

When hospitality revenue management analytics defies our biased intuition: The case of capacity constraints and correlated channel-demand

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Abstract

Sellout projections are critical to revenue management decisions, particularly in the context of multi-channel distribution. This research investigates the unexpectedly complex relationship between the likelihood of a sellout and the correlation in demand across distribution channels. Using a detailed numerical simulation implemented in VBA, the Study reveals that these dynamics are both intricate and counterintuitive. A follow-up empirical investigation, conducted through a scenario-based survey, assessed participants' intuitive judgments when faced with this cognitively demanding computational task. The results show that intuition often fails, overconfidence bias is present - especially among experts - and there is no evidence of framing bias. The primary contribution of this Study is theoretical: it uncovers the complex and unintuitive mathematical relationship between channel demand correlation and the probability of reaching or exceeding capacity. These insights have practical implications for improving revenue management forecasting and for designing interventions such as targeted training or bias-aware decision support systems.

Keywords: Revenue management, capacity constraints, demand correlation.

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1. Introduction

Effective hospitality revenue management (RM) is distribution-channel specific (e.g., Carroll, 2006). In their pursuit of revenue and profit optimization, hotel RM practices often adjust room rates, allocate rooms inventory to rate fences, and set overbooking levels and cancellation terms based on the demand and willingness to pay (WTP) of each distribution channel. For example, the published room rates in opaque distribution channels that conceal the hotel name or location are often lower than in other distribution channels (Hargrave, 2019).

RM practices are channel-specific because each channel presents its own circumstances to increase revenue and reduce costs, and hence increase profits. The revenue-enhancing route is focused on price discrimination where distribution channels offer one effective approach. This is because *identification* and *enforcement*, the two requirements for effective price discrimination (e.g., Tang & Schwartz, 2023, p. 61) could be effectively addressed by channel management. Hotels may not always operate in rate parity, allowing hotels to charge different prices by channel (Baker, 2016; Starkov, 2023). Furthermore, opaque channels such as Priceline and Hotwire (Yang *et al.*, 2019), provide firms the opportunity to “identify” individuals with lower WTP and discourage customers with higher WTP from purchasing heavily discounted prices.

The second strong motivator to carefully manage the channel mix is differentiated costs. It is well established that some channels are considerably more expensive than others (Eisen, 2017) since OTA’s (online travel agencies) commissions make them considerably more expensive than selling through their own website, AKA, brand.com. Consequently, the contribution of the various distribution channels to the hospitality firm’s profitability varies (e.g., Abdullah *et al.* 2022). If a hotel is going to sell out, revenue managers can close off inventory on high commission channels to improve gross margins. It follows that hospitality firms benefit from carefully managing their distribution channels as part of their RM practices (Connolly, 2018).

Ultimately, inventory management falls upon the revenue manager to sell rooms at the highest possible rate. Research has yet to explore RM inventory allocation decisions across channels and this Study demonstrates that the optimal decision is not always obvious. The major contribution of this Study is theoretical. We identify the complex relationships between capacity, multi-channel demand dynamics, and the likelihood of a sellout. The results of our analytical investigation demonstrate that the relation is surprisingly complex and not always obvious and it follows that optimal channel decisions that rely on understanding of these relations might not be that easy.

The unintuitive analytical findings of Study 1 are further explored in Studies 2 and 3. Study 2 empirically investigates whether experts and students can accurately assess the likelihood of a hotel selling out, given varying levels of demand correlation across channels. It also examines whether relevant industry experience influences one’s ability to intuitively grasp these complex relationships and the degree of confidence in that ability. Study 3 explores the potential use of commonly applied heuristics in evaluating such complex correlations.

The results of these additional investigations into human capacities and biases provide interesting insights regarding channel management and demand estimates in hospitality revenue management and provide a variety of avenues for future research.

In the next section we discuss the role of distribution channels and measuring demand across channels - defined in this Study via correlation metrics. A simulation depicting these complex relationships reveal interesting insights concerning inventory management for revenue managers. Based on these findings, we measure and contrast the ability of hospitality revenue managers and of students to adequately

identify the optimal decision, and if two well-known biases could be playing a role. The Study concludes with a discussion of implications and future research.

2. Literature Review

2.1. Channel Demand Correlation

The demand generated by a hotel's various distribution channels, e.g., OTAs, brand.com, walk-ins, phone calls and mobile apps, could be correlated, positively or negatively, or it could be uncorrelated, depending on various factors. The term "correlated" in this Study refers to the common use in statistics where it depicts a causal or non-causal statistical relationship between randomly distributed or bivariate data (e.g., Andrson *et al.*, 1990, p. 481). Several studies explored the correlation among distribution channels' demand. For example, Wlömert & Papies (2016) showed that "*the increase in demand from one channel (say, a free streaming services) is positively correlated with demand from another channel (say, CDs)*". Such positive correlation is observed and reported in the hospitality industry as well. Positive correlation between dine-in demand and delivery demand in the restaurant industry was reported by Ma *et al.* (2020), and in the hotel context, Cazaubiel *et al.* (2022) observed that due to "common demand", prices in different distribution channels are likely to be correlated. Why positive correlation? A positive correlation occurs, for example, when demand for a certain hotel is driven, in large, by seasonal factors. In that case, the non-causal correlation of demand across the hotel's distribution channels is likely to be positive. In other words, seasonality-driven increases and decreases in demand often "move together" across the distribution channels. Accordingly, when a ski-resort hotel experiences increased demand in the winter, the demand is likely to spread across all the hotel's distribution channels (positive correlation).

Occurrences of negative correlation are also common in the hospitality industry, particularly in environments where the distribution channels cater to customer segments that have dissimilar intertemporal patterns of demand. Distribution channels may differ in their customer profiles (e.g., Masiero, & Law, 2016). As such, customer segments with varying, or opposing, demand patterns might place reservations through different channels and, consequently, the distribution channels' demand could have a negative correlation. For example, consider a hotel that, on weekdays, caters mostly to groups, but on weekends attracts family vacationers. The weekday groups are largely booked directly by their event/group organizers, while the weekend transient guests typically book through OTAs such as Expedia and Booking.com. It follows that at this hotel, the non-causal correlation between the distribution channels is likely to be negative: When OTAs reservations are up on weekends, the direct channel's reservations are down, and vice versa on weekdays.

2.2. Capacity constraints

Closely related to the channels' demand factor are the hotels' capacity constraints, which shape the way hotels operate, and, consequently, their performance. Capacity constraints motivate RM decisions due to the perishable nature of the hospitality products (Ivanov, 2014, p. 13), and their detrimental impact is best addressed by RM controls and optimization algorithms (Lacagnina & Provenzano, 2016).

The functional RM connection between the hotel's capacity and demand is clearly demonstrated in the context of RM forecasting. Forecasting is a pillar of any hospitality RM system and the importance of forecasting from both an unconstrained and capacity-constrained context is well recognized (Weatherford, 2016b). The decisions that rely on these capacity-aware demand forecasting insights include operational and tactical decisions such as pricing, scheduling, budgeting, and inventory management (Talluri & Van Ryzin, 2004), as well as long term decisions such as strategic alliances, marketing campaigns, investment in production capacity, etc. Due to the nature of the revenue optimization mechanisms, most hospitality firms desire to operate at, or near, capacity level for revenue and profit optimality reasons. Revenue optimality practices rely on sophisticated price discrimination

policies and procedures. As shown by economic models, if the hotel operates with a single room rate, the optimal revenue is not necessarily at full capacity. However, once the hotel adopts a RM multi-fenced rate system, the more fragmented and specific the price discrimination practice, the more it is profitable to operate near or at capacity. For a comprehensive discussion on price discrimination see, for example, Philips (1983), and for a recent discussion in the context of hospitality and tourism, see for example, Han & Bai, 2022.

However, operating near capacity levels makes it crucial to predict when, by how much, and how often, demand will exceed capacity. The importance of knowing where the demand is, in relation to the capacity, is well acknowledged. For example, Zakhary *et al.* (2011, p. 358) state: “*For the purpose of revenue management, unconstrained demand is the more relevant quantity to consider*”. This is clearly shown when considering overbooking, a common practice that tends to generate higher revenues and higher profits (e.g., Riasi *et al.*, 2019). However, its effectiveness depends on the ability to accurately predict whether demand will exceed capacity and by how much (e.g., António *et al.*, 2019). When predictions are misaligned, that is, when the hotel is not only overbooked but also oversold, there are multiple downsides to the practice that harm revenue and profits in the short, and long term.

2.3. Synthesis

To summarize, the hospitality RM literature acknowledges that demand management across distribution channels is very important. It is also clear that capacity constraints, and the ability to reliably assess whether capacity will be reached, or surpassed, plays a dominant role in RM optimization. Given the importance of these two elements, this Study explores a previously unexplored facet of hospitality RM, one that connects the channel-specific demand with the firm’s capacity. Specifically, the paper explores how a correlation between distribution channels’ demand affects the likelihood of the hotel’s demand reaching, or exceeding, its capacity. The motivation is straightforward. A better understanding of this complex system of relations will support better prediction of where the demand might be in relation to capacity, and subsequently facilitate better and more effective RM decisions. For example, if revenue managers understand how demand materializes across channels, they could remove limited inventory from high-cost channels when a hotel is projected to sellout, or price across discriminate across channels to balance commissions and optimize performance.

This paper is composed of three consecutive studies. The main Study and its contribution are computational. Using an elaborate numerical simulation, Study 1 is first to provide the analytical answer to the following question: Does the likelihood of demand reaching, or exceeding, the hotel’s capacity, depend on the level of correlation between the hotel’s distribution channels’ demand? The insights provided by the analytical solution of this question are multifaceted and somewhat counterintuitive. The Study informs optimal strategies given varying levels of hotel capacities, demand relationships, and the likelihood of achieving a sellout.

Following the insights gained from Study 1, and the surprising complexity of the solution, Study 2 conducts an empirical investigation of the human subjective intuition regarding these relations. Specifically, Study 2 assesses the ability of decision makers to subjectively, and intuitively, assess the answer to the question posed and solved in Study 1. First, it assesses the accuracy of the intuition of respondents from several countries and it contrasts the abilities of experienced hotel revenue managers with that of students of relevant academic disciplines. Study 2 finds that humans do not appear to be able to perform this cognitive task effectively. Given the findings of studies 1 and 2, it is reasonable to expect that people resort to heuristics when attempting to perform this complex cognitive task. Accordingly, Study 3 explores whether there is, indeed, evidence of typical biases as predicted by the heuristics framework of decision making (Tversky & Kahneman, 1974, p.1130) where people apply

“mental shortcuts”. In this Study we specifically explore the potential influence of overconfidence bias and framing effects on the correct assessment of demand and optimal decision

3. Study 1

Study 1 is the main contribution of this paper. It explores the impact of correlation between distribution channels' demand on the likelihood of the total demand reaching capacity. Formally, the investigated relation function, denoted by g , is shown in Eq.1 where the probability, Pr , is impacted by the correlation, ρ , given the gap between the capacity, C , and the total level of demand, $X_1 + X_2$.

$$Pr[(X_1 + X_2) > C] = g[\rho_{x_1, x_2} | C - (X_1 + X_2)] \quad (1)$$

Where

X_i denotes the demand of distribution channel 1.

X_2 denotes the demand of distribution channel 2.

ρ denotes the correlation coefficient.

C denotes the hotel's capacity.

Specifically, Study 1 aims to uncover the shape and characteristics of function g , that is, to describe how the correlation between the two channels' demand impacts the likelihood of reaching capacity, given how close the total demand ($X_1 + X_2$) is to the hotel's capacity, C (See Figure 1). Another way to describe, intuitively, what Study 1 solves is as follows. A hotel faces a total demand (across the two distribution channels) which fluctuates over time, e.g., daily. That total demand can be closer to, or farther from, its capacity. Moreover, the total demand fluctuates around the mean, and sometimes it can reach or exceed capacity. We ask if the level, and direction, of a correlation between the demand of the distribution channels impact the likelihood of the hotel reaching that capacity over time, and, how that likelihood of reaching capacity (given correlation level) is impacted by that distance between the average total demand and the capacity.

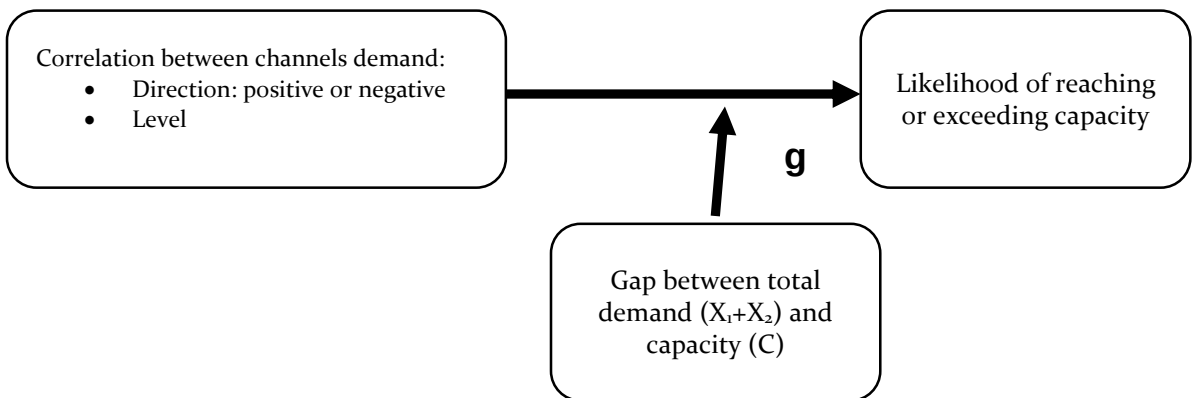


Figure 1. The explored relationship between correlation and reaching capacity given demand.

3.1. Methodology

In lieu of a closed form solution to the problem posed earlier, i.e., describing function g , the Study employed an elaborate numerical simulation to explore the impact of channel's correlation level on the likelihood of reaching the hotel's capacity. The simulation code was written in VBA[®], and its output was tabulated and charted in Microsoft Excel[®].

Y , the dependent variable, is the percentage of times capacity was reached. That is, total daily demand equals or exceeds capacity or $(X_{ij} + X_{2j}) \geq C$.

The independent variables are as follows:

X_1 and X_2 are 2 vectors of randomly generated daily demand levels ($j=1,2, \dots 365$) reflecting distribution channel i ($i=1, 2$). The demand for each channel is normally distributed with a user-controlled average and standard deviation.

That is $x_i \sim N(\mu, \sigma)$ (2)

ρ : the correlation between the daily demand figures of channel 1 and the daily demand of channel 2, with 20 levels ranging from -0.9 to 1, with a step of 0.1.

C : the hotel rooms' capacity with 251 levels, ranging from 100 to 350 with a step of 1 room.

Hence, each run of the simulation cycles through 251 capacity levels. Within each level of capacity iteration, 20 levels of correlation ρ are tested, and for each of these 20 correlation levels, 365 total daily demand numbers (sum of the two channels) are contrasted with the capacity constraint. Finally, the percentage of times capacity was reached during that period of 365 days is recorded. In total, 1,832,300 equations are solved in each simulation run to generate 251 curves. Each of these 251 curves depicts the relation between the likelihood of reaching capacity and the correlation level in a 2D space. Finally, the curves are combined in a 3D chart where the 3rd dimension represents the hotels' capacity.

Robustness was assessed by re-running the simulation over 20 times. In each run we varied the average and standard deviation (μ and σ in Eq. 2) of each of the two channels' normally distributed demand.

3.2. Findings

The simulation results indicate that whether the investigated relation (correlation impact on reaching capacity) is positive or negative, and whether it is linear or nonlinear, depends on the difference between the average total demand and the capacity. That is, it depends on how far the capacity is from the total demand across channels -- the " $C - (X_1 + X_2)$ " element of Eq 1. These complex relationships are shown in Figure 2 where each curve represents the relation in a different level of that capacity/demand gap, starting from the top curve where the capacity/demand gap is lowest, to the bottom curve where the capacity/demand gap is the highest, i.e., where capacity is considerably higher than the average total demand. When that relative capacity is very low, there is no impact of correlation on probability of total demand reaching capacity. This is depicted by a straight line on the very top of the chart. Regardless of the correlation level, the likelihood of reaching capacity at that level is 100%. As the relative capacity increases, that is, as one moves down to lower curves in the upper portion of Figure 2, the relation is negative: the higher the correlation the lower the likelihood of reaching capacity. The shape of the curve becomes increasingly nonlinear, and then it gradually flattens until it becomes flat again at the 50% mark. That is, when capacity equals the average total demand, the likelihood of reaching capacity is exactly 50%, and, once again, the correlation level has no impact on the likelihood of reaching capacity.

As the relative capacity continues to increase, that is, as we move down the lines in the lower portion of Figure 2, the direction of the impact flips. In this case, the higher the correlation between the channels, the higher the likelihood of reaching capacity. The curves' shape changes from convex at the upper portion of the chart to concave at the lower bottom. Finally, at extremely high relative-capacity levels, the likelihood of reaching capacity drops to zero. This is the third identified condition where the correlation levels do not matter as shown by the straight horizontal line on the very bottom of the chart.

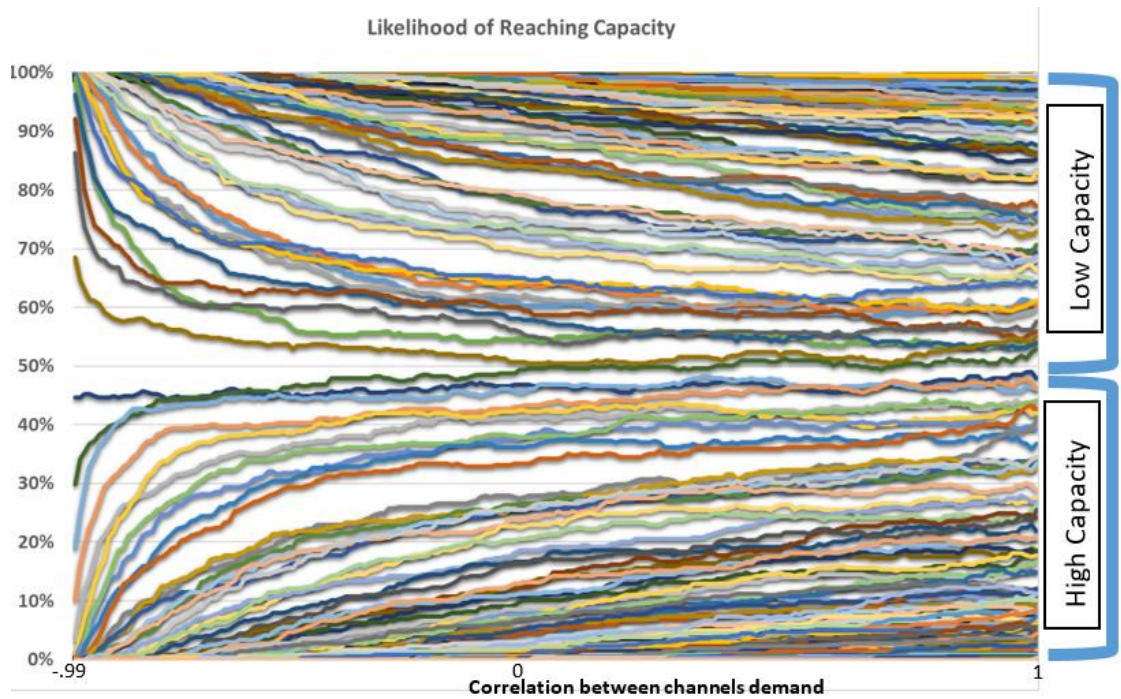


Figure 2. How often capacity is reached given correlation between channels demand at various capacity levels.

Another way to look at the same results is by using a three-dimensional chart. Figure 3 illustrates the same findings from a different perspective, though it might be more difficult to decipher the relations based on Figure 3.

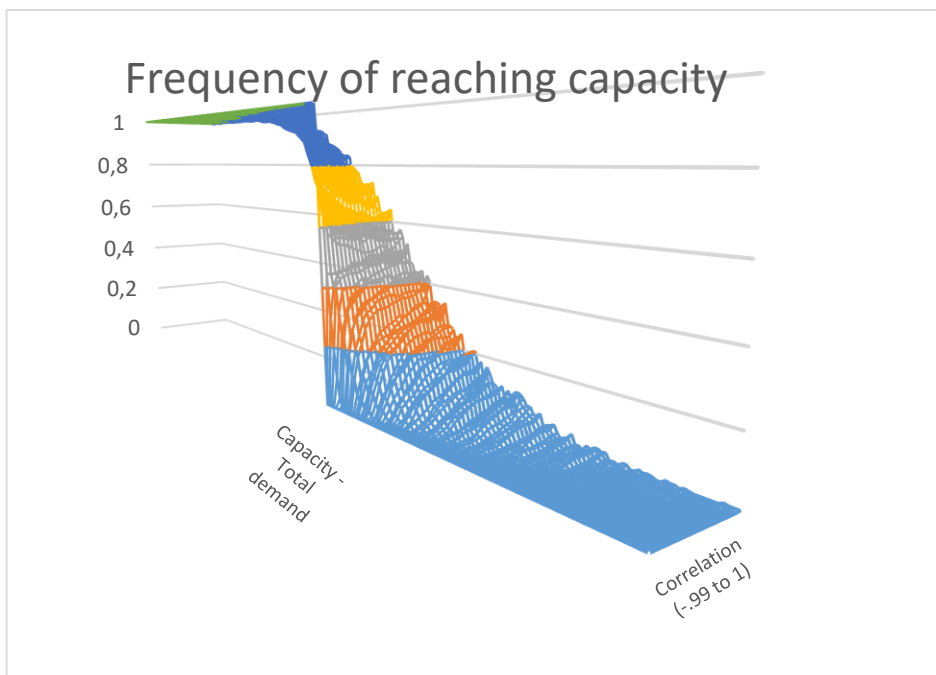


Figure 3. Frequency of reaching capacity given capacity and correlation between distribution channels.

To summarize, Study 1 asks: Does a correlation between the different demand streams affect the probability of the total demand exceeding the hotel capacity? The answer is surprisingly complex, and perhaps somewhat counterintuitive. First, we find that the answer depends on how far the average total demand is from the capacity. When there is a considerable gap between the total demand and the hotel's capacity, the stronger the correlation between the channels' demand, the higher the probability of the total demand reaching the hotel's capacity. These relations reverse in lower capacity. That is, when total average demand is closer to the hotel's capacity, the higher the correlation between the channels' demand, the lower the probability of the total demand reaching the hotel's capacity. These surprisingly complex and counterintuitive relations, discovered in this Study are a major theoretical contribution to the literature in hotel analytics. They lead to better understanding of the analytics involved, and consequently the potential to improve prediction regarding reaching and exceeding capacity¹.

4. Study 2

Study 2 is motivated by the complexity of Study 1's findings, and by their somewhat counterintuitive characteristics. RM decisions often require analytical and statistical inferences skills. Moreover, as reported in a recent Study (Egan & Haynes, 2019, p. 33): *"...managers are not fully processing all the data available to them and potentially still mistrust the automated systems and feel the need for gut feeling and intuition to still play a part in revenue management decision making"*. At the same time, it is well documented that analytical and statistical reasoning is a challenging task for the human mind (See, for example, Kula, & Koçer, 2020; Stanovich, 1999). Furthermore, previous hospitality research indicates that even experienced revenue managers might struggle with complex cognitive tasks, despite being an integral part of their job. They appear to have difficulties with probabilistic inferences when assessing last minute booking volume and the likelihood of sellout – a task that calls for Bayesian updating (Schwartz, 2012). It was also shown that they succumb to other cognitive biases, for example, when assessing the accuracy of demand forecasts and the need to correct and override algorithmic forecasts (Koupriouchina *et al.* 2023; Schwartz and Cohen, 2004a; 2004b).

Given these observations, it is expected that the surprisingly complex task of assessing the impact of demand correlation on the likelihood of the demand exceeding capacity, described in Study 1, might be challenging as well for revenue managers. Accordingly, Study 2 aims to measure the accuracy of subjective intuition about the impact of channels' demand correlation on the likelihood of the demand reaching the hotel's capacity. We ask experienced revenue managers to provide their assessment of these relations given a scenario designed to reflect the problem and its solution, as found in Study 1. We then compare the revenue managers' performance in assessing these relations to that of students in relevant academic disciplines, and we measure the respondents' confidence in their answers. We hypothesize that respondents will have difficulties assessing these relations:

H₁: Humans are incapable of intuitively assessing the impact of channels demand correlation on the likelihood of reaching capacity.

Revenue managers deal with, and think about, these issues of demand and capacity daily: They assess and predict demand and make important decisions based on these assessments constantly (Weatherford, 2016a). The literature on subjective choices and decisions, when probabilistic inferences are involved, indicates that experience matters. For example, a recent Study (Reani *et al.*, 2019) finds that people are more likely to provide a correct answer when the data in the problem is closer to their "lived experience". Accordingly, it is reasonable to expect that revenue managers would perform better than undergraduate students on this task.

H₂: Experience matters: Revenue managers will perform better than inexperienced students in the task of intuitively assessing the impact of channels demand correlation on the likelihood of reaching capacity.

4.1. Methodology

A scenario-based survey captured the intuition of respondents and judged the accuracy of the response based on Study 1's solution ². Participants were asked to read through one of the two randomly assigned scenarios and assess how the correlation between two channels' demand would impact the likelihood of the hotel reaching its capacity on a given night. Each scenario provided context surrounding booking channels: averages and ranges of the demand per channel and the hotel's capacity (290 rooms or 230 rooms). Respondents were asked whether a positive or a negative correlation is more likely to generate more sellout days for the hotel, given the scenario conditions. The two other answer options were "there is no impact of correlation on likelihood of reaching capacity" and "I don't know and have no intuition about this".

The scenario, question, and answer options are provided below. Note that half of the respondents were told that the hotel's capacity is 290 rooms, in which case the correct answer is positive correlation, and the other half was told that it is 230 rooms, in which case the correct answer is negative correlation ³.

Consider the following: Your hotel has 290(230) rooms. Guests book your rooms through two distribution channels: a single OTA and brand.com (your hotel's own website). The average number of rooms booked daily through these channels is: OTA: 150 rooms a day with a typical range of up to +/- 15 rooms around this average. Brand.com: 100 rooms a day with a typical range of up to +/- 15 rooms around this average. The channels' demand can be correlated. A positive correlation means that on days when one channel's demand is higher the other channel's demand is higher as well, and when one channel's demand is lower the other channel demand is lower as well. A negative correlation means that on days when one channels demand is higher, the other channel demand is lower. A sellout day means that your hotel sold all of its rooms. That is, the hotel reached its capacity.

In your opinion, which of the following conditions is likely to generate more sellout days for the hotel?

- a. *The two distribution-channel's demand is positively correlated*
- b. *The two distribution-channel's demand is negatively correlated*
- c. *Correlation between channels demand is not impacting the likelihood of selling out the hotel*
- d. *I don't know and have no intuition regarding this*

Finally, participants used an interval rating scale (ranging from 1 to 100) to report the confidence they had in the accuracy of their answer.

The Qualtrics® survey was administered to a total of 102 respondents, of which 37 were hotel revenue managers, and 65 were undergraduate college students in hospitality management, tourism, and business. Respondents were from several universities and hospitality organizations in the United States, China, and France. The scenario and questions were translated to the local language. Data points on gender, age, education level, and experience level within the hospitality industry were also collected. Answers were coded and charted in Excel®, and proportion tests performed using SPSS®.

4.2. Findings

Hypothesis 1 is supported as only 41.2% (42 of the 102) responses were correct. That is, less than half of the respondents were able to correctly assess the connection between the channel's demand correlation and the likelihood of selling out. Furthermore, recall that respondents were presented with 3 viable answers: a higher likelihood, a lower likelihood, and no impact of channel demand correlation on reaching capacity. Hence, by simply guessing, respondents had a 33.3% chance of correctly assessing

the impact. The hypothesis that the sample proportion of correct answers (41.2%) is better than a simple guess (33%) is not supported at the 95% confidence level ($P > .05$, one tailed z proportion test). In other words, we cannot reject the null hypothesis that the performance of the sample in making these estimates is only as good as guessing, and it supports the notion that humans struggle with this cognitive task.

However, the results are not supportive of the second hypothesis. While at 49%, the proportion of correct answers among revenue managers was higher than the students' lower proportion of 37% correct responses, the difference is statistically insignificant, and we can't conclude that revenue managers perform statistically better than students on this cognitive task ($P > .05$, one tailed z test) ⁴.

To summarize, we find that, overall, this task appears to be difficult, and respondents do not perform well when addressing it. In addition, we find that despite their training, their continuous exposure to this domain of assessing demand, and their superior work experience, revenue managers do not appear to perform better than inexperienced students when it comes to the task of assessing the impact of distribution channels' demand correlation on the likelihood of reaching capacity.

5. Study 3

The findings of Studies 1 and 2 underscore the difficulties associated with correctly assessing the relationship between channels' demand and the likelihood of reaching capacity. This cognitive task is computationally difficult, and respondents do not appear to perform well when asked to make that assessment. Heuristic theory (Kahneman 2011, p. 98) suggests that when people form judgment, and when the task calls for a challenging cognitive process, the human brain frequently resorts to using mental shortcuts to arrive at plausible conclusions or answers. In a way, these mental shortcuts allow us to "replace" the challenging mental task with an easy one. However, the heuristics approach to solving problems, and the cognitive shortcuts associated with it, often result in typical, and rather predictable, incorrect responses and biases (e.g., Haselton & Nettle, 2006). Accordingly, the objective of Study 3 is to explore two commonly observed human biases which appear to be relevant in this context: *framing* and *overconfidence*.

Why bother to identify biases? The motivation is multifaceted and includes potential theoretical and practical contributions. Theoretically, identified biases could serve as supporting evidence that people resort to heuristics when making this judgment. The use of biases detection to indicate heuristics is a common validation approach in research in psychology, see, for example, the work of Baron (1988) and Park & Banaji (2000). If found, the presence of biases indicates that this critical RM task of estimating demand is, indeed, governed, or at least influenced, by a heuristic approach. As such, it will be a theoretical contribution providing empirical evidence to better understand how, and why, revenue managers make these subjective judgments of demand.

Moreover, there is a practical incentive as well. Insights on what specific biases are involved in making these judgments could support future industry efforts to design a practical remedy to the problem (e.g., Harries & Harvey, 2000), that is, to guide the development of strategies to mitigate or reduce the biases. These remedies could include measures such as targeted training and educational interventions (e.g., AlKhars *et al.*, 2019; Doherty & Carroll; 2020; Druckman, 2001), as well as "bias-aware" designs of the RM system's user interface (e.g., Wall *et al.*, 2019; Weinmann *et al.*, 2016).

5.1. Theoretical background

Heuristic behavior can be understood as a cognitive shortcut, or rule of thumb, that individuals employ during the decision-making process. When making judgments, people frequently rely on heuristics, rather than engaging in a thorough evaluation of probabilities and utility. These heuristics are seen as

simple cognitive processes that are often effective in providing quick solutions but are also prone to errors in certain contexts (Angner, 2016, p.195). Cognitive scientists debate whether they are learned (e.g., Chaiken *et al.*, 1989, p.213) or have evolutionary origins (e.g., Petersen, 2015) but they agree that these heuristics serve as a collection of straightforward cognitive processes that frequently yield positive outcomes (e.g., Hogarth, 1981). However, due to their simplified nature, heuristics can lead to mistakes or biases in certain circumstances. Individuals may rely on these mental shortcuts even when the situation calls for a more comprehensive evaluation of probabilities and utility. As a result, decisions made based on heuristics may not always align with optimal outcomes. By employing heuristics, people can perform complicated decision-making tasks simpler, but this strategy can also place constraints on their decision-making and lead to potential deviations from rationality, and consequently result in sub-optimal performance. It follows that understanding the role of heuristics in decision-making processes is crucial in comprehending how individuals navigate specific complex situations. This Study is a first attempt to explore this in the context of our demand correlation and capacity scenario, and we focus on the *framing* and *overconfidence* biases.

5.2. Framing bias

The framing effect refers to the notion that the presentation of information can influence people's reactions, even when the objective outcome remains the same. It represents a cognitive bias in which the presentation of information has a greater influence on judgments than the actual content itself (Beratšová *et al.*, 2018; Chong & Druckman, 2007; Plous, 1993, p.185). The most cited application of the framing effect occurs in prospect theory (Tversky & Kahneman, 1981), according to which human choices are more influenced by prospects of a loss than by the same prospects of a gain. The framing effect has received considerable attention in recent hospitality and tourism literature as well. However, this attention appears to be entirely in the context of how to take advantage of the bias. Specifically, how to move the hospitality consumer (i.e., hotel guest, tourist, restaurant customer, etc.) in the direction of making a desirable choice. For example, recent publications looked at WTP for "poor tourism" (Li *et al.*, 2022), upselling (Mayer *et al.*, 2022; Denizci Guillet *et al.*, 2022) and even consumption of edible insects (Legendre & Baker, 2021).

Given the literature, and the context of the cognitive task explored in studies 1 and 2, it is reasonable to expect that if the question (about the impact of correlated demand on reaching a certain level of total demand) is framed differently, the proportion of correct answers could vary. Details about the specifics of the framing are provided in the methodology section. The formal hypothesis is as follows:

H₁. The proportion of correct judgments regarding the connection between channels demand correlation and the likelihood of reaching capacity, depends on the framing.

Overconfidence bias. Confidence denotes the level of certainty people have about their judgment (Angner, 2016 p. 114), and is another bias that might play a role in this case of making judgments regarding a complicated relation. Behavioral economics and cognitive science literature provides ample evidence that people tend to exhibit over-confidence, that the ramifications of overconfidence could be serious (e.g., Brenner *et al.*, 1996; Harvey, 1997; Moore & Swift, 2011; Yates, 2010), and that overconfidence is more prevalent when the task is difficult (e.g., Lichtenstein & Fischhoff 1977; Moore & Healy, 2008). Recent studies found that over-confidence is not just an individual focused trait - it might even be a socially transmitted phenomenon (Cheng, *et al.* 2021).

Overconfidence is often detected by calibration (Angner, 2016 p. 115)- a measure of how close the probability assigned by the respondents (for example, 90%) is to the proportion of propositions that are true. In the context of studies 2 and 3, the sample of respondents would be perfectly calibrated if the average self-reported confidence level equals the proportion of correct answers. Overconfidence bias

has received very little attention in the hospitality and tourism literature. In fact, we found only 3 studies investigating overconfidence. Kim & Jang (2021) showed that CEO's overconfidence bias is positively associated with the restaurants chain's growth but negatively with their profitability. A very similar approach is found in Seo & Sharma (2018) as well as Seo, *et al.* (2017) who found that overconfident CEOs tend to take more risky decisions and higher debt. However, these three hospitality-related overconfidence studies did not measure overconfidence using the common calibration approach used in cognitive science and behavioral economics, but inferred overconfidence indirectly. Instead of measuring the CEO's confidence regarding the decisions they made by recording how certain they were about the choices and decisions that were explored in that Study, confidence level was assessed based on observed performances of the CEOs in another investment domain -- the CEO's own stock option portfolio decisions and that investment portfolio's performance.

To summarize, cognitive psychology and behavioral economics studies suggest that people tend to be overconfident, and more so when the task is difficult. Accordingly, we hypothesize the following:

H₂. People who engage in this cognitive task have overconfidence and poor calibration: the level of self-reported certainty in their answers is higher than the actual proportion of correct answers.

In addition, the literature also suggests that experts are often prone to over-confidence bias, and sometimes even more than their counterparts who have less or at least claim less expertise in the subject (e.g., Dunning 2011; Kahneman & Klein, 2009; Krugman, 2009). Accordingly, we hypothesize the following:

H₃. Revenue Managers have higher confidence in their answers.

Are experts more likely to be better calibrated? The evidence so far is inconclusive. Some studies suggest that experts do worse on their calibration score than non-experts. Since the expert's confidence is often higher than non-experts, their calibration gap is likely to be larger. That is, they are more likely to exhibit overconfidence than the "humbler" non-experts (e.g., McBride *et al.*, 2012). However, other studies suggest that when experts are "true experts" in that their experience includes continuous relevant feedback regarding how their judgment performed, and when they are highly motivated to perform well (such as a financial reward), experts are more calibrated. That is, true experts who are also motivated are less overconfident than laypeople. For a discussion on this aspect, see, for example, the chapter by Bolger & Wright (1992). Revenue managers appear to fall in that category of "true experts": they continuously assess demand condition, are exposed to continuous feedback, and their motivation is relatively high because better performance is often related to financial bonuses and promotion opportunities. Accordingly, we hypothesize the following:

H₄. Revenue managers are more calibrated than students, when performing the difficult task of assessing the impact of correlated demand on the likelihood of reaching capacity.

5.3. Methodology

Study 3 is very similar to Study 2 with the single difference being the framing of the scenario. Study 3's scenario is positioned as being (loosely) associated with a potential loss, while Study 2's framing association is with a potentially higher gain. Note that the two scenarios refer to the same demand numbers, the same threshold level and therefore the same mathematical solution. It means that in lieu of framing effect, the proportion of correct answers should be the same. Instead of asking about "reaching capacity", Study 3 frames the question as being about "not reaching the hotel's breakeven point". This reframing of the scenario is associated with "losing" in two ways. The first being a reference

to the breakeven point (i.e., the demand below which the profit is negative) and the second being the use of “not reaching” instead of “reaching”.

The scenario, question, and answer options are provided below. Note that half of the respondents were told that the hotel's capacity is 290 rooms, in which case the correct answer is a negative correlation (as opposed to Study 2's positive one), and the other half was told that the hotel's capacity is 230 rooms, in which case the correct answer is a positive correlation (as opposed to Study 2's negative one).

*Your hotel loses money when the demand drops, and less than 290(230) rooms are sold for the day. Guests book your rooms through two distribution channels: a single OTA and brand.com (your hotel's own website). The **average** number of rooms booked daily through these channels is: OTA: 150 rooms a day with a typical range of up to +/- 15 rooms around this average. Brand.com: 100 rooms a day with a typical range of up to +/- 15 rooms around this average. The channels demand can be correlated. A positive correlation means that on days when one channel's demand is higher the other channel demand is higher as well, and when one channel's demand is lower the other channel demand is lower as well. A negative correlation means that on days when one channel's demand is higher, the other channel demand is lower. A **losing day** means that the number of sold rooms dropped below the breakeven threshold of 290 rooms.*

*In your opinion, which of the following conditions is likely to generate **more losing days** for the hotel?*

- The two distribution-channel's demand is positively correlated*
- The two distribution-channel's demand is negatively correlated*
- Correlation between channels demand is not impacting the likelihood of selling out the hotel*
- I don't know and have no intuition regarding this*

5.4. Data.

The modified Qualtrics® survey was administered to a total of 99 respondents of which 33 were hotel revenue managers, and 66 were undergraduate college students in the disciplines of hospitality management, tourism, and business. Respondents were from several different universities and hospitality organizations in the United States, China, and France. Data points on gender, age, education level, and experience level within the hospitality industry were also collected. Answers were coded and charted in Excel®, and proportion and average tests performed using SPSS®.

5.5. Findings

The findings of Study 3 along with Study 2 are shown in Table 1.

Table 1. Correct answers of revenue managers vs. students by framing scenario.

	Revenue Managers	Students	Total / average
Study 2 - Sell out framing			
Observations	37	65	102
Correct answers	18	24	42
Correct answers proportion	49%	37%	41.2%
Study 3 - Below breakeven framing			
Observations	33	66	99
Correct answers	10	29	39
Correct answers proportion	30.3%	43.9%	39.4%
Total - both studies			
Observations	70	131	201
Correct answers	28	53	81

Correct answers proportion	40.0%	40.5%	40.3%
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5.5.1. Framing

At 39.4% correct answers, the performance of the entire sample of Study 3's respondents (revenue managers and students) are as poor as those observed in Study 2, and like Study 2, the success rate is not statistically significantly different from pure guesswork (33.3%). Hence, the finding of Study 2, that this cognitive task is difficult, is confirmed. While students appear to be doing better than revenue managers in this framing, with 44% correct answers compared to the revenue managers lower proportion of 30%, the difference is again statistically insignificant at the 95% confidence level, and it is yet another confirmation to the findings of Study 2 that revenue managers are not different from students in their ability to handle this cognitive task.

H_1 is not supported as the proportion of correct answers of the entire sample in Study 2 (39%) is not statistically different from the proportion of correct answer (41%) of Study 1 (two sample proportion test, $p > 0.05$). That is, the null hypothesis that the two proportions are equal cannot be rejected. Similar rejection of H_1 is found when the hypothesis of a framing bias is tested separately with students, and then with revenue managers. Both groups of respondents do not have statistically different proportions of correct answers in the two scenarios. We conclude that within this context and specific scenario, there is no evidence that the framing of the question (in terms of reaching capacity vs. not falling below breakeven point) had a statistically significant impact on the proportion of correct answers.

Since we find no significant impact of the framing effect on the proportion of correct answers, it is reasonable to combine the data of Study 2 with that of Study 3 to further examine the difference between the two groups, and later to explore, confidence level and calibration (H_2 , H_3 & H_4). Accordingly, we first repeat the evaluation of the correct answers. The proportion of correct answers is 40.3% (81 out of 201, see Table 1) and it is not statistically different from guessing. We then repeat the comparison of revenue managers to students using the combined sample of 70 revenue managers and 131 students. We find that the proportions of correct answers are almost identical, with 40.5% of the students responding correctly, and 40.0% of revenue managers. This observation provides additional support to the notion that revenue managers do not perform better than students on this computational task of evaluating the impact of channel correlation on the likelihood of total demand reaching a certain level.

5.5.2. Confidence and calibration

As noted earlier, since we find no significant impact of the framing effect, we combine the data of the two studies and explore confidence levels and calibration using the combined larger data.

H_2 appears to be supported by both revenue managers' and students' reported numbers. Managers' trust in their answer was 63.7 (out of 100) and students' trust was 48.5. Both are higher than the proportion of correct answers (40%).

H_3 is supported as well. Agreeing with reported published findings in other disciplines, the experts (revenue managers) have more trust in their judgment than non-experts. That is, despite having the same level of correct answers (40%), revenue managers reported a statistically significantly higher level of confidence than that reported by students ($63.7-48.5=15.2$, $p < 0.05$).

H_4 is not supported – that is managers do not have better calibration than students. On the contrary, their calibration score of 23.7 (63.7-40.0) is larger than the students' calibration score of 8 (48.5-40.5). This suggests that revenue managers are considerably less calibrated than students, that is, they exhibit a higher level of overconfidence.

Interestingly, no statistically significant difference ($p < 0.05$) was observed between managers who answered correctly (an average confidence of 62.2) and those who answered incorrectly (confidence of 64.7). Students' confidence levels are also equal across correct and wrong answers (49.8 and 46.9 respectively). In other words, with both revenue managers and students, self-confidence does not appear to be an indication of an effective intuition when it comes to assessing these relations between channels demand correlation and the likelihood of the demand reaching capacity or dropping below the breakeven.

6. Conclusion

The analytical exploration in Study 1 shows that whether positive or negative, correlation amongst channels and the likelihood of reaching a certain level of the capacity, depends on how far that capacity is from the total demand across these channels. When capacity is relatively low (compared to the average total demand the hotel faces) the likelihood of reaching capacity declines as the correlation between the channels increases. When the capacity is relatively high, the likelihood of reaching capacity increases with higher correlation levels. Both the increasing and decreasing functions are non-linear. Intuitively, it can be related to the size of the demand across channels. In the low-capacity scenario, the hotel can sellout from demand derived from one channel (negative correlation), however in the high-capacity scenario, both channels must receive demand to hit capacity (positive correlation). Motivated by Study 1's insights about the complexity of these non-trivial relations, Study 2 explored human intuition in this regard. The findings indicate that humans are mostly incapable of effectively assessing these relations and that both revenue managers and students alike do no better than a simple guess. Given that people resort to heuristics when they need to perform difficult cognitive tasks, Study 3 looked for two commonly observed judgment biases when heuristic is used: the framing effect and overconfidence. We found no evidence for the framing effect but there is a strong indication that overconfidence bias exists, and it is considerably higher with revenue managers compared to the students.

The major theoretical contribution of this paper is the solution to the mathematical question of how correlated demand impacts the likelihood of reaching or exceeding capacity. This Study is first to provide and solve an analytical model to explain and demonstrate these surprisingly complicated and counterintuitive relations between channel correlation and likelihood of reaching capacity. Studies 2 and 3's theoretical contribution is in providing a better understanding of how ill quipped decision makers are when it comes to dealing with this assessment of demand.

The two theoretical contributions, that is, the analytical solution and the empirical observation regarding humans' inabilities, underscore the practical need to handle this task algorithmically in the computerized RM system. For example, consider predictions regarding unconstrained demand that are required to support pricing and overbooking levels decisions. The accuracy of these predictions could be potentially enhanced if the forecasting models, which combine demand estimates for each channel separately, also rely on estimates of how the demand levels across channels are correlated. This is an exciting venue for future research in hotel RM forecasting, especially given that both areas of unconstrained demand and overbooking optimization are, in general, in need of more academic research.

Other opportunities for future research are related to deeper understanding of the correlation impact on the total demand. One of this Study's limitations is that it explored the impact of correlation between two channels only. Future research could look at the characteristics of multi-channel correlations and how are these characteristics related to the impact on the likelihood of reaching capacity. Moreover, when more than two channels are modeled one could look at relatively more challenging scenarios where some of the correlations are positive and some are negative simultaneously. Note that when one

moves from two to multiple channels, the fundamental insight of Study 1 will not be altered. What one could gain from such follow-up studies is a more in-depth understanding of the mechanisms. In other words, one will still find that how the overall correlation between the multiple channels impacts the likelihood of reaching capacity depends on how far the total demand from capacity. The additional insights are going to be more about how one gets to that overall correlation and that total demand, i.e., what the correlations levels and demand levels combinations are.

Endnotes:

¹ Note that these findings are robust. Multiple reruns of the simulation with various levels of demand averages, and standard deviations (Eq. 2), yield the same results and generate no new insights.

² The requirement for approval for research involving human subjects was waved by the university's institutional review board.

³ The two scenarios of (230 and 290) correspond to two specific curves in Figure 2, and this is how the correct answer for each option is established.

⁴ Findings concerning the levels of expressed confidence are reported in study 3 where the data of study 2 and study 3 is combined.

References

- Abdullah, S., Van Cauwenberge, P., Vander Bauwhede, H., & O'Connor, P. (2022). The indirect distribution dilemma: assessing the financial impact of participation in Booking.com for hotels. *Tourism Review*, 77(4), 1024–1042. <http://doi/10.1108/TR-03-2020-0101>
- AlKhars, M., Evangelopoulos, N., Pavur, R., & Kulkarni, S. (2019). Cognitive biases resulting from the representativeness heuristic in operations management: an experimental investigation. *Psychology Research and Behavior Management*, 263–276. <https://doi.org/10.2147/PRBM.S193092>
- Andreson, D., Swenney, D. & Williams, T. (1990). *Statistics for Business and Economics*. West Publishing Company, St. Paul, MN. <https://www.cengage.com/c/statistics-for-business-economics-14e-anderson/9781337901062/>
- Angner, E. (2016). *A Course in Behavioral Economics*. Bloomsbury Academic, New York. <https://www.bloomsbury.com/us/course-in-behavioral-economics-9781352010800/>
- Angner, E. (2018). We're all behavioral economists now. *Journal of Economic Methodology*, 26(3), 195–207. <https://doi.org/10.1080/1350178X.2019.1625210>
- António, N., de Almeida, A., & Nunes, L. (2019). Predictive models for hotel booking cancellation: a semi-automated analysis of the literature. *Tourism & Management Studies*, 15(1), 7–21. <https://doi.org/udel.idm.oclc.org/10.18089/tms.2019.15011>
- Baker, T. (2016). Rate-Parity Struggles Continue for Fragmented Europe. *Hotel News Now*. <https://www.costar.com/article/2107669700/rate-parity-struggles-continue-in-fragmented-europe>
- Baron, J., Beattie, J., & Hershey, J. C. (1988). Heuristics and biases in diagnostic reasoning: II. Congruence, information, and certainty. *Organizational Behavior and Human Decision Processes*, 42(1), 88–110. [https://doi.org/10.1016/0749-5978\(88\)90021-0](https://doi.org/10.1016/0749-5978(88)90021-0)
- Beratšová, A., Krchová, K., Gažová, N., & Jirásek, M. (2018). Framing and Bias: A Literature Review of Recent Findings. *Central European Journal of Management*, 3(2), 23–32. <https://doi.org/10.5817/CEJM2016-2-2>
- Bolger, F., & Wright, G. (1992). Reliability and validity in expert judgment. In Wright, G. & Bolger, F. (Eds) *Expertise and decision support* (pp. 47–76). Boston, MA: Springer US. <https://link.springer.com/book/10.1007/b102410>
- Brenner, L. A., Koehler, D. J., Liberman, V., & Tversky, A. (1996). Overconfidence in probability and frequency judgments: A critical examination. *Organizational Behavior and Human Decision Processes*, 65(3), 212–219. <https://doi.org/10.1006/obhd.1996.0021>
- Carroll, W. (2006). Hospitality Revenue and Channel Management CONVERGE. *Hospitality Upgrade*, 34–36. www.HospitalityUpgrade.com

- Cazaubiel, A., Cure, M., Johansen, B. O., & Vergé, T. (2020). Substitution between online distribution channels: Evidence from the Oslo hotel market. *International Journal of Industrial Organization*, 69, 102577. <https://doi.org/10.1016/j.ijindorg.2019.102577>
- Chaiken, S., Liberman, A., & Eagly, A. (1989). Heuristic and Systematic Information Processing within and beyond the Persuasion Context. *Unintended Thought*, 212-252. <https://cir.nii.ac.jp/crid/1572824499146786048>
- Cheng, J. T., Anderson, C., Tenney, E. R., Brion, S., Moore, D. A., & Logg, J. M. (2021). The social transmission of overconfidence. *Journal of Experimental Psychology: General*, 150(1), 157. <https://doi.org/10.1037/xge0000787>
- Chong, D., & Druckman, J. N. (2007). Framing Theory. *Annual Review of Political Science*, 10(1), 103-126. <https://doi.org/10.1146/annurev.polisci.10.072805.103054>
- Connolly, E. (2018). A Comprehensive Approach to Hotel Channel Distribution. Hospitality Net. Retrieved on 6/19/2023 from <https://www.hospitalitynet.org/opinion/4088628.html>
- Denizci Guillet, B., Mattila, A. S., Peng, Z., & Gao, Y. (2022). The joint influence of the timing and framing of an online upselling message on consumer perceptions: the roles of construal level and reactance. *International Journal of Contemporary Hospitality Management*, 34(7), 2516-2534. <https://doi.org/10.1108/IJCHM-11-2021-1375>
- Doherty, T. S., & Carroll, A. E. (2020). Believing in overcoming cognitive biases. *AMA Journal of Ethics*, 22(9), 773-778. <https://doi.org/10.1001/amajethics.2020.773>
- Dunning, D. (2011). The Dunning-Kruger effect: On being ignorant of one's own ignorance. *Advances in experimental social psychology*, 44, 247-296. <https://doi.org/10.1016/B978-0-12-385522-0.00005-6>
- Druckman, J. N. (2001). Using credible advice to overcome framing effects. *Journal of Law, Economics, and Organization*, 17 (1), 62-82. <https://doi.org/10.1093/jleo/17.1.62>
- Egan, D., & Haynes, N. C. (2019). Manager perceptions of big data reliability in hotel revenue management decision making. *International Journal of Quality & Reliability Management*, 36(1), 25-39. <https://doi.org/10.1108/IJQRM-02-2018-0056>
- Han, W., & Bai, B. (2022). Pricing research in hospitality and tourism and marketing literature: a systematic review and research agenda. *International Journal of Contemporary Hospitality Management*, 34(5), 1717-1738. <https://doi.org/10.1108/IJCHM-08-2021-0963>
- Hargrave, M. (2019). Opaque Pricing. *Investopedia*. Retrieved on 6/23/2013 from <https://www.investopedia.com/terms/o/opaque-pricing.asp>
- Harries, C., & Harvey, N. (2000). Are absolute frequencies, relative frequencies, or both effective in reducing cognitive biases? *Journal of Behavioral Decision Making*, 13(4), 431-444. [https://doi.org/10.1002/1099-0771\(200010/12\)13:4<431::AID-BDM363>3.0.CO;2-1](https://doi.org/10.1002/1099-0771(200010/12)13:4<431::AID-BDM363>3.0.CO;2-1)
- Harvey, N. (1997). Confidence in judgment. *Trends in cognitive sciences*, 1(2), 78-82. DOI:[https://doi.org/10.1016/S1364-6613\(97\)01014-0](https://doi.org/10.1016/S1364-6613(97)01014-0)
- Haselton, M. G., & Nettle, D. (2006). The Paranoid Optimist: An Integrative Evolutionary Model of Cognitive Biases. *Personality and Social Psychology Review*, 10(1), 47-66. https://doi.org/10.1207/s15327957pspr1001_3
- Ivanov, S. (2014). *Hotel Revenue Management: From Theory to Practice*. Varna: Zangador. https://www.researchgate.net/publication/262918029_Hotel_Revenue_Management_From_Theory_to_Practice
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan. <https://us.macmillan.com/books/9780374533557/thinkingfastandslow/>
- Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: a failure to disagree. *American psychologist*, 64(6), 515-526. <https://doi.org/10.1037/a0016755>
- Kahneman, D. & Tversky, A. (1979). Prospect theory: an analysis of decision making under risk. *Econometrica*, 47(2), pp. 263-291. <https://doi.org/10.2307/1914185>
- Koupriouchina, L., van der Rest, J. I., & Schwartz, Z. (2023). Judgmental adjustments of RMS hotel occupancy forecasts: Does user override frequency impact forecasting accuracy at different

- forecasting time horizons? *Tourism Economics*, 29(8), 2143-2164.
<https://doi.org/10.1177/13548166221126572>
- Krugman, P. (2009). How did economists get it so wrong? *New York Times*, 2(9), 2009. Retrieved on 7/24/2023 from <https://www.nytimes.com/2009/09/06/magazine/06Economic-t.html>
- Kula, F., & Koçer, R. G. (2020). Why is it difficult to understand statistical inference? Reflections on the opposing directions of construction and application of inference framework. *Teaching Mathematics and its Applications: An International Journal of the IMA*, 39(4), 248-265.
<https://doi.org/10.1093/teamat/hrz014>
- Lacagnina, V., & Provenzano, D. (2016). An integrated fuzzy-stochastic model for revenue management: The hospitality industry case. *Tourism Economics*, 22(4), 799-792.
<https://doi.org/10.1177/1354816616654250>
- Legendre, T. S., & Baker, M. A. (2021). The gateway bug to edible insect consumption: interactions between message framing, celebrity endorsement and online social support. *International Journal of Contemporary Hospitality Management*, 33(5), 1810-1829.
<https://doi.org/10.1108/IJCHM-08-2020-0855>
- Li, S., Saayman, A., Stienmetz, J., & Tussyadiah, I. (2022). Framing Effects of Messages and Images on the Willingness to Pay for Pro-Poor Tourism Products. *Journal of Travel Research*, 61(8), 1791-1807.
<https://doi.org/10.1177/00472875211042672>
- Lichtenstein, S. and Fischhoff, B. (1977). Do those who know more also know more about how much they know? *Organizational Behavior and Human Performance*, 20(2), 159-83.
[https://doi.org/10.1016/0030-5073\(77\)90001-0](https://doi.org/10.1016/0030-5073(77)90001-0)
- Ma, J., Webb, T., & Schwartz, Z. (2021). A blended model of restaurant deliveries, dine-in demand and capacity constraints. *International Journal of Hospitality Management*, 96, 102981.
<https://doi.org/10.1016/j.ijhm.2021.102981>
- Masiero, L., & Law, R. (2016). Comparing reservation channels for hotel rooms: A behavioral perspective. *Journal of Travel & Tourism Marketing*, 33(1), 1-13.
<https://doi.org/10.1080/10548408.2014.997960>
- Mayer, V. F., Santos, G. E. de O., & Marques, O. R. B. (2022). Option framing for upselling tourism services: Does cognitive availability prevent irrational choices? *Tourism Economics*, 28(2), 476-494.
<https://doi.org/10.1177/1354816620949722>
- Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, 115(2), 502.
<https://doi.org/10.1037/0033-295X.115.2.502>
- Moore, D. A., & Swift, S. A. (2011). The three faces of overconfidence in organizations. In D. De Cremer, R. van Dick, J. K. Murnighan (Eds) *Social psychology and organizations*, (pp. 147-184). Routledge.
<https://www.taylorfrancis.com/chapters/edit/10.4324/9780203846957-16/three-faces-overconfidence-organizations-moore-samuel-swift>
- Park, J., & Banaji, M. R. (2000). Mood and heuristics: the influence of happy and sad states on sensitivity and bias in stereotyping. *Journal of personality and social psychology*, 78(6), 1005.
<https://doi.org/10.1037/0022-3514.78.6.1005>
- Petersen, M. B. (2015). Evolutionary political psychology: On the origin and structure of heuristics and biases in politics. *Political Psychology*, 36, 45-78.
<https://doi.org/10.1111/pops.12237>
- Philips, L. (1983). The economics of price discrimination. Cambridge University Press.
<https://archive.org/details/economicsofprice000ophli/page/n9/mode/2up>
- Plous, S. (1993). *The psychology of judgment and decision making*. Mcgraw-Hill Book Company.
<https://psycnet.apa.org/record/1993-07429-000>
- Riasi, A., Schwartz, Z. & Beldona, S. (2019). Hotel Overbooking Taxonomy: Who and how? *International Journal of Hospitality Management*. 82, 1-4. <https://doi.org/10.1016/j.ijhm.2019.03.018>

- Reani, M., Davies, A., Peek, N., & Jay, C. (2019). Evidencing how experience and problem format affect probabilistic reasoning through interaction analysis. *Frontiers in psychology*, 10, 1548. <https://doi.org/10.3389/fpsyg.2019.01548>
- Schwartz, Z. (2012). Probability blindness” and last-minute booking of hotel rooms: The case of Bayesian updating. *International Journal of Tourism Sciences*, 12(2), 63-77. <https://doi.org/10.1080/15980634.2012.11434659>
- Schwartz, Z., & Cohen, E. (2004a). Hotel revenue management forecasting: Evidence of expert judgment bias. *Cornell Hotel and Restaurant Administration Quarterly*, 45(1), 85-98. <https://doi.org/10.1177/0010880403260110>
- Schwartz, Z., & Cohen, E. (2004b). Subjective estimates of occupancy forecasts uncertainty by hotel revenue managers. *Journal of Travel and Tourism Marketing*, 16(4), 59-66. https://doi.org/10.1300/J073v16n04_08
- Seo, K., Kim, E. E. K., & Sharma, A. (2017). Examining the determinants of long-term debt in the US restaurant industry. *International Journal of Contemporary Hospitality Management*, 29(5), 1501-1520. <https://doi-org.udel.idm.oclc.org/10.1108/IJCHM-06-2015-0274>
- Seo, K., & Sharma, A. (2018). CEO Overconfidence and the Effects of Equity-Based Compensation on Strategic Risk-Taking in the U.S. Restaurant Industry. *Journal of Hospitality & Tourism Research*, 42(2), 224-259. <https://doi.org/10.1177/1096348014561026>
- Stanovich, K. E. (1999). *Who is rational? Studies of individual differences in reasoning*. Psychology Press. <https://doi.org/10.4324/9781410603432>
- Starkov, M.(2023). Why Rate Parity Still Has to Be the Law of the Land in Hospitality. *Hospitality Net*. <https://www.hospitalitynet.org/opinion/4119105.html>
- Talluri, K. & Van Ryzin, G. (2004). *The theory and practice of revenue management*. Springer. [https://www.google.com/books/edition/The+Theory+and+Practice+of+Revenue+Manag/GhdDbEM_50C?hl=en&gbpv=1&dq=Talluri,+K.+%26+Van+Ryzin,+G.+\(2004\).+The+theory+and+practice+of+revenue+management+site:springer.com&printsec=frontcover](https://www.google.com/books/edition/The+Theory+and+Practice+of+Revenue+Manag/GhdDbEM_50C?hl=en&gbpv=1&dq=Talluri,+K.+%26+Van+Ryzin,+G.+(2004).+The+theory+and+practice+of+revenue+management+site:springer.com&printsec=frontcover)
- Tang, C. & Schwartz, Z. (2023). Key Economic Concepts for Hospitality Revenue Management. In Repetti. T. (Ed). *Hospitality Revenue Management & Profit Optimization*. RevME. <https://elearning.costar.com/rmc-industry-professionals>
- Tversky, A. & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211(4481), pp. 453-458. <https://doi.org/10.1126/science.7455683>
- Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124-1131. <https://doi.org/10.1126/science.185.4157.1124>
- Wall, E., Stasko, J., & Endert, A. (2019, October). Toward a design space for mitigating cognitive bias in vis. In 2019 IEEE Visualization Conference (VIS) (pp. 111-115). IEEE. <https://doi.org/10.1109/VISUAL.2019.8933611>
- Weatherford, L. (2016a). The history of forecasting models in revenue management. *Journal of Revenue and Pricing Management*, 15, 212-221. <https://doi.org/10.1057/rpm.2016.18>
- Weatherford, L. (2016b). The history of unconstraining models in revenue management. *Journal of Revenue and Pricing Management*, 5(3), 222-228. <https://doi.org/10.1057/rpm.2016.10>
- Weinmann, M., Schneider, C., & vom Brocke, J. (2016). Digital nudging. *Business & Information Systems Engineering* 58, 433-436. <https://doi.org/10.1007/s12599-016-0453-1>
- Yang, Y., Jiang, L., & Schwartz, Z. (2019). Who’s hiding? Room rate discounts in opaque distribution channels. *International Journal of Hospitality Management*, 80, 113-122. <https://doi.org/10.1016/j.ijhm.2019.02.001>
- Yates, J. F. (2010). Culture and probability judgment. *Social and Personality Psychology Compass*, 4(3), 174-188. <https://psycnet.apa.org/doi/10.1111/j.1751-9004.2009.00253.x>

Zakhary, A., Atiya, A. F., El-Shishiny, H., & Gayar, N. E. (2011). Forecasting hotel arrivals and occupancy using Monte Carlo simulation. *Journal of Revenue and Pricing Management*, 10, 344-366.
<https://doi.org/10.1057/rpm.2009.42>