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Comparison of Periodic Behavior of Consumer Online Searches for Restaurants in the U.S. and China Based on Search Engine Data

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ABSTRACT Increased knowledge about the online search behavior of restaurant consumers is valuable to restaurant management and marketing professionals. However, people in different countries may demonstrate distinctive online search behaviors. There has been a lack of cross-cultural research on the online search behavior of restaurant consumers. In this paper, the periodic nature of online search behavior demonstrated by restaurant consumers from U.S. and China is analyzed and compared using Fourier transform and Parseval's theorem. The search interest records from Google and Baidu, respectively, are used. The results reveal that the online search behavior of restaurant consumers in the U.S. is strongly governed by weekly cycles but less dependent on annual cycles; however, the analogous consumer behavior in China exhibits less dependence on weekly cycles. The theoretical and practical implications of the research are discussed.

INDEX TERMS Online restaurant search, Parseval's theorem, cross-cultural study, search engine.

I. INTRODUCTION

As culture so clearly shapes consumer behavior [36], hospitality and tourism researchers have sought to identify and understand cultural differences to provide useful information to industry practitioners [39]. For example, Money and Crotts [38] indicated that consumers from different cultures tended to seek out travel and planning information from different sources; Baek *et al.* [60] (2006) reported that consumers from different cultures used distinct restaurant selection criteria. Consumers have made extensive use of search engines to seek out commercial information. This makes internet marketing very important [2], [28], [42], [43], [47], [53], [54], [57] and leads sellers and marketers to compete for higher search engine rankings and to increase their bids for internet advertisement space. An optimal marketing strategy should consider consumer search behavior [17], [29], Nica, [61] (2013). It is thus very meaningful to study and compare the patterns of online information search behavior among consumers from different countries. However, there has been a lack of research with such a focus.

In this study, the periodic nature of consumer online search behavior, as it applies to restaurant searches in the United States (U.S.) and China, is analyzed and compared. The search interest records from Google and Baidu, the most popular search engines in the U.S. and China, respectively, are used to generate the material for analysis. Parseval's theorem is used to quantify the weight of the periodic components in the whole search dynamic system obtained by discrete Fourier transform (DFT). The results indicate that periodic patterns exist in the behavior of consumer online searches for restaurants in the U.S. and in China, but consumers from the U.S. and China exhibit distinctive periodic patterns of behavior for online restaurant searches. The cyclic patterns of consumer behavior for online restaurant searches identified in the two study countries are useful to international restaurant management personnel and online marketing professionals. Following this brief introduction, the rest of the study is presented in the following order: literature review, data description, method, results, discussion, and conclusion.

II. LITERATURE REVIEW

A. IMPORTANCE OF CONSUMER ONLINE INFORMATION SEARCH BEHAVIOR FOR MARKETING

The importance of consumer search behavior for business marketing strategy has been well addressed in the literature [4], [13]. Reference [46] noted that marketers could influence consumers' purchasing decisions during the period of information acquisition. Reference [13] argued that information changed consumer behavior, which in turn determined business strategy; Jang [27] indicated that online information searches are beneficial not only to consumers, but also to marketers, because they reduced cost and provided a real-time communication tool to both parties. The internet has fundamentally changed the consumer-marketer communication model. It is no surprise to observe scholars paying substantial attention to marketing strategy and consumer online information search behavior. In the hospitality field, various research groups have used search engine data to predict demand Xiang and Pan, 2011; [9], [20], [43], [58]. Marketers need to understand how consumers search for their product information online and use the information they obtain online to make decisions. Although the subject of consumer online information search behavior has attracted strong academic interest, extensive research in the field is still needed [29].

B. APPLICATIONS OF SEARCH ENGINE DATA IN HOSPITALITY

Search engine data have been used in studies with wide-ranging purposes including, but not limited to, detecting potential influenza outbreaks [21], [44], [55], measuring subjective well-being [1], predicting economic development and status [9], examining the relationship between past orientation and American suicide rates [31], ranking universities [51], and exploring the epidemiology of common gastrointestinal symptoms (Hassid *et al.*, 2017). In the hospitality field, various research groups have used search engine data to predict hotel demand and tourist volume. Zhang *et al.* [59] developed a hybrid model to forecast tourist volume, incorporating search engine data by using the support vector regression with the Bat algorithm. Gawlik *et al.* [20], query-specific search data were used to predict tourism rates; feature selection was utilized to determine the most relevant queries and k-fold cross-validation was applied to test the algorithm performance. The proposed method enabled the accurate forecast of tourism rates in Hong Kong. Li *et al.* [33] forecasted tourism demand with a composite search index, by integrating time-series models with several big data tourism sources. In another project, Xiang and Pan (2011) used the transaction log files of search engines to study online travel query patterns across different tourist destinations; they found that the volume of search queries could indicate the size of a city's tourism industry. Önder and Gunter [41] forecasted tourism demand for a major European destination city, using Google trends. Yang *et al.* [58] also used the web traffic data of a destination organization to forecast that location's hotel demand. More applications of search engine data for predicting travel destination planning and hotel room demand can be found in Choi and Varian [9] and Pan *et al.* [43], respectively. For all those attempts to use search engine data to quantify and predict the business of hospitality, there has been no effort to study the embedded cyclic nature of online searching behavior for restaurants.

C. PERIODICITY ANALYSIS IN BUSINESS

Business practitioners have paid considerable attention to the relationship between consumer behavior and seasonality [5], [7], [40]. Although there is a lack of periodicity analysis in the restaurant industry, several efforts in other hospitality-related fields can be found. For example, Liu *et al.* [34] used a periodicity analysis to model consumer behavior for online hotel search interest in the U.S. Coshall [11], [12] examined the periodic patterns of outbound United Kingdom travelers to international destinations and studied inbound tourist expenditures in the United Kingdom. Spectral analysis was used to study the impact of fluctuations in the Japanese economy on the Hawaiian tourist industry by Latzko [30] and to investigate the periodicity in New Zealand's tourism demand from the U.S. and Australia by Chan and Lim [8]. Because the selling window maybe very small, it is important to study the periodic patterns of business. For example, Choi *et al*. [10] showed that seasonal cycle features heavily affected the performance of the proposed models of fast fashion demand. There is a critical absence of periodicity analysis in the hospitality field [34], which makes it important to conduct this type of research.

III. DATA DESCRIPTION

Baidu and Google are the most popular search engines in the world. The search data for the two platforms are highly correlated and comparable [51]. For the data concerning consumer restaurant search interest in China, the search interest records were downloaded from the Baidu Index (http://index.baidu.com/). The Chinese word for "restaurant" was used as the search keyword and whole nation of China was set as the search location. The Baidu index lacks the digital function of data downloading; although some third-party software is available for downloading that data automatically, the search interest data was manually read from the web for each day, to guarantee the accuracy of the collected data. Currently, the Baidu Index only provides the relevant data starting from January 1, 2011. In this study, the search interest data for the U.S. and China, from 2011 to 2014, are used. In order to collect the consumer online restaurant search interest data for the U.S., the search interest records were downloaded from Google Trends (http://www.google.com/trends/hottrends). In a previously published work by the authors, Google

Trend data were downloaded and used to analyze and model consumer behavior for online hotel search interest in the U.S. For the readers' convenience, the procedures of downloading Google Trends data are provided again, although the procedures are similar to those in the published work. In this work, "Restaurant" was used as the search term, and "United States" was selected as the search location. The search itself was limited to the category of "Food and Drink." Google Trends provides search interest data beginning in the year 2004. However, the data are only provided at weekly or monthly intervals when the query duration is set for a period longer than three months. In order to isolate the daily search interest data over a period of years, the search interest volume was downloaded for three consecutive months. For each download, one month overlapped with a month from the previous download. For example, if the previous download contained data from January through March, the next download contained data from March through May. The downloaded data from Google Trends for each query are relative data. In order to render all the downloaded data comparable, the overlapping data of the consecutive downloads were used to normalize the data as a whole. This made it possible to obtain the relative daily search interest data for the U.S. over a period of years. For the downloaded data, the independent variable is the date, and the dependent variable is the relative daily search interest, which indicates the daily frequency of that particular keyword search. The query for the keyword "Restaurant" reflects the total number of search records including "Restaurant," which is much higher than the number of records for any specific restaurant. Also, the search frequencies for the keywords "dinner" and "eat" are much lower than the frequency for "Restaurant." This is easily verifiable using either the Baidu Index or Google Trends. Thus, the query for "Restaurant" can reflect the overall trend of search interest in restaurants, notwithstanding a scaling factor differential, which does not affect the analyzed value of periods. It is worth noting that the data are relative values, which do not reflect the absolute search frequencies for the keyword. However, this does not compromise the value of analyzing the period and comparing the weight of each frequency component, because normalizing the absolute values changes neither the calculated period values nor the weight percentage of each frequency component.

IV. METHOD

In order to quantify the importance of a specific cyclic pattern in the whole dynamic system, Parseval's theorem [50] was applied to analyze the spectrum obtained through the discrete Fourier transform (DFT) [23]. A signal is usually composed of multiple sine or cosine components. Each component corresponds to a unique frequency or period. Fourier Transform is widely used to analyze the frequency components of a signal. The frequency and period are reciprocal to each other. According to this, the DFT spectrum $X(m\Delta f)$ of a signal $x(t)$ can be represented as:

$$X(T_m) = X(\frac{1}{m\Delta f}) = X(m\Delta f) = \sum_{p=0}^{P-1} x(p\Delta t)e^{-j2\pi mp/N} \tag{1}$$

where T_m is the period of the m^{th} cyclic component, $X(m\Delta f)$ is the m^{th} spectral line ($m = 1, 2, \ldots, P-1$), P is the total number of acquired data points, and Δf is the frequency resolution. Δf is equal to $1/(P\Delta t)$ and Δt is the sampling time interval.

The amplitude of $X(T_m)$ can be computed as:

$$\|X(T_m)\| = \sqrt{X(T_m)_R^2 + X(T_m)_I^2} \tag{2}$$

where $X(T_m)_R$ and $X(T_m)_I$ are the real and imaginary parts of $X(T_m)$.

Parseval's theorem concerns energy conservation in the time and frequency domains of a signal, and it states that the total power of a signal in the frequency domain equals the total power of the signal in the time domain. According to Parseval's theorem, the energy or square of a function in the time domain is equal to the sum (or integral) of the square of its Fourier transform in the frequency domain, which can be expressed as:

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = \int_{-\infty}^{\infty} |X(f)|^2 \, df \tag{3}$$

where $X(f)$ is the Fourier spectrum of $x(t)$.

For DFT, the corresponding energy conservation in the time domain and the frequency domain can be expressed as:

$$\sum_{m=0}^{P-1} |x(m)|^2 = \frac{1}{P} \sum_{k=0}^{P-1} |X(k)|^2 \tag{4}$$

Because the energy in the time domain is the same as the energy in the frequency domain, and the total energy in the frequency domain is the square sum of all the spectral lines, the percentage of the energy carried by a specific spectral line q in the total energy can be used to indicate the weight of the q^{th} cyclic pattern in the whole dynamic system, which can be expressed as:

$$w = \frac{|X(q)|^2}{\sum_{k=0}^{P-1} |X(k)|^2} \tag{5}$$

To make the results for the U.S. and China consumer behavior comparable, both sets of data in the time domain were normalized by the sum of their squares after detrending.

V. RESULTS

The search interest in "Restaurant" in the U.S., from the beginning of 2011 through the end of 2014, is shown in Figure 1(a), and the search interest for the year 2014 is shown in Figure 1(b). Figures 1(a) and 1(b) show that the search interest in the U.S. has some cyclic patterns, although

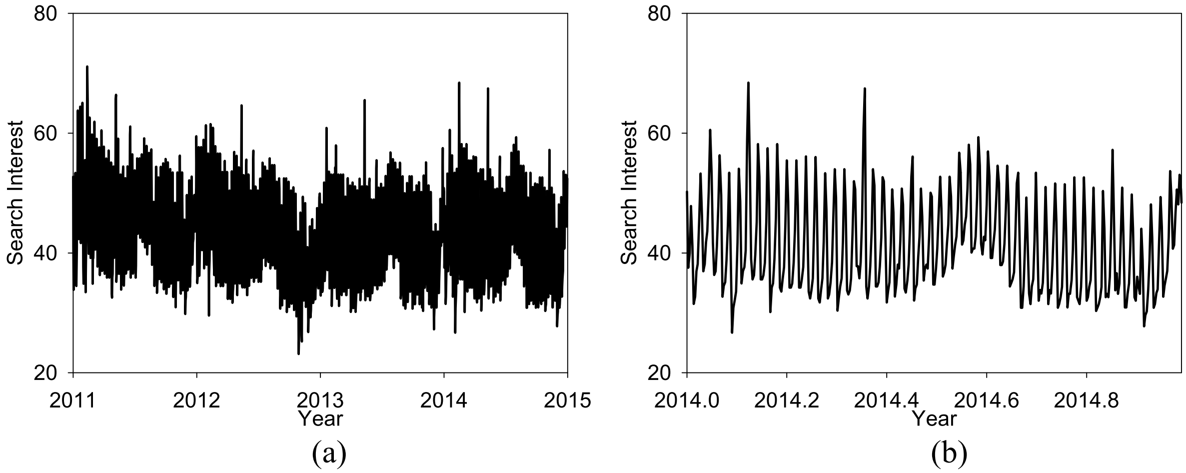

FIGURE 1. Google Search Interest in "Restaurant" in the U.S.: (a) 2011-2014, (b) 2014.

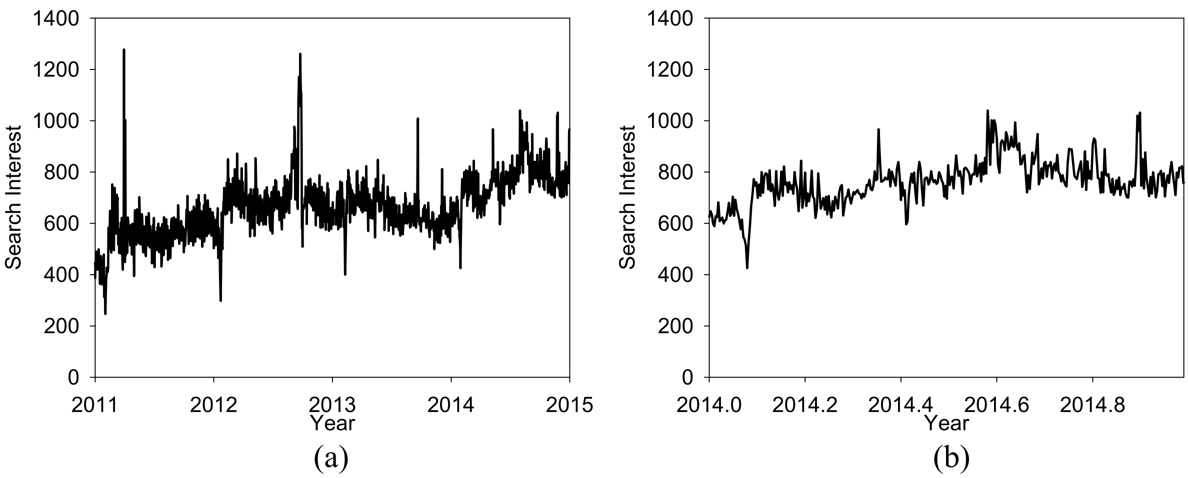

FIGURE 2. Baidu Search Interest in "Restaurant" in China: (a) 2011-2014. (b) 2014.

the number and the period-length of significant cyclic patterns are unclear. The search interest in "Restaurant" in China, from the beginning of 2011 through the end of 2014, is shown in Figure 2(a), and the search interest for the year 2014 is shown in Figure 2(b). Figures 2(a) and 2(b) indicate that the search interest in China also has some cyclic patterns, but the magnitude of the spectral line is relatively lower at shorter frequencies or longer periods; this will be further analyzed using Parseval's theorem. Such cyclic patterns are expected, because human activities are routinely moderated by the calendar year, week, month, and so on.

Before Fourier Transform was applied to analyze the spectrum, the linear trend of the data was removed, based on least squares algorithm. The linear trends removed from the data in the U.S. and China are shown in Figures 3(a) and 4(a). The relative search variations, after detrending for the data in the U.S. and China, are shown in Figures 3(b) and 4(b), which are referred to as "Relative search interest" in this work. The linear trend for the data in the U.S., as shown in Figure 3(a), can be expressed by a linear equation of $x = -0.003t + 44.0$. The linear trend for the data in China, as shown in Figure 4(a), can be expressed by a linear equation of $x = 0.158t + 550.6$. Here t represents time, as measured in daily units. The decreasing or increasing trend in the data of the U.S. or of China may stem from fewer consumers using Google to look for restaurants in the U.S. or from more people using Baidu to search for restaurants in China.

Fourier amplitude spectra, for the search interest for restaurants in the U.S. from 2011 to 2014, are shown in Figures 5(a), 5(b), 5(c), and 5(d); each figure is arranged with periods in different scales. Fourier amplitude spectra, for the search interest for restaurants in China from 2011 to 2014, are shown in Figures 6(a), 6(b), 6(c), and 6(d); as above, each figure is arranged with periods in different scales. The peaks in Figures (5) and (6) clearly indicate the presence of cyclic components in the search interest in both the U.S. and China. The magnitudes and frequencies of the major frequency components are listed in Table 1.

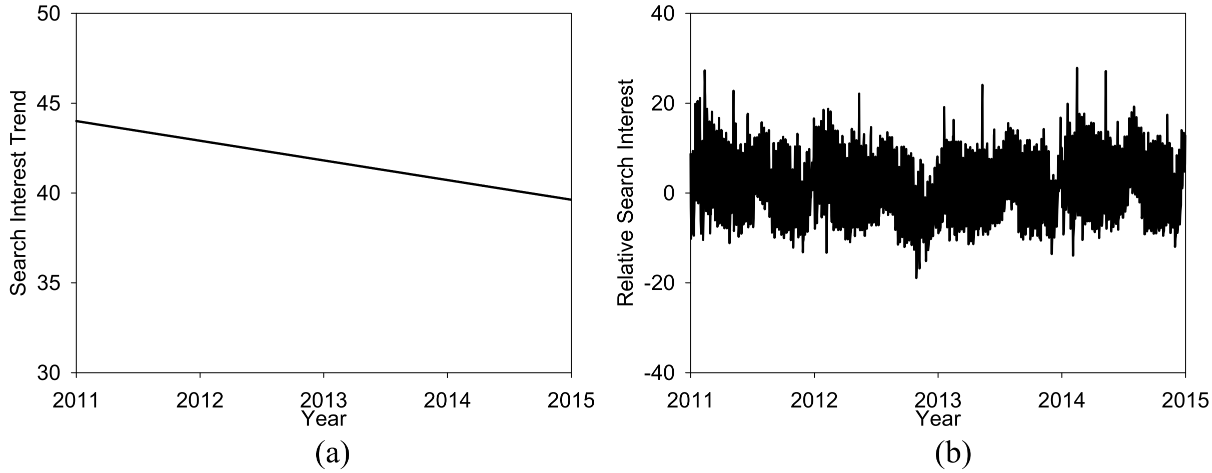

FIGURE 3. (a) The linear trend ($x = -0.003t + 44.0$) for U.S. data., and (b) the relative search interest after detrending.

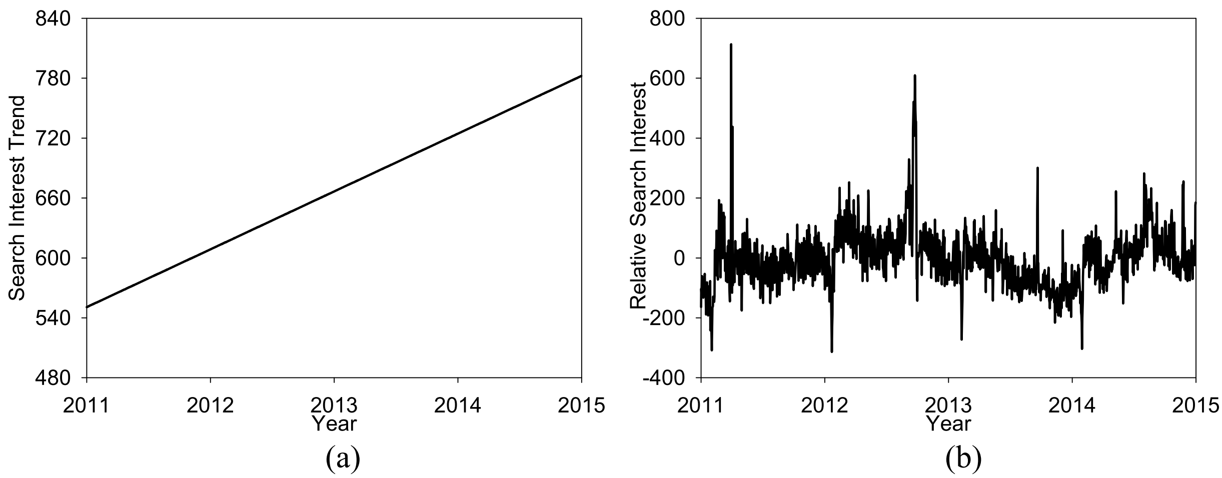

FIGURE 4. (a) The linear trend ($x = 0.158t + 550.6$) for Chinese data, and (b) the relative search interest after detrending.

TABLE 1. Major cyclic components of restaurant search interest in the U.S. and China, 2011- 2014.

Period (Day)	Frequency (1/Day)	Description	U.S.		China	
			Magnitude	Rank	Magnitude	Rank
3.5036	0.2854	Half a Week	0.0095	2	NA	NA
6.9904	0.1431	A Week	0.0245	1	0.0069	2
91.3125	0.0110	Three Months	0.0035	5	0.0064	4
182.6250	0.0055	Half a Year	0.0091	3	0.0091	1
243.5000	0.0041	Eight Months	NA	NA	0.0067	3
365.2500	0.0027	A Year	0.0045	4	0.0059	5

NA implies that the corresponding cyclic component is not significant in the data.

As listed in Table 1, the periods of the 5 major components of the search interest in the U.S. are 6.9904 days (a week), 3.5036 days (half a week), 182.6250 days (half a year), 365.2500 days (1 year), and 91.3125 days (3 months) (in order of magnitude, from high to low). The search interest in China has the same cyclic components as the results for the U.S. However, the cycle with the period of half a week is not dominant and has not been ranked as one of the first 5 dominant cycles; further, the magnitudes of the other frequencies have values distinct from those in the U.S. and they

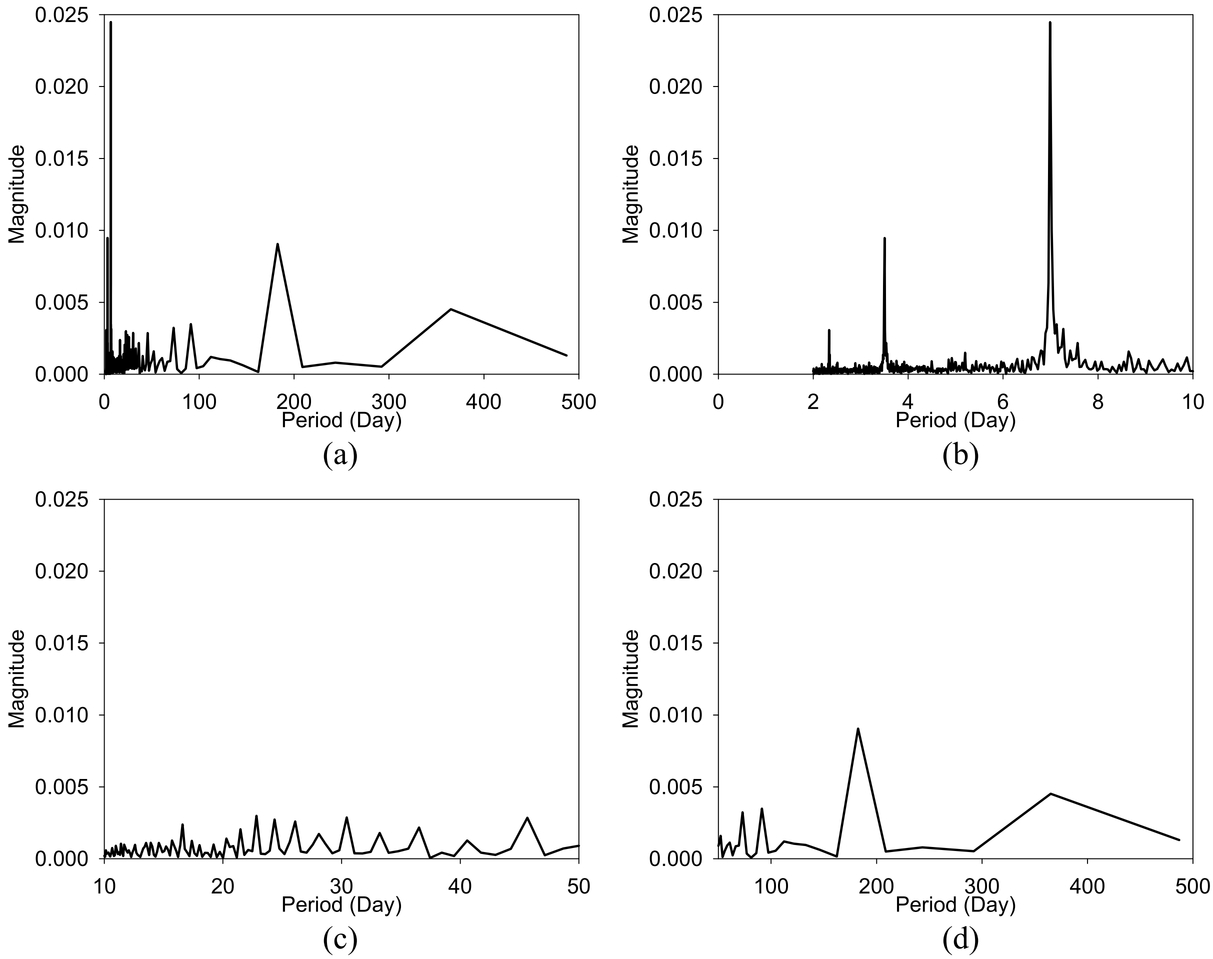

FIGURE 5. Fourier amplitude spectra for restaurant search interest in the U.S., 2011-2014: (a) 0-500 days, (b) 0-10 days, (c) 10-50 days, (d) 50-500 days.

are ranked differently, as shown in Table 1. These periods imply that consumer behavior surrounding online restaurant searches is mainly affected by the year/half a year and the week/half a week cycles in both the U.S. and China. The spectrum of Figure 5(c) and the spectrum of Figure 6(c) each show a peak (or cycle) corresponding to a month (around 30 days); however, the amplitude is very small. This indicates that consumer behavior surrounding online restaurant searches does not regularly repeat in a monthly cycle in either the U.S. or in China. The half a week cycle indicates that consumers have different overall restaurant online search tendencies in a week, which is consistent with the spectral analysis of the supermarket visits [35].

Figure 7 shows the cumulative energy of the searching dynamics in both the U.S. and China, computed according to Eqn. (4). The total energy for the searching dynamics in both the U.S. and China have been normalized to 1, but this value is shown as 0.5 in Figure 7, because only half of the result is displayed in the figure, while the other half is the mirror of the visible half. Each jump on the curves represents a cyclic pattern at the corresponding frequency. The path lengths of the vertical jumps indicate their contributions to the searching dynamics. According to Eqn. (5) and the magnitudes of the spectral lines, the weekly cycle and half a week cycle account for 59.5% and 11.0% of the searching dynamics in the U.S., respectively. The week-related cycles (a week or half a week period) represent a total of 70.5% of the searching dynamics, while the year-related cycles (a year or half a year period) only account for 10.0% of the dynamics. For China, the week-related cycles account for 5.6% of the searching dynamics, while the year-related cycles account for 37.7% of the searching dynamics.

VI. DISCUSSION

The results of this research clearly show that there are cyclic patterns in consumer behavior related to online restaurant searches. While the results for the U.S. and the results for China share cycles with the same periods or frequencies, these cyclic components are weighted differently for their respective searching dynamics.. In the U.S., the week-related searching behavior is dominant (70.5% of the searching dynamics), but this component only accounts for 5.6% of

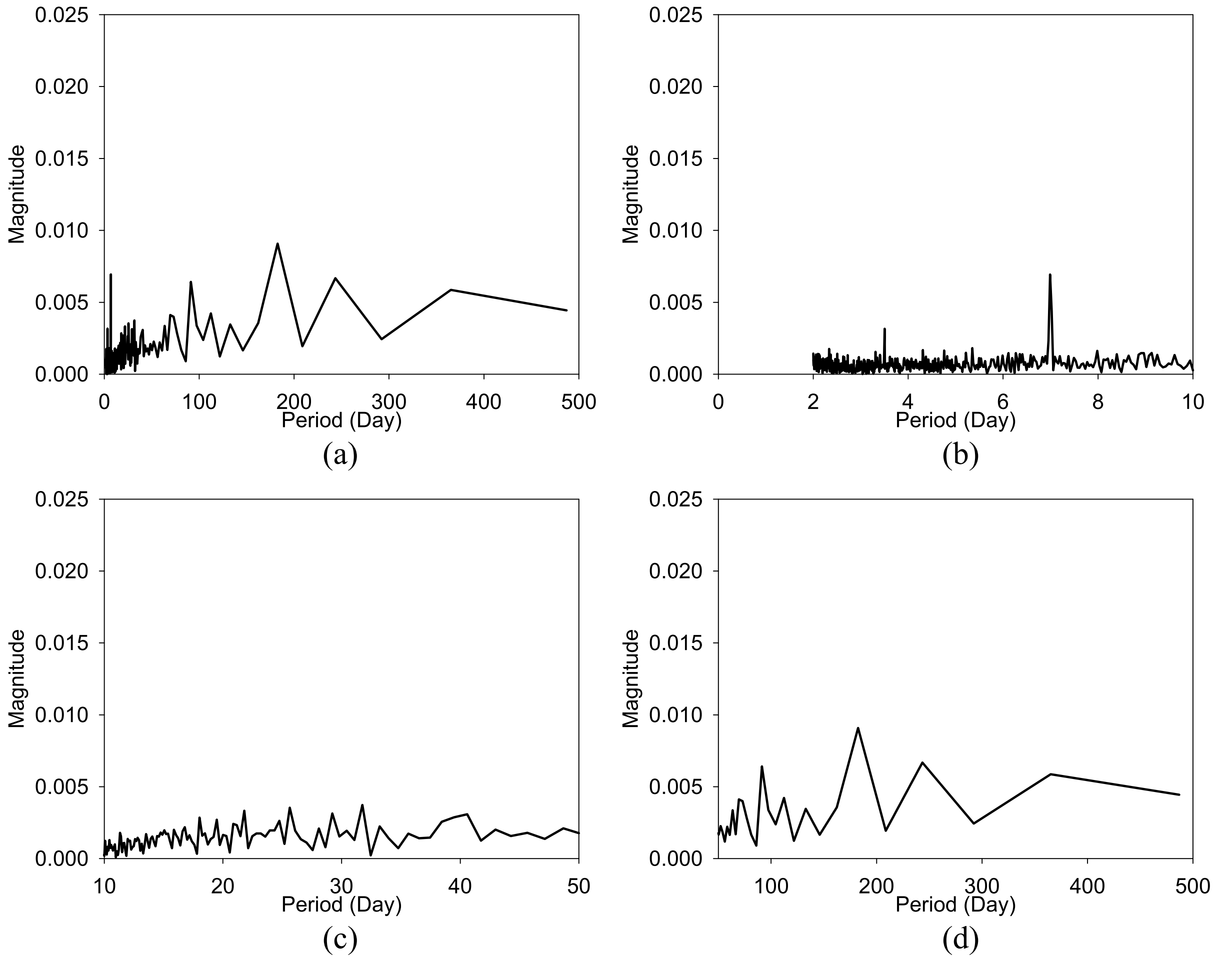

FIGURE 6. **Fourier amplitude spectra for restaurant search interest in China, 2011-2014: (a) 0-500 days, (b) 0-10 days, (c) 10-50 days, (d) 50-500 days.**

the searching dynamics in China. For some parties, especially official ones, the Chinese may make arrangements a week or two weeks in advance. However, the data analysis reveals that the weekly periodic component is not as strong as it is in the U.S. This may imply that Americans more routinely arrange activities involving dining in restaurants on a weekly basis. The total percentage of the year-related cycles accounts for 37.7%, while the week-related cycles only account for 5.6% of the searching dynamics in China. Both of these components together amount to much less than 70.5%, and are not dominant in the searching dynamics, which may indicate that the Chinese do not schedule such dining activities as regularly as the Americans do.

Americans and Chinese differ from each other in many cultural dimensions. Hofstede's [25] study on cultural dimensions is the most frequently cited benchmark of cross-cultural understanding [49]. Hofstede indicated that a country's culture could be described using four dimensions: individualism, power distance, uncertainty avoidance, and masculinity. The uncertainty avoidance dimension refers to the degree to which a society feels threatened by uncertain, ambiguous, or undefined situations, as well as the extent to which society members try to avoid such situations by adopting strict codes of behavior (e.g., legal, religious, technological). For example, people in high uncertainty avoidance cultures typically spend more time and energy on research before they make plans and they prefer to schedule appointments to minimize situational uncertainty. The uncertainty avoidance dimension has been regarded as more important than the other cultural dimensions in terms of its ability to characterize cross-cultural behavior [15]. Previous cross-cultural studies also reported that people from high uncertainty avoidance cultures are more likely to manifest "herd behavior" that could result in strongly cyclic behavior patterns [16], [48]. Because the uncertainty avoidance dimension relates to the cyclic pattern of behavior, it may be used to explain the difference in the cyclic patterns of consumer online search behavior between Chinese and Americans. In terms of the uncertainty avoidance dimension, China is low; the Chinese are considerably less averse to uncertainty than Americans (who would be high on a scale measuring the uncertainty avoidance dimension) [19], [25]. The cyclical online restaurant search

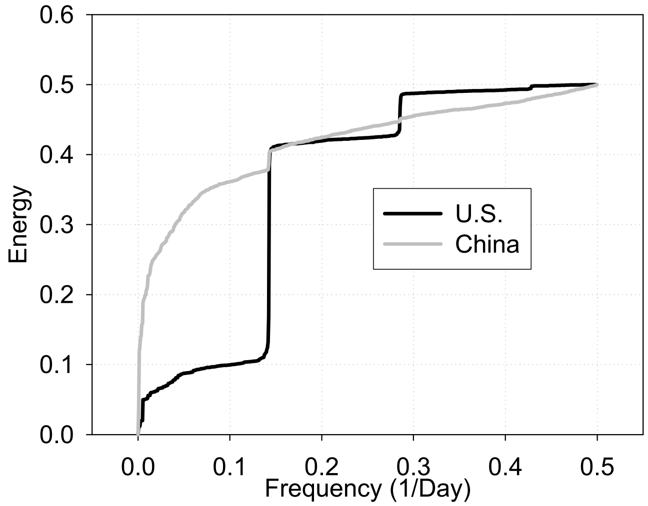

FIGURE 7. Cumulative energy distributions versus frequency of the search dynamics in both the U.S. and China.

behavior of consumers in the U.S. reflects their "herd behavior," which might be a demonstration of high uncertainty avoidance; by contrast, consumers in China did not show the strong cyclical behavior or "herd behavior," and this might serve as a demonstration of their low uncertainty avoidance [16], [48]. This hypothesis generally concurs with the published literature. However, Hofstede [26] himself argued that culture can change; moreover, many cross-cultural studies conducted in the past decade reported that Chinese people were exhibiting changes in their culture and values [18], [22], [56]. Specifically, Wu [56] found Chinese participants to be as high on a scale of uncertainty avoidance as American participants. In the face of these recent findings, which so differ from Hofstede's original findings, it is necessary to examine certain behavioral and cultural dimensions of people negotiating a new era in their own country.

This study makes several contributions, to the body of literature and to business interests. First, the results of the study may represent new evidence of the uncertainty avoidance distinctions between Chinese and Americans. Although culture can change [26] and some recent studies have reported such cultural changes among the Chinese [18], [22], [56], it still appears that both Chinese and American consumers' online restaurant search behavior are shaped by their respective (low and high) levels of uncertainty avoidance as documented in Hofstede's original study [25]. Second, the different cyclic patterns of consumer online restaurant search behavior in the U.S. and China suggest that business practitioners should employ different marketing and restaurant management strategies in each of these two countries. For example, as consumers in the U.S. tend to search for restaurants on a weekly basis, restaurant marketers may want to invest in online advertising that acknowledges this tendency, as it is likely to be more effective. Consumers in China do not search for restaurants on a weekly basis, but considering the large population and the market need, restaurant managers in China may want to stay alert and ready for their native consumers every day. This would require them to maintain sufficient inventory and labor to accommodate their potential patrons on a daily basis. Third, understanding the patterns of search behavior is useful for building a demand-prediction model, because the behavior related to online information searches can be regarded as the input of a demand-prediction model, while the predicted demand can be regarded as the output.

VII. CONCLUSION

In this research, the cyclic consumer behavior of online restaurant searches in the U.S. and China was analyzed. Parseval's theorem was used to quantify the weight of cyclic patterns in the whole searching dynamics. The study showed that consumers in both the U.S. and China follow cyclic patterns for online restaurant searches with the same periods, but Americans are more likely to arrange dining activities on a weekly basis, while the Chinese do not arrange this activity as regularly as Americans. This finding agrees with the Hofstede's original finding of an uncertainty avoidance difference between the two countries. This work is expected to be useful for international restaurant management personnel and online marketing professionals. Future work aimed at analyzing the cyclic patterns of online restaurant search behavior in other countries is needed.

REFERENCES

[1] Y. Algan, E. Beasley, F. Guyot, K. Higa, F. Murtin, and C. Senik, "Big data measures of well-being: Evidence from a Google well-being index in the United States," in *Proc. OECD Stat. Work. Papers*, 2016.

[2] P. F. Bangwayo-Skeete and R. W. Skeete, "Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach," *Tourism Manage.*, vol. 46, pp. 454–464, Feb. 2015.

[3] J. L. Bertrand, X. Brusset, and M. Fortin, "Assessing and hedging the cost of unseasonal weather: Case of the apparel sector," *Eur. J. Oper. Res.*, vol. 244, no. 1, pp. 261–276, 2015.

[4] A. Bhatnagar and S. Ghose, "Online information search termination patterns across product categories and consumer demographics," *J. Retailing*, vol. 80, no. 3, pp. 221–228, 2004.

[5] H. C. Bjørnland, "Detrending methods and stylized facts of business cycles in Norway—An international comparison," *Empirical Econ.*, vol. 25, no. 3, pp. 369–392, 2000.

[6] B. J. Bronnenberg, C. F. Mela, and W. Boulding, "The periodicity of pricing," *J. Marketing Res.*, vol. 43, no. 3, pp. 477–493, 2006.

[7] E. Broszkiewicz-Suwaj, A. Makagon, R. Weron, and A. Wyłomanska, "On detecting and modeling periodic correlation in financial data," *Phys. A, Stat. Mech. Appl.*, vol. 336, nos. 1–2, pp. 196–205, 2004.

[8] F. Chan and C. Lim, "Spectral analysis of seasonality in tourism demand," *Math. Comput. Simul.*, vol. 81, no. 7, pp. 1409–1418, 2011.

[9] H. Choi and H. Varian, "Predicting the present with Google trends," *Econ. Rec.*, vol. 88, no. s1, pp. 2–9, 2012.

[10] T.-M. Choi, P. C.-L. Hui, N. Liu, S. F. Ng, and Y. Yu, "Fast fashion sales forecasting with limited data and time," *Decision Support Syst.*, vol. 59, pp. 84–92, Jan. 2014.

[11] J. Coshall, "Spectral analysis of international tourism flows," *Ann. Tourism Res.*, vol. 27, no. 3, pp. 577–589, 2000a.

[12] J. T. Coshall, "Spectral analysis of overseas tourists' expenditures in the United Kingdom," *J. Travel Res.*, vol. 38, no. 3, pp. 292–298, 2000b.

[13] E. K. Clemons, "How information changes consumer behavior and how consumer behavior determines corporate strategy," *J. Manage. Inf. Syst.*, vol. 25, no. 2, pp. 13–40, 2008.

[14] A. Constantinides and N. Mostoufi, *Numerical Methods for Chemical Engineers With MATLAB Applications With CDROM*, vol. 443. Upper Saddle River, NJ, USA: Prentice-Hall, 1999.

[15] J. C. Crotts, "The effect of cultural distance on overseas travel behaviors," *J. Travel Res.*, vol. 43, no. 1, pp. 83–88, 2004.
[16] B. Deleersnyder, M. G. Dekimpe, J.-B. E. M. Steenkamp, and P. S. H. Leeflang, "The role of national culture in advertising's sensitivity to business cycles: An investigation across continents," *J. Marketing Res.*, vol. 46, no. 5, pp. 623–636, 2009.
[17] A. I. El-Ansary, "Marketing strategy: Taxonomy and frameworks," *Eur. Bus. Rev.*, vol. 18, no. 4, pp. 266–293, 2006.
[18] G. O. Faure and T. Fang, "Changing Chinese values: Keeping up with paradoxes," *Int. Bus. Rev.*, vol. 17, no. 2, pp. 194–207, 2008.
[19] D. R. Fernandez, D. S. Carlson, L. P. Stepina, and J. D. Nicholson, "Hofstede's country classification 25 years later," *J. Social Psychol.*, vol. 137, no. 1, pp. 43–54, 1997.
[20] E. Gawlik, H. Kabaria, and S. Kaur. (2011). *Predicting Tourism Trends With Google Insights*. [Online]. Available: http://mfile.narotama.ac.id/files/Umum/JURNAR%20STANFORD/Predicting%20tourism%20trends%20with%20Google%20Insights.pdf
[21] J. Ginsberg, M. H. Mohebbi, R. S. Patel, L. Brammer, M. S. Smolinski, and L. Brilliant, "Detecting influenza epidemics using search engine query data," *Nature*, vol. 457, no. 7232, pp. 1012–1014, 2009.
[22] S. Harris and C. Carr, "National cultural values and the purpose of businesses," *Int. Bus. Rev.*, vol. 17, no. 1, pp. 103–117, 2008.
[23] J. W. Harris and H. Stöcker, *Handbook of Mathematics and Computational Science*. Cham, Switzerland: Springer, 1998.
[24] B. G. Hassid, L. W. Day, M. A. Awad, J. L. Sewell, E. C. Osterberg, and B. N. Breyer, "Using search engine query data to explore the epidemiology of common gastrointestinal symptoms," *Dig. Diseases Sci.*, vol. 62, no. 3, pp. 588–592, 2017.
[25] G. Hofstede, *Culture's Consequences: International Differences in Work-Related Value*. Beverly Hills, CA, USA: Sage, 1980.
[26] G. Hofstede, *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations*. Newbury Park, CA, USA: Sage, 2001.
[27] S. Jang, "The past, present, and future research of online information search," *J. Travel Tourism Marketing*, vol. 17, nos. 2–3, pp. 41–47, 2005.
[28] S. N. Kadir, N. M. Tahir, I. M. Yassin, and A. Zabidi, "Malaysian tourism interest forecasting using nonlinear auto-regressive moving average (NARMA) model," in *Proc. IEEE Symp. Wireless Technol. Appl. (ISWTA)*, Sep. 2014, pp. 193–198.
[29] M. Laroche, "Advances in Internet consumer behavior and marketing strategy: Introduction to the special issue," *J. Bus. Res.*, vol. 63, no. 9, pp. 1015–1017, 2010.
[30] D. A. Latzko, "Economic conditions and Japanese tourism to Hawaii," *Asia Pacific J. Tourism Res.*, vol. 10, no. 2, pp. 151–156, 2005.
[31] D. Lee, H. Lee, and M. Choi, "Examining the relationship between past orientation and US suicide rates: An analysis using big data-driven Google search queries," *J. Med. Internet Res.*, vol. 18, no. 2, p. e35, 2016.
[32] K. Levenberg, "A method for the solution of certain problems in least squares," *Quart. Appl. Math.*, vol. 2, no. 2, pp. 164–168, 1944.
[33] X. Li, B. Pan, R. Law, and X. Huang, "Forecasting tourism demand with composite search index," *Tourism Manage.*, vol. 59, pp. 57–66, Apr. 2017.
[34] J. Liu, X. Li, and Y. Guo, "Periodicity analysis and a model structure for consumer behavior on hotel online search interest in the US," *Int. J. Contemp. Hospitality Manage.*, vol. 29, no. 5, pp. 1486–1500, 2017.
[35] D. B. MacKay, "A spectral analysis of the frequency of supermarket visits," *J. Marketing Res.*, vol. 10, no. 1, pp. 84–90, 1973.
[36] D. Maheswaran and S. Shavitt, "Issues and new directions in global consumer psychology," *J. Consum. Psychol.*, vol. 9, no. 2, pp. 59–66, 2000.
[37] D. W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," *J. Soc. Ind. Appl. Math.*, vol. 11, no. 2, pp. 431–441, 1963.
[38] R. B. Money and J. C. Crotts, "The effect of uncertainty avoidance on information search, planning, and purchases of international travel vacations," *Tourism Manage.*, vol. 24, no. 2, pp. 191–202, 2003.
[39] R. D. Mueller, A. Palmer, R. Mack, and R. McMullan, "Service in the restaurant industry: An American and Irish comparison of service failures and recovery strategies," *Int. J. Hospitality Manage.*, vol. 22, no. 4, pp. 395–418, 2003.
[40] E. B. Nieves-Rodríguez, J. J. Cao-Alvira, and M. M. Pérez, "The influence of special occasions on the retail sales of women's apparel," in *Ideas in Marketing: Finding the New and Polishing the Old*. Cham, Switzerland: Springer, 2015, pp. 213–221.
[41] I. Önder and U. Gunter, "Forecasting tourism demand with Google trends for a major European city destination," *Tourism Anal.*, vol. 21, nos. 2–3, pp. 203–220, 2016.
[42] B. Pan, Z. Xiang, H. Tierney, D. R. Fesenmaier, and R. Law, "Assessing the dynamics of search results in Google," *Inf. Commun. Technol. Tourism*, pp. 405–416, 2010.
[43] B. Pan, W. D. Chenguang, and H. Song, "Forecasting hotel room demand using search engine data," *J. Hospitality Tourism Technol.*, vol. 3, no. 3, pp. 196–210, 2012.
[44] C. Pelat, C. Turbelin, A. Bar-Hen, A. Flahault, and A. J. Valleron, "More diseases tracked by using Google trends," *Emerg. Infectious Diseases*, vol. 15, no. 8, p. 1327, 2009.
[45] M.-O. Richard, J.-C. Chebat, Z. Yang, and S. Putrevu, "A proposed model of online consumer behavior: Assessing the role of gender," *J. Bus. Res.*, vol. 63, no. 9, pp. 926–934, 2010.
[46] J. B. Schmidt and R. A. Spreng, "A proposed model of external consumer information search," *J. Acad. Marketing Sci.*, vol. 24, no. 3, pp. 246–256, 1996.
[47] B.-Y. Shih, C.-Y. Chen, and Z.-S. Chen, "An empirical study of an Internet marketing strategy for search engine optimization," *Human Factors Ergonom. Manuf. Service Ind.*, vol. 23, no. 6, pp. 528–540, 2013.
[48] M. L. Sykes and O. Schnusenberg, "Predicting herding behavior using Hofstede's cultural dimensions," in *Proc. Int. Bus. Res. Conf. (IB)*, 2011, p. 47.
[49] R. G. Tian, "The implications of rights to culture in transnational marketing: An anthropological perspective," *High Plains Appl. Anthropologist*, vol. 20, no. 2, pp. 135–145, 2000.
[50] G. P. Tolstov, *Fourier Series*. North Chelmsford, MA, USA: Courier Corporation, 2012.
[51] L. Vaughan and E. Romero-Frías, "Web search volume as a predictor of academic fame: An exploration of Google trends," *J. Assoc. Inf. Sci. Technol.*, vol. 65, no. 4, pp. 707–720, 2014.
[52] L. Vaughan and Y. Chen, "Data mining from Web search queries: A comparison of Google trends and Baidu index," *J. Assoc. Inf. Sci. Technol.*, vol. 66, no. 1, pp. 13–22, 2015.
[53] Y. Wang and D. R. Fesenmaier, "Identifying the success factors of Web-based marketing strategy: An investigation of convention and visitors bureaus in the United States," *J. Travel Res.*, vol. 44, no. 3, pp. 239–249, 2006.
[54] H. Werthner and F. Ricci, "E-commerce and tourism," *Commun. ACM*, vol. 47, no. 12, pp. 101–105, 2004.
[55] H. Woo, Y. Cho, E. Shim, J. K. Lee, C. G. Lee, and S. H. Kim, "Estimating influenza outbreaks using both search engine query data and social media data in South Korea," *J. Med. Internet Res.*, vol. 18, no. 7, p. e177, 2016.
[56] M.-Y. Wu, "Hofstede's cultural dimensions 30 years later: A study of Taiwan and the United States," *Intercultural Commun. Stud.*, vol. 15, no. 1, p. 33, 2006.
[57] Z. Xiang and B. Pan, "Travel queries on cities in the United States: Implications for search engine marketing for tourist destinations," *Tourism Manage.*, vol. 32, no. 1, pp. 88–97, 2011.
[58] Y. Yang, B. Pan, and H. Song, "Predicting hotel demand using destination marketing organization's Web traffic data," *J. Travel Res.*, vol. 53, no. 4, pp. 433–447, 2014.
[59] B. Zhang, X. Huang, N. Li, and R. Law, "A novel hybrid model for tourist volume forecasting incorporating search engine data," *Asia Pacific J. Tourism Res.*, vol. 22, no. 3, pp. 245–254, 2017.
[60] S. H. Baek, S. Ham, and I. S. Yang, "A cross-cultural comparison of fast food restaurant selection criteria between Korean and Filipino college students," *Int. J. Hospitality Manage.*, vol. 25, no. 4, pp. 683–698, 2006.
[61] E. Nica, "Marketing implications of consumer behavior," *Econ., Manage., Financial Markets*, vol. 1, pp. 124–129, 2013.

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