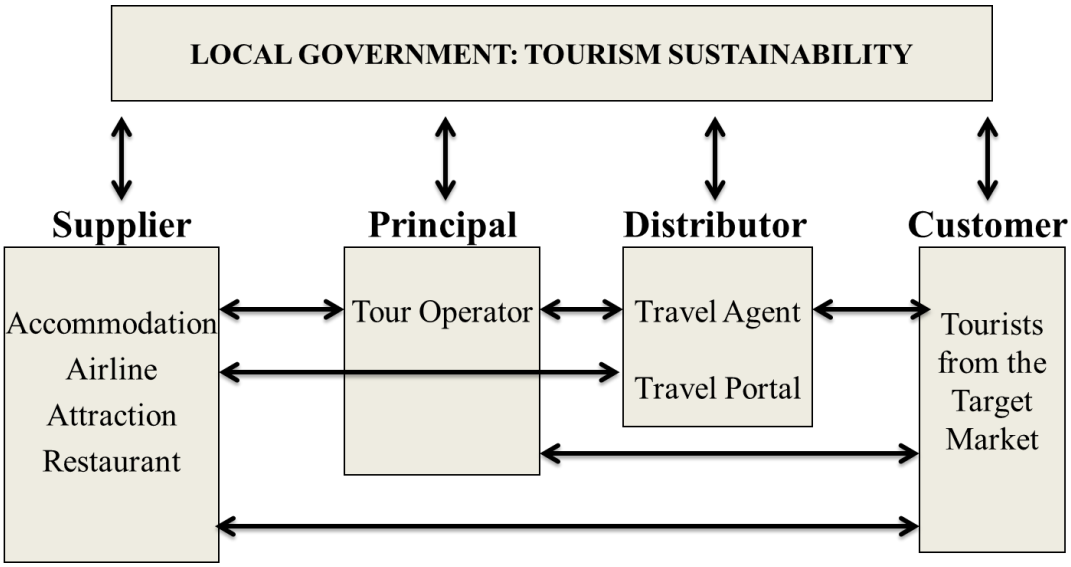

Figure 2. Features of Collaborative Tourism Supply Chain Forecasting

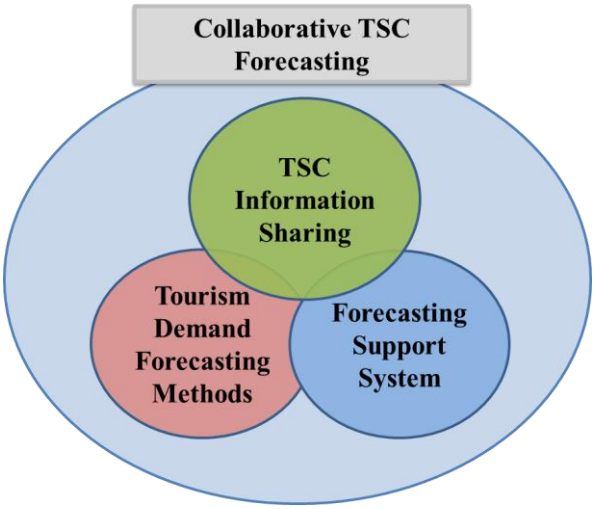

Figure 3. Collaborative Tourism Supply Chain Forecasting Framework