Tourism R

Google Popular Times toward Understanding of Tourist Customer Patronage Behavior

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Google Popular Times: towards a better understanding of tourist customer patronage behavior

Introduction

Whether visiting a city for the first time or just looking for variety when eating out in one's hometown, consumers will inevitably be looking for suitable times to visit particular restaurants. For example, they may want to time their visits to avoid excessive crowds. Tourists and city inhabitants worldwide repeatedly confront such challenges. Increasingly, social and mobile technologies may help consumers to make these decisions. However, as argued in this paper, these applications may be useful to a range of tourism industry stakeholders and researchers, not just consumers. The most commonly used application for this purpose (and subsequently examined in this paper) is Google Popular Times (Google, 2017), where the applications ease of use and updated social feedback has boosted its popularity. To the extent that the information in the application matches theoretical assumptions and is logically consistent, such information may be useful in future customer behavior research for many business sectors, especially the tourism sector. However, this kind of data source has received relatively little attention in prior research in terms of its potential to contribute to tourism and hospitality research aimed at predicting and understanding customers.

The use of social information systems (Schmidt et al., 2019) as a source of support for tourism and hospitality (e.g., decision making) is becoming more important in both practice and research as highlighted by Buhalis (2020). Vast amounts of information can be collected automatically and user-generated content and recommendations allow the exploration of tourist satisfaction (Narangajavana et al., 2019). The advantages and drawbacks of social network utilization in travel and tourism were discussed by Kacetl and Klimova (2018). Geo-tagged photos in social media have also been used to create travel recommendations as described in Memon et al. (2015). Further, Liu et. al. (2018) suggested that the experience of sharing on social networks drives tourism consumption. Discussion has also explored the impact of real-time co-creation on tourism and hospitality (Buhalis and Sinarta, 2019). The advantages and challenges of data-centered platforms in tourism are discussed by Keller et al. (2017). The impact of technology on services and hospitality have also been investigated (Buhalis et al. 2019; Buhalis, 2020).

Google Popular Times is not only a location-based service according to Junglas and Watson (2008) but also a data source. Google Popular Times (2017) uses aggregated and anonymized data from Google location histories (Google, 2017) to provide insights into the popularity of places and especially places related to tourism and leisure. Thus, information about the relative number of visitors, as well as visit duration times, can be combined with customer reviews and other information (such as the type of place) from Google Places (2017).

Importantly, the data collected by Google Popular Times (2017) may provide insights with less potential bias about what individuals are actually doing. In the past, the collection of data in relation to the number of visitors and duration of visits to geographical places like restaurants or museums were required manual observation and were subsequently labor-intensive. Based on Google Popular Times (2017) it may be possible to observe and predict consumer visiting behavior more accurately, enabling customers as well as suppliers to use this information for better decision making. Such a view is supported by research into online environments that found consumer online behavior is more valuable for forecasting than data gained from surveys (e.g. Holland and Mandry, 2013; Lohse et al., 2000). As a result, tourism suppliers are better able to respond to staffing and visitation duration questions.

Despite these potential advantages, there is only sparse research drawing upon Google Popular Times data. Therefore, this work undertook a systematic literature review (Cooper, 1998; Webster and Watson, 2002) with the following keywords “Google popular times”, “popular times”, and “Google” utilizing leading scientific databases including ACM Digital Library, AISel, IEEExplore, SpringerLink, and ScienceDirect to reveal the paucity of in-depth research. From this limited literature Neves et al. (2016) suggests that data based on Google Popular Times is indicative of cultural characteristics and Plebani et al. (2017) argued that it is an alternative data source for multi-party business process resilience. Less related to this work, “popular times” has been used to explore car traffic data through Google Maps. This lack of research is somewhat surprising given the usefulness of the prediction of consumer behavior in relation to places, the number of visitors, and visit duration for tourism research and practice (e.g., Arndt and Gronmo, 1977; Dacko, 2012; Davies and Prentice, 1995; Todd and Lawson, 2001).

In the past, manual collection of this data involved considerable time, cost, effort, and often resulted in incomplete and possibly biased datasets based on surveys or human observation. Location-based information provided by smartphone users, addresses this challenge and elicits further advantages (Moussouri and Roussos, 2015). Moussouri and Roussos argued that addition to the advantages above, visitor modeling is easier and more precise, and that large sample sizes and long-term investigations are more feasible due to substantially decreased costs. Furthermore, possible relationships to other important sources for decision making such as online reviews (Gretzel and Yoo, 2008; Vermeulen and Seegers, 2009) has also been underutilized within research to date. Thus, there is an opportunity to close the research gap in these areas. However, Google services such as Google Trends have been tested to be more reliable and favorable than standard data (e.g., survey-based data) for use in forecasting (Vosen and Schmidt, 2011). Therefore, this paper aims to investigate how behavioral data from Google Popular Times may support predictions in relation to customer behavior. In doing so, the aim of this study is to establish both a methodology and findings that demonstrate the use of Google Popular Times data to better understand and predict consumer behavior. Further, suppliers themselves may be in a better position to initiate actions that may influence customer behavior to increase individual and collective value. For example, by identifying demand patterns and thus identify appropriate points in time for triggering effective marketing actions, activities, and messages.

The paper will proceed with a discussion of the background of Google Popular Times and related concepts. The research model is then presented followed by the research methods and data collection approach. The results are described in the fifth section. Finally, the conclusion provides a discussion of the final implications of the work.

Background

Reviews and evaluations of touristic sites can be important sources to support improved decision making. This is especially so for touristic products which are services and cannot be tested in advance. Therefore, reliable information of touristic sites is a central issue in the decision-making process for many different stakeholders. Collecting and reviewing travel information plays an import role in the travel decision-making process to reduce risk as tourism-related products and services are expensive and require high consumer involvement (Jeng and Fesenmaier, 2002). Social media therefore, has been widely adopted by travelers to organize and share their journeys (Chung and Buhalis, 2008; Leung et al., 2013). Furthermore, social media has changed the way tourists search for restaurants (McCarthy et al., 2010; Zhang et al., 2017). Subsequentially, providing precise information on touristic sites such as restaurants may now be crucial for customer satisfaction and competitiveness (Buhalis, 1998). Social media supplements vendor-created information with information from other consumers. At the same time, social media touristic sites to interact with potential customers in a relatively directed and efficient way (Kaplan and Haenlein, 2012).

Google Popular Times provides the user with information about prior visits and the current number of visits within a geographical place (Google, 2017). The data are aggregated and anonymized from users based on their Google location history (Google, 2017). Thus, the location-based service provides information about a wide range of geographical places (Junglas and Watson, 2008). However, the data are only available if there is a minimum number of past visits.

According to Google there are three types of data that are collected during the opening times and the information is updated hourly (Google, 2017; Google Places API, 2017)

- Popular times graph,
- Visit duration, and
- Live visit data.

As an illustrative example, the famous "Hofbräuhaus" (Hofbräuhaus, 2017) in Munich is displayed in Figure 1. As demonstrated in the figure it shows aggregated information about the number of visitors for a given day of the week relative to peak demand and the live visit data showed that, at the time it was viewed, the location was not busy (Google, 2017). The data shown is in a relative range. According to Google (Google, 2017; Google Places API, 2017) popularity, which can also be described as the number of visits, is shown "relative to the typical peak." This peak can also differ from place to place. This kind of data representation is similar to Google Trends (2017) and past research (e.g. Choi and Varian, 2012; Google Trends, 2017; Vosen and Schmidt, 2011) has shown that this data can be used as a strong predictor.

Fig. 1 Distribution of visitors over time at the Hofbräuhaus Munich as shown in Google Popular Times (Hofbräuhaus, 2017).

In general, the display results from a mapping process of the geographical position of the user (e.g., via GPS) and place location (i.e., restaurant) within a defined visiting time. GPS, Wi-Fi, and cellular information is used to determine the geographical location (Zandbergen, 2009). Based on timestamps and the location mapping, services like Google Popular Times (2017) can be offered. Information about the geographical position of a place is provided by Google Places API (Google Places API, 2017; Singhal and Shukla, 2012). The data provided by Google Popular Times can be seen as actual visiting data originating from customers using Android smartphones or Google apps on various operating systems (e.g., Apple iOS) activating location services. It can be said that in this way Google Popular Times uses the "wisdom of the crowd" approach (Surowiecki, 2005) for knowledge creation. The "wisdom of the crowd" approach collects many data points from ordinary visitors and aggregates them to replace the views of experts. Additionally, it addresses a criticism of traditional search engine methods that require matched keywords to produce relevant information (Paraskevas et al. 2011).

Research Model

This study will focus on city center restaurants in Munich (Germany) within an inductive research approach (Krishnaswamy et al., 2009). Munich is considered to be a famous and livable city in Europe (Munich, 2017; Valencia, 2017), and restaurants are an important place for various stakeholders in the tourism and hospitality sector (Keller et al., 2017; Lennon, 2003; Xinyue and Yongli, 2008). As this subject is important in research (e.g., Gretzel et al., 2015; Rishika et al., 2013; Ye et al., 2011), the study investigates a restaurant sample.

A characteristic of human behavior is that people prefer to avoid a loss within a given situation (Kahneman and Tversky, 1979). Therefore, they will look for additional information, especially where there are several options and there is a level of uncertainty (Tversky and Kahneman, 1975). Through online information, customers can find useful information using review platforms and sites (Gretzel and Yoo, 2008; Vermeulen and Seegers, 2009). These are particularly popular as people perceive them to be trustworthy, as the information comes from other customers not just the supplier (Zhang et al., 2010). Additionally, people tend to use this as a heuristic – the "wisdom of the crowd" (Surowiecki, 2005). If enough people share an opinion, this opinion becomes the truth for other people facing a similar decision. Google has implemented consumer reviews into Google Popular Times (based on Google Places) which are available to users, thereby supporting decision-making processes. This is particularly interesting given that Google Popular Times gathers behavioral data. Therefore, the impact of pre-existing customer reviews on consumer behavior can be revealed and measured with less bias because people decide for, or against, a visit and this behavior is assessed (e.g., where the limitations of surveys such as misleading answers are absent).

Online reviews are an important information source for tourists (Gretzel and Yoo, 2008). Reviews are used to evaluate different services related to an individual's preferences. Restaurant reviews often include topics such as food quality, service, or price as a foundation for decision making (Chaves et al., 2014). Prior research has found that the number of online reviews tends to have a positive impact on a consumer's purchase intention and can be seen as a heuristic (Park et al., 2007; Zhang et al., 2010, 2017). Further, crowd-generated knowledge enjoys a high degree of trust (Surowiecki, 2005) in accordance with social proof theory (Aronson et al., 2005; Rao et al., 2001), where the behavior of others are integrated and the combined intelligence feeds the decision-making process. However, too much information may cause negative reactions. In literature, the phenomenon is known as “information overload” (Feather, 1998; Sthapit et al., 2019). Thus, information must be compressed and customer oriented.

Using review sites through various applications, people can more easily find information (gather intelligence), reduce search costs, and facilitate the decision-making processes (Chen et al., 2004). This work aims to transfer these approaches to Google Popular Times and contribute to the field of consumer behaviour data by enriching prior results and establishing additional insights. Accordingly, the study will establish multiple hypotheses for the empirical testing of the suitability of Google Popular Times as a source of information that supports tourism decision making processes. At the outset, we posit that the preceding conceptual motivations suggest that the data patterns resulting from Google Popular Times data analyses will predict that, the more reviews available for a given restaurant, the more people are likely to visit the restaurant on average. Therefore, the following hypothesis is proposed:

H1: The number of customer reviews for a given restaurant can predict number of visitors on average.

Also, in line with prior research findings (e.g. Tsao et al., 2015; Zhang et al., 2014), we further expect that the overall rating of the reviews will predict the number of visitors. In other words, the more positive reviews available, the greater the number of visitors. This should be indicated by data gathered from Google Popular Times. Specifically, its review platform is based on a five-star system (1 star: very bad; 5 stars: very good). If the average evaluation of a restaurant increases, the number of visitors should also increase. The presence of this condition should facilitate the decision-making process. Moreover, it could be advantageous for a restaurant’s owner, where a rise in user evaluation may be a good indicator for future activities (e.g., integration of reservation systems). Therefore, the following hypothesis is proposed:

H2: The average rating of customer reviews can predict the average number of visitors.

For restaurant selection, Google Popular Times can be a beneficial tool for consumers to plan leisure activities given a valuable characteristic of the application are differentiated predictions. Specifically, for each day of the week and time of day in which a restaurant is open, user information is available (Dacko, 2012). Current research suggests, for example, that consumer behavior may vary by both days of week and time of day in terms of time budgets and available leisure-time (Bussiére, 2016; Dubois and Louvet, 1996; Hawes, 1977; Jerath et al., 2014). Importantly, timing aspects can be valuable in tourism, where services are highly perishable and planning for capacity and staff is critical. An understanding of these patterns overtime may enable major destinations, such as a city center, to more proactively manage tourism and overall people flows. For example, recognizing that a city center has a temporal rhythm that can be influenced by full-time work as well as touristic preferences, where typical work schedules may reduce free time to visit restaurants during the morning but increase in the evening. It is expected that there will be strong evidence of such time-of-day effects in the Google Popular Times data. Accordingly, the following hypothesis is proposed:

H3a: For any restaurant, the higher its relative eveningness, or average percent of evening visitors, the lower the overall numbers of visitors on average per day.

Similarly, recognizing that many consumers may tend to view a city center more as a place of leisure than work during weekends in comparison to working weekdays (Neuhaus, 2015), and where their own leisure time is also increased on weekends (Young, 1988), the data is likely to show day-of-week effects. Consequently, there may be some restaurants that specialize offerings and ambience to appeal to weekend consumers more than weekday consumers. Yet, as with restaurants with high eveningness, restaurants aiming for the weekend market may be less appealing during workdays, in comparison to restaurants with greater weekday or all-week appeal. Therefore, the following hypothesis is proposed:

H3b: For any restaurant, the higher its relative "weekend-ness," or average percent of weekend visitors, the lower the overall number of visitors on average per day.

Importantly, to the extent that there is found to be significant systematic differences in restaurants for these variables, it may be useful to then control for such influences when seeking to explain and identify other factors that may also influence the number of restaurant visitors on average per day.

Google Popular Times provides various pictures of the restaurant, where available. These pictures are either provided by the restaurant, customers, or both. In line with prior research, pictures may help the consumer to better understand and evaluate the service (Blanco et al., 2010; Jiang and Benbasat, 2007). Therefore, pictures are an important resource for consumer decision making. Again, drawing upon social proof theory (Fuller et al., 2007; Rao et al., 2001) and the wisdom of crowds view (Surowiecki, 2005), it is likely that customers may be motivated to upload pictures of good and bad aspects of restaurants via Google Popular Times. The consumer can evaluate if the service fits with individual preferences and visual information may further enable evaluations, which may lead to increased visits (Salleh et al., 2016). Therefore, the following hypothesis is proposed:

H4: A higher proportion of pictures correlates with the average number of visitors.

Furthermore, Google Popular Times provides information about the different price segments of restaurants - from cheap (€) to very expensive (€€€€). Consumer behavior is known to be influenced by price range information (Kahneman and Tversky, 1984; Zeithaml, 1988) as price is a factor in the trade-off between cost and benefit from a consumer's point of view (Monroe, 1990; Varki and Colgate, 2001; Zeithaml, 1988). Psychological theory, suggests consumers may use price heuristics to infer the quality of a product or services (Gilovich et al., 2002; Kahneman and Tversky, 1984). For example, if the price segment of a restaurant is high, the consumer expects high-quality food and service and, all else being equal, a consumer would prefer a restaurant with quality food and service (Namkung and Jang, 2007). As restaurant prices increase, proportionally fewer consumers in any population with a normal income distribution may find such restaurants to be affordable. Conversely, as restaurant prices decrease, a greater number of consumers may find such restaurants to be affordable and accessible. Therefore, the following relationship is hypothesized between the price segment and the average number of visitors:

H5: Compared to higher price category restaurants, lower price categories of restaurants will have a relatively higher average number of visitors.

Google Popular Times provides another potentially useful source of information to service providers as it enables an investigation of visit duration based on actual consumer behavior. Taking into account how busy a restaurant is in terms of the number of customers visiting at any given time, constraints on restaurant service capacity would suggest that the greater the number customers, the shorter the length of stay (Fitzsimmons et al., 2006). If a restaurant is very busy, for example, the staff may be incentivized to lessen the wait of customers yet to be served. Furthermore, restaurant managers tend to reduce the dining duration in restaurants with high demand to maximise increase revenue (Noone and Kimes, 2005). Thus, the following hypothesis is proposed:

H6: An increasing average number of visitors predicts a decreasing length of stay.

Given the above conceptual and empirical motivations from prior research in support of the hypotheses, the following research model is proposed (Fig. **2**). The following section will present the collection and analysis of the data from Google Popular Times.

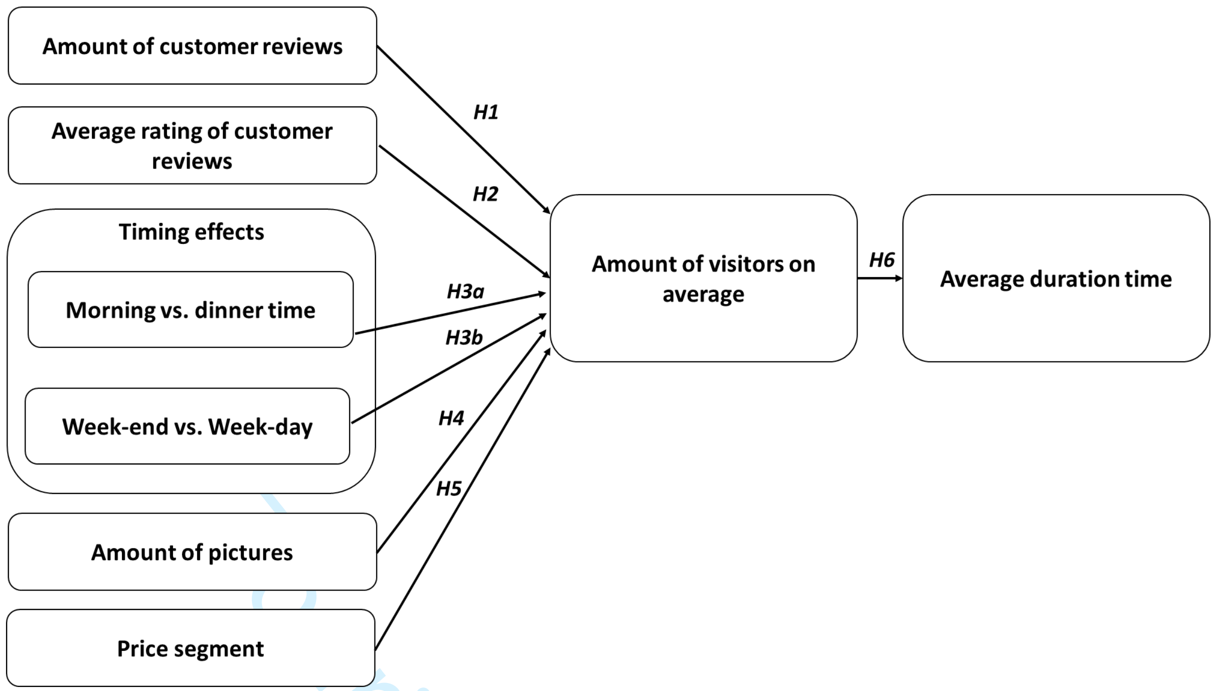

Fig. 2 Research Model showing the relations investigated in the hypotheses testing

Research Methods and Data Collection

One challenge for data collection is that Google Popular Times data is not provided via an API or in a structured form from Google. Another challenge was Google blocking access after a specific number of HTTP-requests. Therefore, it was necessary to build a software tool to conduct this research. According to general recommendations (Avison and Fitzgerald, 2003; Naumann and Jenkins, 1982), a web crawling and analysis tool was designed, implemented, and tested. Using PHP and VBA, as well as Python for the programming and testing which enabled us to ultimately create a software tool (artifact) able to collect the data (Peffers et al., 2007).

Before, the data collection was performed, the software tool was validated and pre-tested against data manually collected for N=96 restaurants. This pre-test showed that the data collection tool performed successfully and reliably.

Following the pre-test, data collection was run for restaurants in Munich using a computer/server located in South Germany. Data was only collected from restaurants in the Munich city center for the data sample to enable a sufficiently homogenous sample. Specifically, the common geographic area for all restaurants allowed the exclusion of the influence that public transport availability may have on the findings. Furthermore, the restaurants in the city center of Munich are primarily visited by tourists and not by townspeople. Therefore, it is expected that there will be a high correlation between restaurants, tourists and Google Popular Times as an information tool in decision-making processes. After data cleaning (e.g., removing extra restaurants where named twice, fake restaurants with fantasy names) a final sample of approximately 20,000 time periods for *N*=192 restaurants were obtained. This dataset represents a full census of the restaurants in the observed area for the investigation tool. The average number of reviews per restaurant was 136 and the range for star ratings was between 2.5 to 4.8 stars. Visit duration data were available for 130 of the 192 observed restaurants. The average number of pictures per restaurant, as shown on Google Popular Times, was 77. The range for the restaurant price segments was from a low of 1 (€) to a high of 4 (€€€€) and the average price segment of the observed restaurants was 2.39 (€€). The price segment was not displayed for five restaurants in the sample. Visitor information was available for all restaurant opening hours. All of the different data objects were collected through a programmed software tool crawling the Google website as described above.

In accordance with the research model and hypotheses, bivariate linear regression analyses (Boscovich, 1757, 1760; Recker, 2013) and Bravais-Pearson correlation analyses (Cleff, 2014; Lee Rodgers and Nicewander, 1988) were chosen for statistical analyses. This approach is commonly used in research investigating consumer behaviour (e.g., Clark et al., 2005; Moschuris, 2008; Wohlfeil and Whelan, 2006). Regression analyses was applied to investigate the relationships between the independent variables (e.g., the number of reviews, the average rating of reviews) and the dependent variables (number of visitors on average, visit duration). Therefore, for H1, H2 and H6, the following regression equations (Keller, 2014) were defined respectively:

Equation 1 -- the regression equation for H1:

$$Average\_Number\_of\_Visitors = \beta_0 + \beta_1 * \mathrm{Amount\_of\_Reviews} + \epsilon$$

Equation 2 -- the regression equation for H2:

$$Average\_Number\_of\_Visitors = \beta_0 + \beta_1 * \mathrm{Average\_Rating\_of\_Reviews} + \epsilon$$

Equation 3 -- the regression equation for H6:

$$Duration\_of\_Visiting = \beta_0 + \beta_1 * \text{Average\_Number\_of\_Visitors} + \epsilon$$

Additionally, for H1 and H2 and subsequently for H3a and b, further analyses were performed to incorporate time of day and day of week as controls, given that a restaurant's eveningness and weekend-ness may also influence the hypothesized relationships.

Table 1 Overview of the collected data

	Observed Restaurants	Mean	*SD*
Average number of visitors		21.94	6.59
Amount of pictures		77.05	59.75
Price segment		2.39	0.57
Average rating		4.09	0.40
Amount of reviews		138.32	154.26
Amount of visitors on weekdays	*N*=192	19.35	6.75
Amount of visitors on weekend		24.98	10.33
Amount of visitors at morning time		7.05	6.52
Amount of visitors at dinner time		38.91	9.89
Average visit duration	*N*=130	1.72	0.48

Results and discussion

In-line with the research model, the impact of the number of reviews on the number of visitors was investigated. Firstly, a bivariate regression analysis was undertaken to gain insights into the relationship and obtained the results as shown in Table 2. The data analysis revealed a positive beta coefficient ($\beta = 0.308$, p=0.00) and supported the first hypothesis. Additional analyses incorporating control variables of restaurants' eveningness and weekend-ness also reveals a positive beta coefficient ($\beta = 0.285$, p=0.00). In accordance with the conceptual rationale of this study, people are likely to use the number of reviews to facilitate their decision making, e.g., when going out to a restaurant. To avoid a loss, they trust in the knowledge other people gained during their experiences and integrate this information in their own decision-making. The more reviews available, the more people trust in the opinions of the prior visitors and utilize this information. Therefore, the number of reviews predicts a simultaneously increasing number of visitors. Among the implications of the finding is the suggestion that restaurant managers can potentially anticipate positive changes in demand at least in part by monitoring the extent of the increasing number of reviews.

Table 2 Regression results

		β	**t**	***p*-value (Sig.)**
H1	Constant		33.619	.000
	Amount of reviews	.308	4.520	.000
H2	Constant		7.13	.000
	Average rating of reviews	-.18	-2.59	.010
H3a	Constant		16.05	.000
	Restaurant eveningness *(percent evening visitors)*	-.434	-6.641	.000
H3b	Constant		8.006	.000
	Restaurant weekend-ness *(percent weekend visitors)*	-.127	-1.763	.079
H6	Constant		13.107	.000
	Average number of visitors	-.193	-2.230	.028

For the second hypothesis, drawing upon the findings of prior research the study hypothesized that the positive valence of customer reviews predicts the average number of visitors. Contrary to these expectations, the preliminary data analysis revealed a significant negative beta coefficient (β = -0.18; p=0.010) for the impact of positive customer reviews on the average number of visitors. Additional analyses incorporating the control variables of restaurants' eveningness and weekend-ness also reveals a negative beta coefficient (β = -.164, p=0.013). Nevertheless, this result is quite interesting and should be addressed in future research. Perhaps there are certain specific location-related, visual, or other characteristics of restaurants that tend to draw a large number of visitors passing by into the restaurants on a more spontaneous rather than planned basis. Yet, such customers retrospectively leave less-favorable reviews compared to customers frequenting restaurants having lower average numbers of visitors.

The research of Noone and Mattila (2009a) suggests that crowding negatively impacts customers willingness to spend more time or money. Additionally, Noone and Mattila (2009b) found that the service experience in a restaurant is dependent on the nature of consumption. If the consumption goal is primarily utilitarian, a non-crowded restaurant environment results in higher evaluations of service quality. On the other hand, crowded environments tend to receive higher service quality evaluations if the consumption goals are hedonic. Therefore, further research in relation to this issue of crowdedness may be beneficial to understand and explain this phenomenon.

Following on with the analysis, timing influences on demand was investigated as indicated in H3a and H3b based on the literature and findings of prior research that suggested time-of-day as well and day-of-week effects influence customer behavior (Bussiére, 2016; Dubois and Louvet, 1996; Hawes, 1977; Jerath et al., 2014). For H3a, the data analysis revealed a negative beta coefficient (β = -.434, p=0.000) and supported the hypothesis. For H3b, the analysis also revealed a negative beta coefficient (β = -.127, p=0.079) with partial support at $p<0.1$. However, analyses incorporating both variables of restaurants' eveningness and weekend-ness reveals a similar beta coefficient for restaurant weekend-ness yet at an even higher level of significance (β = -.136, p=0.040). The findings, therefore, support both hypotheses, firstly revealing a valuable insight into restaurants' temporal consumption behaviors and secondly further establishing the reliability and usefulness of the application as an indicator for planning leisure time activities. Among the implications of the findings is the suggestion that restaurant managers can make more informed decisions on multiple service elements.

In testing H4, the study evaluated whether a higher number of pictures correlated with the average number of visitors. Based on a Bravais-Pearson correlation analysis it was found a positive and significant correlation (r=0.328; p=0.01). Additional analyses controlling for timing effects found similarly significant results. Therefore, there was support for H4 and that pictures are an important source of information to consumers that may facilitate more-positive evaluations and lead to increased visits as the number of pictures increase. Clearly, an important implication is that restaurants should encourage patrons to post pictures coinciding with their dining experiences.

Hypothesis H5 examined the relationship between price segment and the average number of visitors where it was posited that, compared to higher price category restaurants, lower price category restaurants will have relatively higher average numbers of visitors. The findings indicated a significant negative correlation (r=-0.23; p=0.00) and additional analyses controlling for timing effects found similarly significant results. This suggests that a higher price segment leads to a lower average number of visitors and supports H5. The findings therefore suggest that while consumers may use higher price as a heuristic for quality, as restaurants' prices decrease, increasing numbers of consumers also find such restaurants to be more accessible. An implication for restaurant managers is the capacity to make pricing decisions with greater confidence in the expected outcomes, including the expected number of visitors.

Lastly, the relationship hypothesized in H6 was tested, where the larger the number of visitors the less time visitors are likely to spend in the restaurant. The regression analysis found a negative and significant beta-coefficient (β = -0.193; p< .05) as shown in Table 2. The finding supports the hypothesis, suggesting that constraints on restaurant service capacity when a restaurant is very busy may, for example, lead staff to be incentivized to lessen the wait of customers yet to be served. Clearly, such information provided by Google Popular Times may be potentially very useful to restaurant managers in their efforts to optimize reservation timing based on such consumer behaviors and capacity constraints.

Table 3 Correlation analysis results

		Proportion of pictures	Price category of restaurants
H4	Proportion of pictures	1	.23 **
H5	Price category of restaurants	.328 ***	1

***p < .01; ***p < .001*

Conclusion

This study has sought to demonstrate that the data provided through Google Popular Times matches theoretical assumptions to a high degree and is logically consistent. The findings as a result are potentially useful not only to consumers as tourists but also to a wider range of industry stakeholders and researchers. With actual behavioral data collected from aggregated and anonymized data from the Google Location History (Google, 2017), Google Popular Times offers the potential for both deeper and broader insights to those who are seeking to understand, analyze, anticipate, or predict consumer and tourist behavior.

Substantively, while the findings only establish correlations, they do provide some evidence for the view that customer reviews are significantly influential to the average number of visitors. Furthermore, the data supports expectations regarding differentiated customer behavior across the week as well as the time of day. The study also investigated visitor numbers impact on visit duration and found that there was a negative effect as hypothesized. Additionally, the analysis of actual customer behavior data has revealed another interesting point: the apparent negative impact of the valence of customer reviews on the average number of visitors. This finding is particularly interesting because it stands in contrast to the expectations of the study based on conceptual considerations as well as prior research. Such a finding may be useful to establish more clearly in future research. Therefore, future research could address this point more specifically and expand studies using both kinds of data—actual behavioral data as well as data gathered in experimental settings. Furthermore, it was also found that there was support for systematic relationships between both the price segments and the number of pictures, to the average number of visitors based on actual behavioral data.

In sum, the study offers a contribution by demonstrating how data from Google Popular Times can be used as predictors of the visiting behavior of consumers and to establish further behavioral insights. Importantly, the approach to gathering and analyzing actual customer data, as well as data on such a large scale, was previously far less practical due to manual counting visits and duration times. The study found that the provided information stands in line with theoretical considerations such as the “wisdom of the crowd” theory and the social proof theory (e.g., number of reviews predicting number of visitors). Therefore, the findings of this research are statistically valid as well as theoretically consistent. Multiple stakeholders, especially researchers, can therefore benefit from these results.

In terms of further consumer behavior and tourism management implications, the study validates the view that the tool provides valuable information to industry stakeholders in multiple ways. First, Google Popular Times and Places generally overcomes the restrictions of recent information systems in tourism as described by Leung (2019) as it automatically integrates different data sources, aggregates the data, and is updated without any effort by the user. While customers as tourists may benefit from knowing whether crowdedness or quietness will be experienced at a certain restaurant at a particular time, tourism and restaurant managers can benefit from the research by not only enabling further optimization of service operations and business processes, but also by adopting this approach for comparisons with other restaurants or geographical places in support of benchmarking (Camp, 1995). If, for example, a restaurant manager is more aware of when time-of-day impacts customer behavior, they can seek to more proactively manage it by offering specials in the mornings or implement price discounts at lunch times in comparison to the evenings. Finally, the results suggest it is important for restaurants to encourage customers to leave pictures and reviews.

Our research supports that Google Popular Times can be a useful tourism management decision support system tool in other ways as well. This understanding can help restaurants to continually and dynamically improve their service offerings in relation to differentiated customer preferences. For instance, building on prior research (Jeng and Fesenmaier, 2002) restaurants can better understand their consumers and refine their customer segmentation over time (Auty, 1992). Decisions about opening times can also be validated, which is a consideration for both restaurant owners and visitors (Auty, 1992). The research findings can also be further combined with increasingly sophisticated revenue management applications in restaurants in areas including demand forecasting, dynamic scheduling, and service resource planning (Ansel and Dyer, 1999).

As no research is without certain limitations, the following limitations were identified in this study. The first relates to the observed number of restaurants, the type of place (restaurant), and the location (region and country). The study concentrated on city center restaurants and on one city center in particular. As Google Places does not give detailed information on shopping malls, the data does not enable restaurants and shops within shopping malls to be examined. Furthermore, only visitors who use Google software and a smartphone were observed in the study thereby likely excluding some visitors from the analysis. Additionally, there were restrictions or limitations that were not able to be covered due to the characteristics of certain restaurants. For example, high priced restaurants might have relatively few seats because they tend to focus on a smaller customer segment. Unfortunately, Google does not provide this information. However, this might be a good starting point for future research, combining different data sources and benefitting from the advantages of different data collection methods. Finally, in the general population of visitors to a given restaurant, to the that extent actual behaviors vary between Android phone and mobile app users and non-users, there may be some possible bias in the sample, although it is not possible to know without further extensive research.

Accordingly, future research should expand sampling to other cities and countries as well as other types of geographical places (e.g., hotels, theme parks, etc.). In doing so, further geographical constraints or dependencies may also be discovered. Future studies could also explore the possible impact of different online reviewer profiles and reviewer behaviors such as the number of contributions (Zhang et al., 2010). Social review platforms like Yelp or TripAdvisor should be addressed in up-coming research, particularly the possible advantages initially linking to the SoCoMo-Framework (Buhalis and Foerste, 2015, 2013). Additionally, the progressing research stream to real time and ambient intelligence tourism (Buhalis and Sinarta, 2019; Buhalis, 2020) should investigated in the future. With the SoCoMo-Framework signposting opportunities on how marketing measures, especially in tourism, can be impacted by social and context factors

(Buhalis and Foerste, 2015), the integration of real customer data like Google Popular Times and Places could be one approach to develop an information base without the need to deal with customer privacy concerns. The behaviors of users on social networking sites like Facebook or Instagram including their related fan pages or posts could also be explored in combination with Google Popular Times for restaurants. Integrating these and other aspects of the data source into social CRM systems (e.g., Alt and Reinhold, 2012) and processes (Plebani et al., 2017) may provide valuable insights for both research and practice. Importantly, further complementary capabilities supporting and consistent with the progression to real time and ambient intelligence tourism should also be explored and critically evaluated. Especially in terms of being able to help maximize the benefits associated with continually sensing tourism environments and responding both strategically and tactically in a more humancentric manner.

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Fig. 1 Distribution of visitors over time at the Hofbräuhaus Munich as shown in Google Popular Times (Hofbräuhaus, 2017).

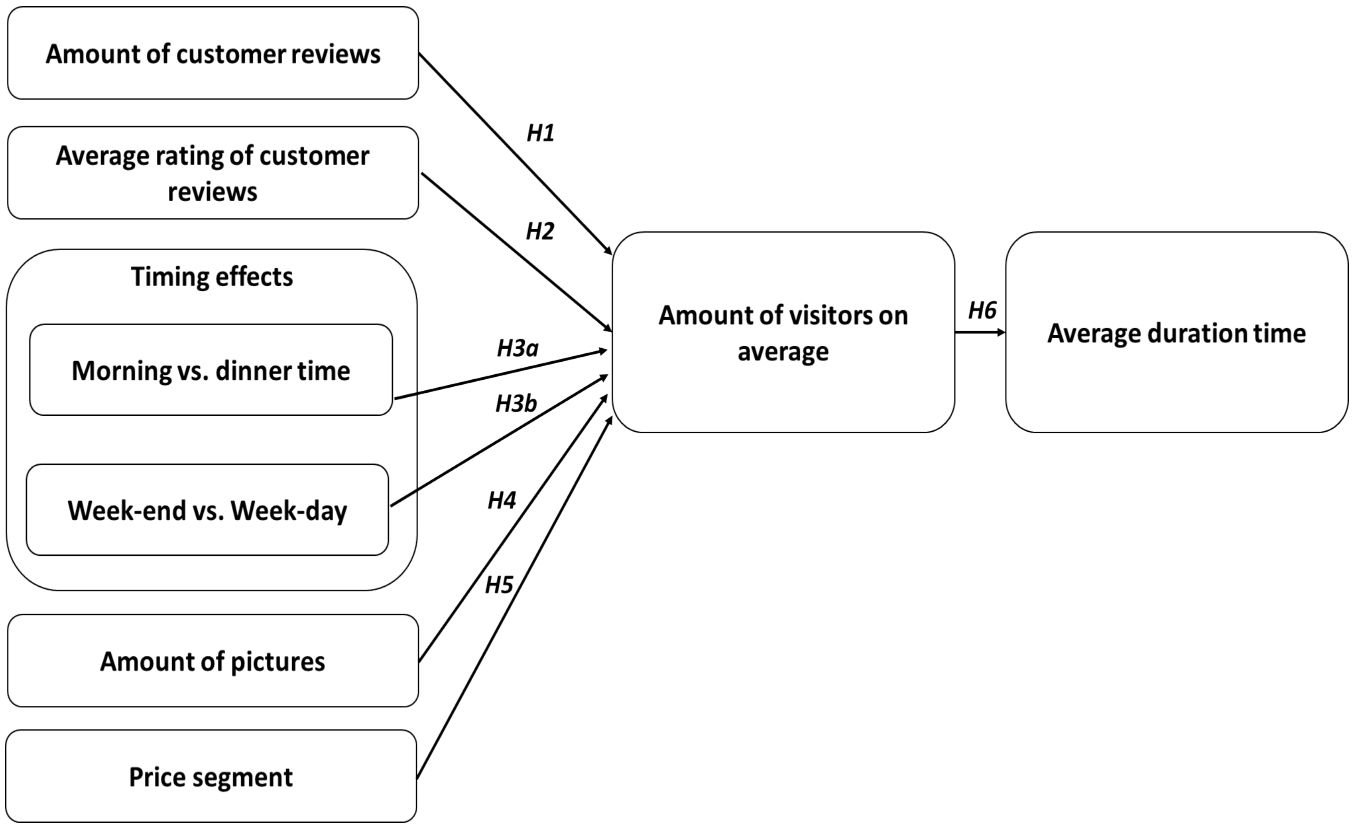
Amount of customer reviews
Average rating of customer reviews
Timing effects
Morning vs. dinner time
Week-end vs. Week-day
Amount of pictures
Price segment
H1
H2
H3a
H3b
H4
H5
Amount of visitors on average
H6
Average duration time

Fig. 2 Model

Google popular times: towards a better understanding of tourist customer patronage behavior

Abstract

Purpose – *This paper aims to investigate actual tourist customer visiting behavior with behavioral data from Google Popular Times to evaluate the extent that such an online source is useful to better understand, analyze, and predict tourist consumer behaviors.*

Design/methodology/approach – *Following six hypotheses on tourist behavior, a purpose-built software tool was developed, pre-tested, and then used to obtain a large-scale data sample of 20,000 time periods for 198 restaurants. Both bi-variate linear regression and correlation analyses were used for hypothesis testing.*

Findings – *Support was established for the hypotheses, through an analysis of customer reviews, timing effects, the number of pictures uploaded, and price segment information provided by tourists to a given restaurant. Also, a relationship to average duration time was found to be positive. The findings demonstrate that data provided through Google Popular Times matches theoretical and logical assumptions to a high degree. Thus, the data source is potentially powerful for providing valuable information to stakeholders (e.g., researchers, managers, tourists).*

Originality/value – *This paper is the first to both conceptually and empirically demonstrate the practicality and value of Google Popular Times to better understand, analyze, and predict tourist consumer behaviors. Value is thereby provided by the potential for this approach to offer insights based behavioral data. Importantly, until now such an approach to gathering and analyzing this volume of actual customer data was previously considered far less practical in terms of time and expense.*

Keywords - *Tourist consumer behavior, tourist destinations, online reviews, restaurant visits*

Paper type - *Research paper*