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A Bayesian statistics approach to hospitality research

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ABSTRACT

Bayesian statistics approach contraposes inferential statistics by the fact that it introduces experts' opinion in the quantitative analysis. While this approach has played an increasingly important role in various fields of research, its application to hospitality research has been limited. Bayesian statistics helps resolve the issue of the shortage of observations, which is a frequent problem in certain areas of the hospitality industry. Secondly, the Bayesian approach is particularly well suited when the variables used are already subjective or abstract. Therefore, this study aims to explain how a Bayesian statistics approach contributes to the advancement of hospitality management and demonstrates how this approach can be applied to analyse guests' online reviews for a hotel.

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Introduction

Bayesian statistics is a statistical approach that allows researchers to assign an ex ante distribution (named 'prior distribution' or just 'prior') to an unknown parameter (θ) based on previous beliefs (Giovagnoli, 2008). In other words, the researcher does not discard her previous beliefs but, instead, includes them in the analysis. The Bayesian approach is compelling in the sense that it provides a unified approach to modelling, incorporation of prior information, and inference (Rossi & Allenby, 2003). The past three decades have seen a dramatic increase in the use of Bayesian methods in various fields (e.g. forecasting, marketing, etc.), but its application to the hospitality research has been limited.

This article aims to demonstrate how the Bayesian approach can be applied to hospitality research and to discuss the methodological contribution that this branch of statistics can make to the hospitality literature. In particular, the article shows how Bayesian statistics is able to introduce ex ante expectations (prior) in the statistical analysis and correct those expectations through the sampling process. In other words, Bayesian statistics relies on the assumption that everyone has a prior expectation regarding the statistics that the study is investigating (Giovagnoli, 2008) and adjusts this expectation according to the observations collected. The statistics account therefore for the intangible experience/opinion of the researcher, practitioner or the expert.

This approach is particularly important for social sciences, because the abstract human component is particularly important and, *a fortiori*, especially relevant to the field of hotel management where observations might be limited and the irrational human emotional component is crucial. More specifically, there are two main advantages provided by the Bayesian approach that will help

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advance hospitality management theory. First of all, in some cases the hospitality industry is confronted with data whose volume is copious but its utility limited (Lam & McKercher, 2013); while, in other cases, time data are even unavailable. Bayesian statistics allows researchers to still carry out an analysis by leveraging experts' opinion. Secondly, the hospitality industry, unlike other industries, is confronted with abstract or even summative variables such as creativity, customer satisfaction, customer experience, or value perception. Bayesian statistics can lead the research into areas where data are already representing a subjective choice. This paper applied Bayesian statistics for the analysis of customers' online reviews for a hotel to shed light on the potential of the Bayesian approach.

What is Bayesian statistics?

The researcher begins with a prior belief about a parameter (θ) and its probability distribution ($\pi(\theta)$) (Giovagnoli, 2008). The argument is the following: everyone has an ex ante belief about something (Rigollet, 2016). A customer formulates expectations about the quality of the hotel service, the restaurant comes up with certain predictions about the creativity of a chef and a hotel has previous expectations concerning the productivity of an employee who has graduated from a certain school. Those expectations are particularly important when the observer does not have much data. However, in terms of Bayesian statistics, prior beliefs are better than no information at all. In a second stage, the observer collects data ($x_1, \ x_2, \ \ldots, \ x_{n,}$) and based on those observations she will correct her previous beliefs. As more and more data are collected, previous beliefs assume a decreasing role (Rigollet, 2016). It is important to note that the sampling depends on θ, and more importantly, that the distribution (f) of the data depends on this parameter: $f(x| \ \theta)$ (Giovagnoli, 2008). However, as previously mentioned, what it is of interest is not the belief of the researcher itself, nor how the data are distributed based on this belief but how the observations collected change and refine the knowledge about the parameter. Mathematically expressed, the variable of interest is $\pi(\theta|x)$. This is called by the literature 'posterior distribution'. To convert prior distribution into posterior distribution, one needs to apply the Bayesian theorem (Rossi & Allenby, 2003):

$$\pi(\theta|x) = \frac{f(x| \ \theta)\pi(\theta)}{f(x)} \tag{1}$$

As $f(x)$ is the marginal distribution and does not depend on our previous belief, it is a simple constant and does not play a major role (Giovagnoli, 2008; Rigollet, 2016). We can thus, rewrite Equation (1) as follows:

$$\pi(\theta|x) \propto f(x| \ \theta)\pi(\theta) \tag{2}$$

Finally, recalling that $f(x| \ \theta) = f(x_1| \ \theta)f(x_2| \ \theta)\ldots f(x_n| \ \theta)$, which is the likelihood function $L(\theta)$, we can conclude that:

$$\pi(\theta|x) \propto L(\theta)\pi(\theta) \tag{3}$$

Equation (3) is called the posterior distribution, which is the likelihood function weighted by a previous (prior) belief (Rigollet, 2016). Even though this is different from classical (or frequentist) statistics, one can reconstruct the result by assuming that there is no prior. In other words, the prior can be removed by assuming that it is equal to 1 ($\pi(\theta) = 1$) and Equation (3) will simply display the likelihood (Rigollet, 2016). Nonetheless, invariant priors (priors that provide no information at all) exist only under very restrictive conditions (Giovagnoli, 2008). Instead and more generally, some scholars adopt an objective approach to Bayesian statistics and use a so-called 'uninformative' prior or 'reference' prior, i.e. a prior that carries little (if no) information (at all) and lets the data drive the results (Giovagnoli, 2008; Van Dongen, 2006). This kind of prior treats all events as equally possible (Giovagnoli, 2008). The idea is to be as objective as possible and avoid influencing the likelihood function with prior subjective beliefs that might skew the results (Van Dongen, 2006). An example of an uninformative prior is the uniform distribution (Van Dongen, 2006). An uninformative prior has some drawbacks and specifically, Bayesian statistics relies on the idea that we always have an *ex ante* expectation and this should be used (Giovagnoli, 2008). From here, the next question is: How do we choose the correct prior?

In fact, even though it is true that sometimes improper priors lead to an accurate posterior distribution (Taraldsen & Lindqvist, 2010), it is also true that sometimes the choice of the prior influences the posterior distribution (Rossi & Allenby, 2003). To see if a prior influences the posterior one can resort to techniques that assess the sensitivity, even though such techniques may lead to trivial answers (Wasserman, 1996). Hence, it is essential to detect a correct prior even though it is not always possible (Wasserman, 1996). For the purpose of this article, we will adopt a textbook approach and, for the sake of simplicity, avoid the vast literature around the choice of the prior. A practical approach is to use a 'conjugate prior' which is a prior that, from a mathematical point of view, has the same type of distribution as the posterior (Giovagnoli, 2008). Likewise, if a researcher is facing a normal distribution in her sample, she should use a normal distribution as a prior and this will result (also) in a normally distributed posterior (Giovagnoli, 2008). Similarly, if the sample is generated by a binomial process, then a beta distribution should be adopted as a prior (resulting in a Beta distribution for a posterior) and if the sample is generated by a Poisson, a Gamma distribution should be adopted for which the prior is indicated (Donovan & Ruth 2019; Giovagnoli, 2008).[1]

The Bayesian approach in the tourism and hospitality literature

The Bayesian approach has recently begun to be applied in the tourism and hospitality literature. Most research used Bayesian techniques to estimate business efficiency focusing on the analysis of cost efficiency. In particular, Assaf applied the Bayesian approach to measure the efficiency and performance of various businesses in the tourism and hospitality sectors (e.g. Assaf, 2009; Assaf, 2011; Assaf & Barros, 2011; Assaf & Magnini, 2012). For example, Assaf (2009) explored the technical efficiency of U.S. airlines using a Bayesian random stochastic frontier model and found that inferences from the Bayesian estimation indicate that the random model fits the data well and outperforms the traditional stochastic frontier model. Later, Assaf (2011) uses the Bayesian random coefficient frontier model to find technological differences in the efficiency measurement of U.K. airports. Assaf and Barros (2011) applied the stochastic frontier method in a Bayesian framework, while using the data envelopment analysis DEA efficiency scores as priors in order to measure and compare the efficiency of leading tour operators and hotel companies across several Asia Pacific countries. Assaf and Tionas (2015) developed a Bayesian stochastic frontier model that integrates destination quality into the estimation of tourism performance and provided a ranking of technical efficiency and destination quality for 101 tourism destinations. Assaf et al. (2017) discussed its benefits and the flexibility the Bayesian approach offers in the estimation of complicated performance models and introduced several advanced versions of Stochastic Frontier models. Arbelo et al. (2018) measured profit efficiency and its determinants for hotels in Spain from 2010 to 2014, using a Bayesian stochastic frontier approach. According to Arbelo et al. (2018), the model using a Bayesian stochastic frontier approach provides more accurate confidence intervals than the traditional frequentist approach. Recently, Assaf et al. (2021) introduced a Bayesian non-parametric stochastic frontier model that addresses the endogeneity problem as a competitor to DEA.

Tourism demand forecasting is another research area where Bayesian approaches have been often applied. Wong, Song and Chon (2006) examined three Bayesian vector autoregressive (VAR) models by introducing different restrictions (priors) to the unrestricted VAR model and found significant improvements in forecast accuracy. Similarly, Ampountolas (2019) implemented VAR models and compared them to the Bayesian VAR to examine the accuracy of predicting demand and the findings showed that the significant improvement in forecasting performance was obtained using the Bayesian model. According to Ampountolas (2019), the VAR models flexibility and ability to fit the data under a minimal set of conditions bring with it a risk of overfitting the data; however, Bayesian methods can address these issues by incorporating priors into a VAR model so that the number of parameters to be estimated can be reduced (Canova, 2011; Doan et al., 1984). Ampountolas (2019) addressed that the Bayesian part of the model provides an additional set of restrictions through prior probability distribution functions. Assaf et al. (2019) analysed international tourist flows in nine countries in Southeast Asia to exhibit the power of the Bayesian global vector autoregressive (BGVAR) model to capture the spillover effects of international tourism demand in this region. Further, Kulshrestha, Krishnaswamy and Sharma (2020) propose a Bayesian Bidirectional Long Short-Term Memory (BBILSTM) approach for tourism demand forecasting.

On the other hand, Assaf et al. (2018) explained the ability of the Bayesian approach for Structural Equation Modelling (SEM) estimation and discussed the advantages versus the covariance-based approach. In response to Assaf et al. (2018)'s suggestion, Papastathopoulos et al. (2020) applied the Bayesian SEM multigroup approach for demographic analysis of residents' support for tourism development in the UAE to overcome the major issue of the non-normal distributions of data.

Other research showed how the Bayesian approach can be applied for various topics in tourism. Adhikary and Adhikari (2019) adopted the Bayesian regression to identify individual differences in tourism information seekers, as the Bayesian approach produces estimates of individual units across all parameters. Perles-Ribes and his colleagues have applied Bayesian structural time-series models to analyse the impact of several political events on tourism destination. For example, Perles-Ribes et al. (2016) explored the effects of the Arab uprisings on tourism destinations located along the Mediterranean coastline and Bayesian structural time-series model was designed to estimate causal impacts in online marketing campaigns. Perles-Ribes, Ramón-Rodríguez, Such-Devesa, et al. (2019) applied the classical Box-Jenkins method (ARIMA) and the Bayesian structural time-series models to analyse the impact of the instability associated with the political situation in Catalonia on the arrivals and spending of international tourists in the region. Furthermore, the immediate impact of Brexit on British tourism in Spain was explored by the Bayesian structural time-series models (Perles-Ribes, Ramón-Rodríguez, & Ortuño, 2019).

Although several scholars in the tourism and hospitality literature used the Bayesian approach, its application remains limited. Therefore, in the next section, we try to illustrate the potential of Bayesian statistics applied to the hospitality industry using customers' online reviews for a hotel.

Analysis of customers' online reviews using Bayesian statistics

Customer reviews are a reflection of guests' experience during their stay in a hotel (see Berezina et al., 2015 for a comprehensive discussion on online hotel reviews). In microeconomic terms, reviews are linked to customers' utility, because the utility function measures the degree of satisfaction that a customer obtained from the consumption of a certain amount of a good.

The utility is an ordinal measure rather than a cardinal measure: a consumer can assign an order to her preferences but cannot easily measure those preferences in other terms, a customer can say that she prefers option A over option B but cannot state how happy option A or B makes her. Now, the problem is that online reviews pertaining to travel ask the customers to grade, on a scale (for instance from 1 to 10), their experience. In other words, they ask the customers to summarize their experience with a number and by doing so they aim to translate an ordinal measure (the utility) into a cardinal one. Therefore, the result is subjective and it can hardly be compared with another review (as the utility function is entirely subjective). Yet, reviews play a role in customers' decision-making process (Pan et al., 2007). While classical statistics would treat those variables as objective and conduct an objective analysis, discarding experts/practitioners' opinions, Bayesian statistics, would include the latter ones. This article argues that, as we face abstract and subjective statistics (i.e. customer feedback), it is also appropriate to account for this fact.

Data collection

To exhibit the advantages of using Bayesian statistics for the analysis of customers' online review, the Gstaad Palace, a very well-known, five-star hotel located in the Swiss Alps, was chosen. The Gstaad Palace built in 1913 has appeared in several movies and thus fits the purpose of this article. Firstly, it is reasonable to assume that every costumer has a certain level of expectation when booking at The Gstaad Palace. The use of an uninformative prior can be ruled out. Secondly, costumers' feedback distribution differs from a normal distribution (for a relatively small sample that does not involves the application of the central limit theorem). This last fact makes this exercise more complete. We retrieve customers' feedback from Booking.com, on 24 January 2020 (at 9pm CET). The database is composed of 73 observations, from eight pages. Booking.com offers reviewers the opportunity to select a 'review score' ranging between 1 and 10, with 1 indicating a 'very poor' experience while 10 indicates a 'superb experience'.

We first point out what would be the consequences of being as objective as possible. Indeed, the classical statistical approach would argue that we cannot use subjective expectations and that we should conduct statistical inferences from the data only, provided those data are available. Furthermore, researchers that advocate for an 'uninformative' prior (a prior that has no subjective view concerning Gstaad Palace's customer reviews) would argue that we should expect that any score from 1 to 10 is equally likely. Stated differently, we should presume that the distribution is uniform and that the probability of being evaluated 1 is equal to the probability of being evaluated 10 (ex ante). This is the concept expressed by an 'invariant' prior.

Bayesian statistics, instead, argues that everyone has an opinion concerning an event and that this opinion should be taken into consideration. In other words, 'going Bayesian' simply means including experts' opinions in the analysis. The argument is: it is better to rely on subjective opinion ex ante, than going into the situation blind. Indeed, data observation should correct ex post our prior and subjective expectations. The combination of experts' opinions and data observation would then lead to a model that is closer to the reality than a model that is entirely data driven. Besides, where there is a lack of data, a subjective expectation is better than no information at all. This argument is indeed more convincing in the hospitality industry where researchers and practitioners deal with unmeasurable (or even intangible) variables such as customer satisfaction, creativity, customer experience or happiness.

Now, to understand the argument whereby 'Bayesian statistics' is crucial in our example, we should ask ourselves how many of us would bet (using a terminology taken from probability theory) that a random customer would grade the experience at the Gstaad Palace 'very poor' and how many of us, instead, would bet that she will grade it as 'superb' or any degree in between.

Data analysis

Practically speaking, Bayesian statistics suggest that it is important to consider that the possible scores are restricted to a limited interval ranging from 1 to 10. It would also advocate that the feedback of the previous respondent should not influence the feedback of another respondent (even though we should test this hypothesis). Finally, Bayesian statistics would come up with a preliminary guess concerning the mean and the variance of the feedback. For a five-star hotel, it is plausible that the distribution would be left-skewed (for a discussion, consider Mariani & Borghi, 2018). Thus, from a Bayesian standpoint, the researcher would expect, a priori, a Poisson distribution.

$$P(S = r_i) = \frac{e^{-\lambda}\lambda^{r_i}}{r_i!}$$

Indeed, the probability that a score (S) is equal to r_i follows a sample distribution with a mean of λ and variance (also equals to[2]) λ. The question is now: what are our expectations concerning λ?

As pointed out, we select a conjugate prior for a Poisson distribution, which is a Gamma(a,b) distribution:

$$\pi(\lambda) = \frac{\lambda^{a-1} b^a e^{-b\lambda}}{\Gamma(a)} \quad \text{where} \quad \Gamma(a) = (a-1)!$$

For a Gamma distribution, we also know that the mean is $\frac{a}{b}$ while its standard deviation is $\sigma = \sqrt{\frac{a}{b^2}}$. It follows that, $\lambda = \frac{a}{b}$ and $\lambda = \sqrt{\frac{a}{b^2}}$.

We can then calculate the posterior distribution once we include the n observations collected:

$$\pi(\theta|r_1, r_2, \ ..r_n) \propto L(\theta)\pi(\theta)$$

$$\pi(\theta|r_1, r_2, \ ..r_n) \propto \frac{e^{-n\lambda}\lambda^{\sum_{i=1}^{n} r_i}}{\prod_{i=1}^{n} r_i!} \frac{e^{-\lambda b}\lambda^{a-1}b^a}{\Gamma(a)}$$

If we do not consider the constant terms, we find that:

$$\pi(\theta|r_1, r_2, \ ..r_n) \propto e^{-\lambda(b+n)}\lambda^{\sum\limits_{i=1}^{n} r_i + a - 1}$$

Note that the posterior distribution is also a Gamma (Gamma($a+\sum\limits_{i=1}^{n} r_i$, $b+n$)) distribution.[3] It follows that the posterior mean is $\frac{a+\sum_{i=1}^{n} r_i}{b+n}$ and the posterior variance is $\frac{a+\sum_{i=1}^{n} r_i}{(b+n)^2}$.

We are finally ready to conduct our analysis based on the sample collected from Booking.com. If we refer to classical statistics, we would conclude that the sample distribution, provided in Figure 1, has an average score of 9.4, a standard deviation (sdt) of 1.001 and a median of 9.6.

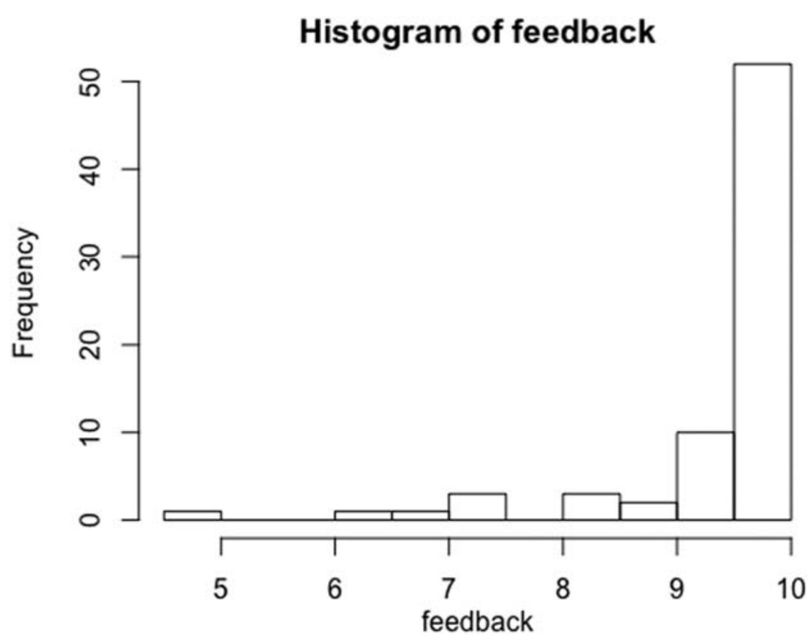

Figure 1. Customer scores' distribution ($n = 73$).

Table 1. Posterior distribution for different priors.

Prior λ	Posterior gamma	Posterior mean	Posterior sdt
10	Gamma (687.1, 73.1)	9.399452804	0.358585395
9	Gamma (687.1,73.11111111)	9.39802432	0.3585309
8	Gamma (687.1, 73.125)	9.39623932	0.3584628
7	Gamma (687.1, 73.1428571)	9.39394531	0.35837529
6	Gamma (687.1, 73.1666667)	9.39088838	0.35825867

If, instead, we 'go' Bayesian we can derive different scenarios according to researchers' subjective prior opinion. Table 1 shows the results that a researcher would have according to a range of priors she may have chosen.

First of all, it emerges from Table 1 that priors have little impact on the posterior distribution. This is due to the number of observations available. If the number of observations (n) increases, then a researcher can discard subjective opinions about the expected distribution. Bayesian statistics is not different from inferential statistics and thus does not skew our analysis.

Second, it is worth mentioning that, unlike a classical statistic, Bayesian statistics do not produce just an estimator but a whole distribution (Rigollet, 2016).

So, where does the power of Bayesian statistics come from? To answer this question, we can just reduce the sample and ask ourselves what happens if the sample is limited? If the sample is limited, then, classical statistics is not much help. Going to the extreme, let's consider the situation whereby the number of observations is 0. In that case, classical statistics would provide no information. Yet, Bayesian statistics is able to give us some value (Table 2).

In that case, our distribution depends entirely on our *ex ante* expectations. However, two points are noteworthy. First of all, Bayesian statistics is still able to provide some information (although this assertion is debatable to some extent). Second, this information is not provided as information that is 100% certain, but it comes with a distribution (and so a variance) and therefore concerns about the accuracy persist.

Finally, we should ask ourselves the following question: How fast do Bayesian statistics converge with objective statistics? The answer is: very fast! To prove this point, just add extra information ($n = 1$) and see how the posterior distribution reacts. We take the very first observation available on Booking.com (but we could choose randomly), which reported a score of 10. In that case, the previous table is reshaped as (Table 3).

Classical statistics would tell us that the mean is 10, and the standard deviation is zero. Bayesian statistics again comes up with a distribution. Also, it assigns a substantial weight to customer feedback and although a researcher may have started with a very low expectation (e.g. 6), the posterior mean is closer to the mean than the one we would have if the sample were complete ($n = 73$) both in Bayesian terms (approximatively 9.39 for every scenario) and in classical statistics terms (9.4).

More formally, one can calculate the so-called sufficiency of the sample, i.e. the amount of data that is needed to have full information regarding a parameter and that makes any additional information redundant (Giovagnoli, 2008). More interestingly, having now the posterior distribution the so-called predictive distribution can be calculated. It is easy to predict the probability that the next review would have a certain score (1, 2, … , 10). Of course, hypothesis testing can also be conducted.

Table 2. Posterior distribution for different priors if $n = 0$.

Prior λ	Posterior gamma	Posterior mean	Posterior sdt
10	Gamma (1,0.1)	10	10
9	Gamma (1,0.111)	9	9
8	Gamma (1,0.125)	8	8
7	Gamma (1,0.14285714)	7	7
6	Gamma (1,0.1666)	6	6

Table 3. Posterior distribution for different priors if $n = 1$.

Prior λ	Posterior gamma	Posterior mean	Posterior sdt
10	Gamma (11,1.1)	10	3.01511345
9	Gamma (11,1.11111111)	9.9	2.98496231
8	Gamma (11,1.125)	9.77777778	2.94811092
7	Gamma (11,1.14285714)	9.625	2.90204669
6	Gamma (11,1.16666667)	9.42857143	2.84282125

Discussion: how can Bayesian statistics contribute to hotel management?

Further to the above example, there are two main factors related to the Bayesian approach that may contribute to the science of hospitality management.

First, incorporating hoteliers' previous expectations of a certain variable allows us to still conduct a solid quantitative analysis when data are lacking or incomplete. As the literature points out, the hospitality industry suffers from a lack of data in certain cases (see for instance Lam & McKercher, 2013). Bayesian statistics provide a scientific way to cope with this shortcoming. Moreover, researchers' priors are quickly adjusted to objective statistics with limited sampling.

Second, data on the hospitality industry are different from other industries insofar as data are often proxies of unobservable, qualitative and subjective factors. To explore this further, let's consider the degree of a customer's satisfaction. Satisfaction is linked to the utility function. The utility function is an ordinal measure and not a cardinal one. It cannot be measured. Any expedient to assess it (asking for instance to evaluate on a scale from 1 to 10) results indeed in a numerical figure but this number is still questionable and subjective. While in finance the interest rate is objective, while in macroeconomics the exchange rate is a measure, while in physics the distance is a measurable variable in the hospitality industry 'a pleasant experience' or the 'creativity of a chef' cannot be measured. Practitioners try to capture those components with numbers that mimic other disciplines. Bayesian statistics is a valid approach that allows researchers to deal with subjectivity. The argument is: given that we are dealing with subjective numbers then shouldn't the analysis also include subjective aspects? As a result, the analysis does not return an estimator (as in classical statistics) but a distribution of it. This is a powerful tool that can be used to conduct the analysis.

Conclusion

The hospitality industry is particularly exposed to qualitative data: experience, creativity, satisfaction, happiness, tasting good, tasting bad and so on are all specific components of the hospitality industry that cannot be measured. Those components are subjective. The classical quantitative approach can indeed *help* to explore those components but cannot provide a perfectly clear picture of those components. The Bayesian approach discussed in this article shows how data-driven analysis can be combined with hoteliers' opinions to provide a sophisticated analysis of a particular phenomenon.

Specifically, this article presents the Bayesian procedure. Bayesian statistics starts by formulating expectations of a certain variable (e.g. customer satisfaction). The main argument is that amid uncertainty everyone has, nevertheless, expectations about the outcome of that uncertain situation. Bayesian statistics aim to include this aspect in the analysis. The second step would be to adjust (*ex post*) this expectation once the data collection process starts. The results would have to be a combined statistic that incorporates both the data and practitioners' opinions.

This article illustrates via an example the strengths of the Bayesian approach. There are two main suitable features of Bayesian statistics that can contribute to the hospitality management literature. The first one is the ability to cope with the absence of data, a scenario that is very likely in the hospitality industry. The second one is the fact that Bayesian statistics allows researchers to introduce experts' opinion in the quantitative analysis and therefore 'measure the unmeasurable' including intangible variables such as creativity, experience, satisfaction or happiness.

Notes

1. The article is limiting its analysis to the analytical derivation of a posterior distribution. There are cases, however, on which Equation (2) cannot be computed analytically (Johnson et al., 2007). Different methods have been developed to deal with this problematic, including what has become the most popular method, i.e. the Markov chain Monte Carlo (MCMC), which uses 'a Markov chain to sample from the posterior distribution' (Johnson et al., 2007). Those methods aim to solve more complex statistical models (Carlin & Chib, 1995), which are beyond the scope of this paper.
2. The mean of the Poisson distribution (λ) is also equal to the variance of the Poisson distribution.
3. For a more detailed solution see Appendix 2 in Donovan and Mickey (2019).

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