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Dynamics of Hotel Website Browsing Activity: The Power of Informatics and Data Analytics

ABSTRACT

PURPOSE – This paper aims to investigate the temporal dynamics of users' browsing activity on a hotel website in order to derive effective marketing strategies and constantly improve website effectiveness. Users' activities on the hotel's website on yearly, monthly, daily, and hourly bases are examined and compared, demonstrating the power of informatics and data analytics.

METHODOLOGY – A total of 29,976 hourly weblog files from August 1, 2014 to December 31, 2017 were collected from a luxury hotel in Hong Kong. ANOVA and post-hoc comparisons were used to analyse the data.

FINDINGS – Users' browsing behaviours, particularly stickiness, on the hotel website differ on yearly, monthly, daily, and weekly bases. Users' activities increased steadily from 2014 to 2016, but dropped in 2017. Users are most active from July to September, on weekdays, and from noon to evening time. The month-, day-, and hour-based behaviours changed through years. The analysis of big data determines strategic and operational management and marketing decision making.

PRACTICAL IMPLICATIONS – Understanding the usage patterns of their websites allow organisations to make a range of strategic, marketing, pricing, and distribution decisions to optimise their performance. Fluctuation of website usage and level of customer engagement have implications on customer support and services, as well as strategic partnership decisions.

VALUE – Leveraging the power of big data analytics, this paper adds to the existing literature by performing a comprehensive analysis on the temporal dynamics of users' online browsing behaviours.

KEYWORDS – Browsing activity; Weblog data; Hotel website; Temporal analysis; Website stickiness; Strategic and tactical management.

Introduction

With the rapid development of information technology, hotel and tourism industries increasingly embrace smart solutions to develop their competitiveness and better exercise total quality management (Buhalis, 2020; Buhalis and Leung, 2018; Claver-Cortés et al., 2008; Llach et al., 2016). A range of technology solutions emerge online to facilitate tourism and hospitality distribution supporting the hospitality industry service supply chain (Law et al., 2020; Leung, 2019; O'Connor, 2019). These disruptive technologies will increasingly influence the competitiveness and profitability of tourism and hospitality organizations (Buhalis et al., 2019). Information technology competency and knowledge management, based on big data, generate the intelligence that is critical for the competitiveness of the hospitality industry (Jalilvand et al., 2019; Köseoglu et al., 2019; Mariani, 2019). This will increasingly drive revenue and yield management decisions making a direct contribution to profitability through dynamic pricing, personalised pricing, and distribution channel management (Viglia and Abrate, 2019).

The Internet has become a major information source for travel-related decisions, such as destination choice and hotel booking (Law et al., 2014; O'Connor, 2019). Travellers tend to search for information and visit the website of a hotel prior to their visits, in order to gain an initial impression of the hotel online (Bilgihan and Bujisic, 2015; Paraskevas et al., 2011). Qi et al. (2013) stated that more than half of the visitors to Macau searched and booked their rooms at a hotel website. The industry report by Fuel (2019) also showed that 87% of travellers will visit a hotel's website before making a decision. Being the most cost-effective channel for hotels to directly reach their customers, hotels spend a large proportion of their budget on maintaining effective websites (Morosan and Jeong, 2008; SiteMinder, 2017). However, the increasing power of new industry players, such as online travel agencies (OTA, e.g., Expedia and Agoda), has brought significant impacts to the hotel industry. OTAs offer extra information on destinations, room rate comparisons, and last-minute discounts, which are valuable to most travellers (Masiero and Law, 2015). Thus, the market share of hotel websites has been substantially shifted towards OTAs, especially for independent hotels (Starkov and O'Brien, 2015). Martin-Fuentes and Mellinas (2018) demonstrate the reliance of hotels on online travel agencies (OTAs) as their critical distribution channels. A hotel over-relying on these intermediaries will not only suffer from high distribution costs but may also lose control over operations and sales. The fierce competition posed by this group of new industry players has urged hotels to put up more promotions and advertising on their websites to encourage direct bookings from customers (eMarketer, 2017).

As users browse through a hotel website, they leave traces of their behavioral patterns in the form of weblog data and cookies (Benevenuto et al., 2012). Using big data analytics can identify customer patterns and understand their preferences in using technologies (Chen et al., 2017). Providing knowledge to enable developers to capture behaviour of large pools of customers can improve products and services. Utilising these weblog data allows hotels to understand customers' usage behaviours and preferences, thereby devise corresponding marketing strategies to enhance users' experiences (Lee, 2018). Analysing customers' interactions with the hotel website is conductive to a more engaging online platform (Kumar and Thakur, 2018; Llach et al., 2016). Anders (1999) stated that reaching a large audience and keeping them on the site (i.e., achieving stickiness) is a major objective of online branding. Bringing the aforementioned reasons together, the current study focuses on users' stickiness to hotel websites, so as to help hotels remain competitive by devising more effective advertising strategies and convert more browsers to bookers.

The marketing literature generally affirms that timing is an important element influencing the effectiveness of online promotions and mobile advertising (Hui et al., 2013; Luo et al., 2014; Zhang and Krishnamurthi, 2004). Hui et al. (2013) stressed that marketers should shift from advertising via multiple channels to one-time contact simply at the *right time*. The differences in consumer behaviours during weekdays and weekends have resulted in different pricing models (Scholten et al., 2009). However, the existing literature in the hospitality and tourism domain focuses on identifying users' characteristics (Park and Chung, 2009) and their navigation on the website, such as the most popular access path (Leung and Law, 2008; Schegg et al., 2005) and transactional path (Shao and Gretzel, 2010). Little evidence has been provided regarding the time-based differences in users' behaviours on hotel websites, except two studies. Leung et al. (2016) examined the differences in website users' browsing behaviours between weekday and weekend. They found that users tend to view more pages on the website during weekdays than weekends. In a more recent study, Law et al. (2018) went beyond prior studies to analyse users' behavioral patterns on a daily (diurnal) and hourly (intradiurnal) basis. However, their study revealed patterns of users' browsing behaviours based on weblog data collected for one year only, leaving month-based and year-based browsing patterns of website users remain unexplored. If weblog file pertaining to a longer time period can be collected and used, more accurate findings on users' behaviours may be revealed (Kaur and Aggarwal, 2015). Thus, a more comprehensive understanding on fluctuations on demand and browsing activities along different temporal dimensions, including hour, day, month, and year, provides useful implications. Firstly, it ensures quality customer services and adequate customer support especially during peak periods. Secondly, it improves marketing mix formulation and concentrates promotional efforts. Given the possibility to perform real-time communication with online users, understanding the temporal dynamics of online consumer activities may allow marketers to disseminate timely messages to either boost website usage during off-peak times or convert browsers to purchasers during peak times. Lastly, tracking the changes of temporal dynamics in different years is important to reflect the updated trends in consumer behaviours. Therefore, this study seeks to perform a longitudinal weblog analysis, to understand the browsing patterns of website users, and thereby introduce inspirations into academia and provide practical suggestions on the strategic use of hotel websites.

This study contributes to research on online consumer behaviours by retrieving a significant number of weblog data covering users' browsing patterns on hourly, daily, monthly, and yearly basis. With the 4-year weblog data from a hotel website, this paper seeks to achieve four research objective: (1) to understand the yearly patterns of visitors' website stickiness; (2) to understand the month-based patterns of visitors' website stickiness; (3) to understand diurnal patterns of visitors' website stickiness; and (4) to understand intradiurnal patterns of visitors' website stickiness.

Literature Review

Online consumer behaviours and weblog data

Digital presence is closely related to hotel competitiveness and profitability as digital marketing, social media performance, and electronic word of mouth (eWoM) through reviews, influence engagement, loyalty, occupancy, and therefore revenue (Anagnostopoulou et al., 2020; Buhalis and Mamalakis, 2015; Viglia et al., 2016). Digital presence and strategies also influence human resource recruitment, onboarding, and competitiveness (Ladkin and Buhalis, 2016). However, the online service environment is largely different from a face-to-face context in terms of the degree of personal contact, the way of information delivery, the timing of purchase, and the presentation of products (Rose et al., 2011). The continuous rise of the Internet adoption and online sales have led to extensive research efforts in understanding online consumer behaviours, which involve a wide range of activities related to consumer decision making. These activities include information search and product enquiry (e.g., Ho et al., 2012; Oulasvirta et al., 2005), comparison and evaluation of choices (e.g., Kuo et al., 2004), engagement in online social networks (e.g., Brown et al., 2007; Correa et al., 2010), navigations (e.g., Liu and Kešelj, 2007; Smith and Ng, 2003), information and technology adoption (e.g., Morosan and Jeong, 2008; Ozturk, 2016), purchase and payment (e.g., Chen et al., 2017; Li et al., 2017), experience and information sharing (e.g., Xiang et al., 2018; Yang, 2019), and repurchase (e.g., Nguyen et al., 2018). These online consumer behaviours are frequently conceptualised and operationalised as (cognitive) beliefs, (affective) attitudes, and (conative) intentions (Morosan and Jeong, 2008). Lamest and Brady (2019) identify managerial challenges experienced by general managers, marketing, and financial managers using digital customer data.

A prominent stream of online consumer behaviour research focuses on identifying the antecedents of online consumer behaviours, such as consumer characteristics, socio-cultural factors, situational and economic factors, website design features, and product type (Nguyen et al., 2018; Rose et al., 2011; Sun et al., 2017). For example, Yang (2019) examined the effects of consumers' perceived social distance on their information sharing intentions. Li et al. (2017) showed that good quality hotel websites will enhance consumers' trust, which will in turn increase their booking intentions. Ongsakul et al. (2020) demonstrated how hotel website quality influences hospitality performance, telepresence, and behavioral intentions. Another line of research focuses on revealing differences in consumer behavioural patterns, thereby enhancing knowledge on customers and perform marketing strategies and segmentation. For example, Chen et al. (2017) analysed usage patterns on mobile application in terms of time, frequency, and interactivity, so as to identify high-value customers. Liu and Kešelj (2007) proposed a new approach to classify user navigation patterns using contents on web pages and Weblog data to facilitate better web personalisation and organisation.

The current research falls within the latter research area as it seeks to reveal the browsing patterns of website users, denoted as website stickiness. This study defines website stickiness as the ability of the website to draw visitors and retain them by browsing more information

(Roy et al., 2014; Xu and Liu, 2010; Zott et al., 2000). Following Plaza's (2011) suggestion, this concept is operationalised as the number of visitors the website attracted, the number of pages each visitor viewed, and the number of hits performed. The conceptualisation and operationalisation demonstrate the complexity of the concept by combining both the ability of the website and users' behaviours. Existing research on website stickiness focused on identifying its drivers (Chen and Lin, 2015), and its favourable customer responses, such as higher purchase intention (Elliot et al., 2013; Lin, 2007) and positive word-of-mouth (Roy et al., 2014).

It is evident that research on online consumer behaviour in general, and on consumer browsing behaviours in particular, has been dominated by studies utilising survey data (Darley et al., 2010; Nguyen et al., 2018). Moreover, most existing research examined website stickiness from customers' perspective using self-reported intentional measures (Chen and Lin, 2015; Lin, 2007; Roy et al., 2014), which may not reflect actual behaviour and therefore represents bias (Webb and Sheeran, 2006). The Internet represents a rich source of customer data, such as text data and clickstream or weblog data. Weblogs or clickstream data record the interactions of users with a particular website (Leung and Law, 2008). Weblog mining refers to the application of data mining techniques to identify usage patterns from Weblog data, which help organisations learn about their customers and improve web applications (Benevenuto et al., 2012; Kaur and Aggarwal, 2015). Analysing log files is one of the most effective tools in allocating marketing efforts for service providers (Tyagi et al., 2010). Existing weblog mining research in the marketing context mainly focused on understanding the role of the Internet as a new channel for advertising, browsing and usage behaviours of the Internet, and online shopping behaviours (Bucklin and Sismeiro, 2009). Benevenuto et al. (2012) used clickstream data to understand users' activities on online social networking platforms, including frequency and duration of usage, and the types and sequences of activities performed. In tourism research, Anuar et al. (2009) utilised weblog files to study users' browsing activities performed on tourism destination websites. Additionally, Yang (2017) collected weblog text files from a number of tourist attractions in Shanghai to identify the cooperation structure among tourist attractions.

Scholars generally believe that weblog files are free from human intervention and truly record and reveal users' browsing activities (Melanie et al., 2008). Thus, they represent objective sources for studying consumer behaviours (Leung and Law, 2008). Weblog data has also been applied in the hotel context to extract online consumer behaviours. Schegg et al. (2005) first collected weblog files from 15 Swiss hotels, providing both practical and academic insights on website evaluation and consumer behaviours. Through analysing weblog data from one international five-star hotel in Hong Kong, Leung and Law (2008) concluded that most hotel website visitors were from the local area and they were mostly interested in “dining options information.”

Temporal aspect of consumer behaviours

Time is an integral aspect of consumer behaviour, and therefore should be considered when marketers develop their advertising strategies (Hui et al., 2013; Zhang and Krishnamurthi, 2004). Consumers demonstrate habitual patterns in their behaviours, such as the days and times when they perform purchases on groceries (Geiger, 2007; Hassan et al., 2015), when they travel to and within a destination (Dickson et al., 2013; Vu et al., 2015), and when to visit a particular attraction (Birenboim et al., 2013; Vu et al., 2015). Despite the lower consumption efforts involved, consumers also exhibit rich temporal dynamics in the online environment. For example, Yang and Leskovec (2011) identified six temporal clusters of attention on the contents for three online social media platforms. Backstrom et al. (2009) as well as Kaur and Aggarwal (2015) identified the times with peak traffics to and activities on a single website. In their study on e-retail stores such as Amazon and eBay, Kooti et al. (2016) observed daily and weekly dynamics in online purchase behaviours. They found that more purchases took place at the beginning of the week and fewer purchases over the weekends; and most purchases took place during working hours, i.e., morning and early afternoon. Research in the hotel context generally concords the existence of temporal patterns in consumer’ online search and browsing activities. Leung et al. (2016) pointed out that the average number of pages viewed on weekends only accounted for 60% of that on weekdays. Besides weekday-weekend differences, Law et al. (2018) found that the hotel website they studied encounter the highest traffic during the period from noon to evening.

Despite a few previous studies’ attempt to understand the time-varying behaviours of users on hotel websites, they are limited to one-year worth of data (Law et al., 2018; Leung et al., 2016). Besides, except weekday-weekend differences and the intradiurnal differences exhibited in a day, other variations, such as month-based (or seasonal) and year-based variations, remain largely unexplored. Obtaining data covering a longer time period may unveil more accurate findings and deeper insights into user's browsing behaviours (Kaur and Aggarwal, 2015). As such, this study overcomes the limitations of prior studies and contributes to existing literature by retrieving four year's data and performing a comprehensive analysis on the temporal dynamics of users' behaviours on a hotel website (Law et al., 2019). It seeks to identify the temporal patterns in users' stickiness to the hotel website (i.e., the number of visitors, number of pages viewed, and number of hits) on yearly, monthly, daily, and hourly bases.

Methodology

This study collected weblog data files from a hotel (Hotel A) in Hong Kong to explore customers' website stickiness behaviours. Hotel A is an independent luxury hotel located at the Tsim Sha Tsui East of Hong Kong, with more than 260 guest rooms and three restaurants. The website of Hotel A is selected for two reasons. Firstly, the average daily rate (ADR) of Hotel A matches the average room rate in Hong Kong in 2018 (ADR = 1,376 HKD) (Hong Kong Tourism Board, 2018). Secondly, as previously mentioned, the threat of OTAs is more serious for independent hotels, and thus Hotel A is chosen to represent independent hotels in Hong Kong.

The weblog mining process involves four stages, including weblog data retrieval, data pre-processing, pattern identification, and pattern analysis (Kaur and Aggarwal, 2015). As the first step, a total of 29,976 hourly weblog files from August 1, 2014 to December 31, 2017 were collected from Hotel A's website server. The weblog files were imported into a weblog analysis tool (e.g., Weblog Expert professional version) to generate daily reports, which show aggregated information of user activities on five aspects: (1) general activity (e.g., visitors, views, and hits), (2) access activity (e.g., most downloaded files and most requested images), (3) referrer (e.g., search engines), (4) browsers (e.g., Google Chrome), and (5) error types. Since the current study is interested in website stickiness, only general activities including the number of visitors, number of pages viewed, and hits performed, were included in subsequent data analysis.

In the data pre-processing stage, all extreme browsing weblog data (i.e., unusually small or large visitor numbers, page viewed numbers, hit numbers) were eliminated. The output from the Weblog Expert were then imported to Microsoft Excel and Statistical Package for the Social

Sciences (SPSS) for further statistical analysis. After the first round of analysis, 154 outliners were detected and excluded. At last, a total of 29,822 valid observations were retained for subsequent data analysis. In the next stage, patterns in data are identified using descriptive statistics, and later on analysed using statistical tools. Since the F-test used in ANOVA is a robust method against the violations of normality assumption (Schmider et al., 2010), thus data distribution is not a concern.

Results

Descriptive statistics

Descriptive reports generated from the 29,822 weblog data indicate that there were in total 5,454,871 visitors to the website of Hotel A from August 1, 2014 to December 31, 2017 (i.e., 4381 visitors on average per day). During this period, a total of 15,078,923 pages have been viewed with 246,195,066 hits. All mean values for the number of visitors, pages viewed and hits shown in the following tables and figures are expressed in per hour basis. On average, there are 182 visitors accessing the website per hour, with each viewing 2.76 pages on the website. The average time that a visitor spent on the website is around 5 minutes, while the main browser used by them is Chrome. The following presents the results of the temporal analysis of website stickiness (i.e., the number of visitors, pages viewed, and hits performed) in the sequence from yearly, to monthly, to daily, and hourly bases. Besides providing a general yearly pattern, the yearly differences in the three temporal dimensions (monthly, daily, and hourly) are also examined and discussed.

Year-varying website stickiness

As shown in Figure 1, the number of visitors to the hotel website increased steadily from 146/hour in 2014 to 179/hour in 2015 and to 201/hour in 2016, but it slightly dropped to 199/hour in 2017. More fluctuations have been observed in terms of the number of pages viewed and the number of hits performed on the website. Specifically, both figures increased significantly from 2014 to 2016, but a sharp fall is noticed in 2017. Further, there is a constant decrease in the average number of pages viewed by each visitor to the website from 3.23 pages in 2014, to 2.97 pages in 2015, to 2.93 in 2016, and to 2.29 in 2017.

***** Please place Figure 1 here *****

Month-varying website stickiness

The monthly browsing weblog data were categorised into 4 groups, corresponding to the four quarters in a year, including (1) January to March, (2) April to June, (3) July to September, (4) October to December. Since data were collected only from August in 2014, and full year data for year 2014 was not available, all data in 2014 have been removed in the monthly analysis to maintain consistency. ANOVA and post-hoc comparison were used to further elaborate and compare the differences among the four quarters.

According to Table 1, there are significant differences among the four quarters in terms of the number of visitors, number of pages viewed, and number of hits, indicating that stickiness of hotel website visitors vary from quarter to quarter. The results of the post-hoc comparison show that in year 2015, the first two quarters (January to March and April to June) represent the low user season, during which there were less people visiting the website and performing less hits. The number of pages viewed, however, is the highest during these two quarters. Interestingly, quarters 3 and 4 (i.e., July to September and October to December) are the peak seasons, with highest number of visitors to the website, performing more hits, but viewing less pages on the website.

In 2016, a different pattern was observed. The first two quarters maintained moderate levels of visitors, but less number of pages were viewed. The third quarter is still the peak season, with the most number of visitors, viewing the largest number of pages and performing the most number of hits. Different from the previous year, the last quarter became the low season, as both the numbers of visitors and hits are the smallest. The pattern, however, changes again in 2017. Besides the third quarter, quarters 1 and 4 became the more popular seasons, as indicated by the increased number of per hour visitors comparable to quarter 3. The number of pages viewed and number of hits are the highest in the first and fourth quarter. The second quarter attracted the least visitor activities and is again the low season of the year. Despite the existence of differences in patterns observed among the three years, the third quarter (i.e., July to September) is consistently shown to be the peak season, and the second quarter (i.e., April to June) is the off-peak season.

***** Please place Table 1 here *****

Diurnal website stickiness

Table 2 presents the day-varying website stickiness of users, which reveals substantial differences among the seven days in a week in terms of the number of hits, pages viewed, and visitors. In general, significant differences are observed between weekdays and weekends, and users tend to be less active during weekends than weekdays. Additionally, an interesting pattern is observed when comparison is made among the four years. In 2014 and 2015, users have been more active on Mondays and Tuesdays, as evident from the highest number of visitors, number of pages viewed, and number hits per hour. Users then became less active as the week passed by as shown in the gradual reduction of visitors, pages viewed and hits in the website. However, this pattern has changed in 2016 and 2017. In the later years, users have been more active during Wednesday and Thursday, but not on Mondays and Tuesdays. Nevertheless, weekends, particularly Saturdays, are still shown to be the day with the least activities throughout the week. Interestingly, in 2017, users became more active on Fridays and Saturdays. They viewed more pages on Fridays than on any other days of the week. This suggests that users' browsing patterns have changed over time.

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Intradiurnal browsing activities

Understanding the time patterns of using websites is also important. The hourly data were further categorised into four groups, including (1) Night from 00:00 to 05:59, (2) Morning from 06:00 to 11:59, (3) Afternoon from 12:00 to 17:59, (4) Evening from 18:00 to 23:59, to allow better interpretation of the results. Table 3 shows users' browsing behaviours by hour from 2014 to 2017. The F-tests show that significant differences have been observed among the four sessions in terms of the number of hits, number of pages viewed and number of visitors for all four years. The post-hoc comparison results show that all four hour sessions differ significantly unless specified in the table (the mean difference in the number of visitors for hour session afternoon (3) and evening (4) in year 2017 is not significant; the mean difference in the number of hits for hour session afternoon (3) and evening (4) in year 2016 is not significant).

***** Please place Table 3 here *****

As shown in Table 3, the night session (i.e., 00:00 to 05:59) is generally the least popular time session with the least number of visitors and number of pages viewed. Also, the afternoon session (i.e., 12:00 to 17:59) is the most popular time period with the greatest number of visitors and pages viewed. This observed pattern is the same across three years from 2014 to 2016. In 2017, however, afternoon and evening sessions do not demonstrate significant difference in the number of visitors. This means that the number of visitors is the highest from noon time till mid-night (12:00 to 23:59) in 2017. On the other hand, in terms of the number of hits that users performed on the website, the afternoon hour session is also the most active session, with the highest number of hits in 2014 and 2015. In 2016, however, the afternoon and evening sessions do not demonstrate significant difference in the number of hits. Interestingly, in 2017, the number of hits is the highest in the evening (18:00 to 23:59).

Discussions and conclusions

Discussions

Findings in the current study show that website stickiness of hotel website demonstrates rich temporal dynamics on yearly, monthly, daily, and hourly bases. The number of visitors to the hotel website increased steadily from 2014 to 2016, but dropped in 2017, while the number of pages viewed and hits performed on the website increased from 2014 to 2016, but dropped significantly in 2017. This sudden decrease in the number of hits and pages viewed may be attributed to the redesign of the hotel website happened in 2016. Specifically, with the new website, visitors may be able to retrieve the desired information with reduced number of clicks. Tarafdar and Zhang (2008) stated that a website allowing visitors to easily reach out the pages and obtain the needed information without excessive clicks reflects its ease-of-navigation and high effectiveness. Also, Leung and Law (2008) point out that the less number of hits performed on a website, the more attractive the hotel website is and the better the hotel's performance. Despite the sudden decrease in the number of hits and pages viewed may represent lower website stickiness behaviours of users, it may be a good indication that Hotel A's website is performing well after the reconfiguration of the website.

On monthly basis, users are more active during summertime from July to September, while significantly less activities were observed during April to June. This finding may be associated with the high tourist arrival figures during summer holiday in Hong Kong. According to the Hong Kong Tourism Board (2017), tourist arrivals in Hong Kong dropped significantly in the second quarter, and increased rapidly in the third and fourth quarter in 2017. With more visitors to the city, more people will access the hotel website for information search, planning, and booking. This is in line with the existing literature that users are looking for information in the immediate period before arriving to the destination, rather than well in advance (Babin and Kim, 2001). Moreover, the surge in visitor number, pages viewed, and hits in summer time may also be attributed to the increased promotional efforts of the hotel during that period. Nevertheless, the month-based variations reveal that website stickiness is in line with tourism seasonality (Yang et al., 2014; Wu et al., 2017). In other words, peak seasons usually generate more website visitors and hits because of the high demand of tourism-related products, whereas low seasons usually witness fewer visitors and hits due to low demand. The discrepancy between the number of visitors and hits, and the number of pages viewed may also be explained by seasonality. More precisely, low seasons leave people ample time to browse more web pages and allow them to make decisions after obtaining a thorough understanding of the tourism suppliers and products, whereas high seasons normally urge visitors to make a decision quickly before the rooms are sold out.

Regarding diurnal patterns, the current study found that users tend to be more active during weekdays than on weekends, which concurs with the findings of existing research (Law et al., 2018; Leung et al., 2016). A more detailed analysis shows that users' website stickiness have changed significantly from 2014 to 2017. At first, users were more active at the beginning of the week (Mondays and Tuesdays) and became less active as the week passed by. They may probably discuss with friends and family during the weekend and come back to the working week to make bookings. This is in line with other studies about online purchases (Kooti et al., 2016; TrekkSoft, 2019). However, this pattern has lasted only for two years. Users became more active in the middle of the week in 2016. This reflects that users may take a mid-week break from their work to perform online search for their trips. Thus, users might have become more interested in the hotel and its services in the middle of the week, when they started to look for leisure or entertainment activities for Fridays or weekends. This finding supports recent finding of Keller's (2018) that Thursdays are the most depressing day of the week for full-time workers, and therefore they look for entertainments and fun on Thursdays. Interestingly, users became more active on Fridays in 2017. Escapism and less work assigned on the last working day of the week may explain this pattern (Keller, 2018). Nevertheless, Saturdays were always the day with the least activities. This is probably because users are doing their weekly chores and often are occupied with outdoor activities such as weekly shopping (Hassan et al., 2015).

In terms of intradiurnal dynamics, it was found that users frequently visit the hotel website and view more pages in the afternoon, while significantly less at night. The finding is consistent with other studies (e.g., Law et al., 2018). Integrating the two findings on diurnal (higher website stickiness on weekdays than on weekends) and intradiurnal dynamics implies that users tend to visit the hotel website during office hours, when they can sit down and browse information. Evening and night times are typically dedicated to social routines, such as dinner with friends and family. It is interesting to observe that users have gradually become more active in the evening as can be seen from the increased website stickiness from 18:00 to 23:59 in 2017. This shows that many of the travel decisions were made with friends and family whilst browsing websites have their hedonic value and are often treated as a form of indoor entertainment (Babin and Kim, 2001).

Theoretical implications

Existing studies on website stickiness focused on identifying its antecedents and its structural relationships with customers' responses. For example, Lin (2007) showed that users' attitude towards and trust in the website and quality of the website content contribute to the formation of website stickiness, which predicts users' intention to purchase. Roy et al. (2014) found that stickier users have a higher tendency to spread positive WoM about the website. This study enriches the existing knowledge on online consumer behaviour by investigating the temporal variability of website stickiness per se, which sheds light on the importance of considering the factor of time in research related to this complex construct. Although existing research supports the temporal patterns of consumers' online search and browsing activities (Backstrom et al., 2009; Kaur and Aggarwal, 2015; Law et al., 2018; Leung et al., 2016), they all focused on identifying diurnal and intradiurnal patterns based on data covering one single year. The current study supplements prior studies by obtaining data covering a longer period in order to provide more robust findings and identify seasonality and changes in website stickiness over time. In particular, this study shows that website stickiness patterns do not change only throughout the day and between days, but these patterns also change throughout years.

Additionally, this study contributes to the overall conceptual development of website stickiness. Findings of prior studies show that website stickiness is a multi-faceted construct, which can be represented with various dimensions, including frequency of visit, duration of stay, and amount of information viewed (Elliot et al., 2013; Lin et al., 2010; Roy et al., 2014). These studies tend to advocate the advantages of sticky websites, due to the positive association found with customers' responses (Elliot et al., 2013; Lin et al., 2010). Considering other aspects of website stickiness, including the number of visitors, pages viewed, and hits performed (Plaza, 2011), the current study shows that website stickiness is a complex construct which needs to be carefully considered. Specifically, being sticky and having users to access many pages may indeed signify low website performance, since users cannot locate the needed information easily. This should inspire scholarly works on website stickiness to reconsider its definition as well as its impacts on consumers' responses in the future.

Management implications

Understanding the fluctuations of online consumer behaviours supports decision making and enables managers to address a number of challenges and opportunities. From a technology point of view, organisations need to ensure the scalability of their websites and also their technological systems including e-commerce booking and payment systems. Technology need to be able to predict peak periods and deploy sufficient resources to deal with the extra traffic and pressure on systems and to recover fast from downtimes. Website developers should perform load tests and simulate traffic to their websites in order to ensure that the capacity of their websites are able to meet demand and activities during peak periods. Operationally, understanding the fluctuation of times when consumers engage with websites determines when customer services and support are required for resolving possible questions and support transactions. It is at that times when help desks need to be staffed and sales support need to be available. Practitioners should clearly recognise that these hours may be unsociable and may not reflect normal working hours of marketing, sales or reservations, but rather when consumers would like to interact and transact. On the other hand, off-peak periods may be useful for staff relaxation, data backup, and website maintenance and upgrade, so that customer experiences will not be affected.

Appreciating seasonality, not only in weeks and months but also in hours, may improve marketing mix formulation and concentrates promotional campaigns and expenditure. Bringing the right message online and on social media, when prospective customers aim to engage in dialogue, find additional information and make reservations is critical to facilitate bookings. During popular time periods, Hotel A may want to grasp the opportunity to push more real-time promotional messages to encourage unplanned purchases and convert website browsers to actual customers (Hui et al., 2013). This may increase the effectiveness of its marketing efforts as a larger user base could be reached during those time periods. Hotel operators should not overlook the time periods with less activities. According to Yang et al. (2014), website traffic volume reveals the purchase intentions of customers, and is closely related to hotel occupancy. Little traffics and activities imply that resources are being underused, therefore affects profitability. Thus, more events and promotional activities could be offered to boost traffic or activities on the website during off-peak periods, such as the second quarter. To fully utilise the hotel website as a marketing and distribution channel, more collaboration with popular search engines and social media sites should be done during off-peak seasons, quite days and hours, to enhance visibility of the website to the target audience. All these have direct implications to the competitiveness and profitability of organisations.

Finally, pricing may reflect patterns of demand but also patterns of engagement. If for example people who spend time late at night concentrate on finding lower rates, in contrast with business customers who may appreciate facilities or convenience over price, may lead to differential pricing and alternative offers being available at different times. Understanding what is the time horizon for the delivery of the service and in particular when customers try to book services in real time (Buhalis and Sinarta, 2019) call for the integration of contextual information and interoperability with complementary systems towards dynamic packaging and pricing. Therefore, timing enhances the effectiveness of dynamic pricing and revenue management.

Limitations and future research

Fluctuations in demand and activity reflect the aggregate effect of individual users' time loyalties (East et al., 1994). To summarise, users of the website of Hotel A is the most active from July to September, on weekdays, from noon to evening time. They are least active from April to June, on weekends, and at night. Although a relatively large amount of data from 2014 to 2017 has been obtained and analysed in this study, the results of time-vary browsing behaviours may not be generalised to the whole industry or worldwide due to the geographic constraints. Likewise, other socio-economic factors (i.e., users background and experiences) and contextual factors (i.e., whether users are at home or at work) may have influenced the results, since these factors are likely to activate different goals (Luo et al., 2014).

Furthermore, the role of external factors such as major events (e.g., Hong Kong Arts Festival), political instability (e.g., the Umbrella Movement in 2014), changes in government policy, and public holidays in major source markets, have not been considered in the current study. Future studies may develop more complex models or include dummy variables to identify the role of events in influencing online browsing activities. In particular, not only the presence of such events, but also their duration, scale, and popularity should be considered. Future research is suggested to take more sample of hotels in different regions that experience different seasonality patterns to further strengthen the findings mentioned above.

Additionally, the underlying rationale of consumers' stickiness to websites represents a promising area of research, which may be explored using qualitative studies, so as to further exploit the meaning and conceptualisation of this multi-dimensional construct. Temporal studies in offline context show that the day and time when people purchase will affect their satisfaction and enjoyment (Geiger, 2007; Shannon and Mandhachitara, 2008). Thus, future studies may also explore the potential differences in customer e-satisfaction and enjoyment when they browse a website at different times.

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