The New Science of Service Innovation: Part 1 Select Research on Data

Cornell Hospitality Research Summit

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The New Science of Service Innovation: Part 1 Select Research on Data

Abstract

Select Research on Data from the 2014 Cornell Hospitality Research Summit

Few businesses have the level of direct access to customer and employee data as that found in the hospitality and service industries. Fortunately, new analytical techniques and technology have improved the availability of those data. Unfortunately, the volume of data creates challenges of its own. The Cornell Hospitality Research Summit (CHRS) held in October 2014 was organized to examine service innovation in a new light, focusing on a scientific and disciplined approach to the topic. This report is the first of four that features expanded summaries of select research on service innovation. This first report focuses on innovative applications of data analysis that are occurring both in the industry and in academic research. Topics include search engine optimization, the use of analytics for energy efficiency, analysis of online reviews, and optimizing hotel group room rates, as well as how to promote organizational learning.

This report highlights seven data-based research presentation from the summit:

• “Optimizing Hotel Booking Choices on OTA Websites,” by Jean-Pierre van der Rest. Paolo P. Cordella, Gerard Loosschilder, and Zvi Schwartz (page 4);
• “Applied Analytics for Hospitality Energy Efficiency and Associated Core Operations Transformation,” by Har Amrit Pal Singh Dhillon, Saju Ramachandran, and Parminder Singh (page 8);
• “How Recognizing Visitor Intent Fuels Customer-Focused Experiences,” by Matthew Butler and Lane Cochrane (page 14);
• “Solving the Online Review Puzzle,” by HyunJeong Han, Srinagesh Gavirneni, Shawn Mankad, Joel Goh, and Rohit Verma (page 18);
• “Data, Knowledge, and Intelligence in Hospitality Industries” by Scott Erickson and Helen Rothberg (page 22);
• “Optimizing Hotel Group Room Rates,” by Jian Wang (page 24);
• “How Hotels’ Organizational Learning Depends on Two Different Learning Curves,” by Jie Zhang, Nitin Joglekar, and Rohit Verma (page 28).

Keywords
Cornell Hospitality Research Summit, hotels, online travel agency (OTA), search engine marketing (SEM), search engine optimization (SEO)

Disciplines
Hospitality Administration and Management | Tourism and Travel

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When we think of science, we think of knowledge gained through a systematic process that includes collecting and testing information, often with the desire to find solutions to particular real-world problems. The summit theme, “The New Science of Service Innovation,” was based on the idea that using information in a systematic fashion is an essential step in elevating the conversation about innovation between industry and academe in hospitality.

In this four-part series of CHR reports, we have attempted to highlight the thinking and scientific findings of presenters who shared their insights at the summit. We include in our series of reports appendices that list and offer a brief summary of all the excellent presentations at the CHRS, while offering more detailed research summaries of selected studies.

Service Innovation
Distinguishing service innovation from other types and forms of innovation is important within the hospitality sector. While many discuss invention and technology interchangeably with the word innovation, we believe that the hospitality industry needs to pay close attention to both product and process innovations, because so much of service delivery is built on a co-created experience with guests, necessitating process innovation for execution. With this in mind, we define service innovation as the introduction of new or novel ideas that focus on services. This includes new ways to deliver value, new service concepts, or new service business models. Throughout the summit we found agreement from many practitioners that along with the rapid increase in big data to facilitate the optimization of revenue, shifts in
technology, continuous operational improvements, investments in employee performance, and management of the customer experience are keys to the delivery of service innovation. These areas of service innovation were embodied in the four summit tracks and are reflected in the four reports exploring service innovation.

The Emerging Importance of Data

The massive amount of data available from hotel and restaurant guests has made the understanding of big data critical for industry operations. New data analysis techniques are making it possible for the industry to offer better guest service while also improving revenue by matching services to guests’ needs. The data-focused presentations at the CHRS demonstrated the use of data to optimize prices, improve operating efficiency, and track customer behavior. The continuing evolution of the internet was the subject of much discussion, as the web facilitates guest intelligence and affects hospitality distribution and customer service in new and rapidly evolving ways. As one participant noted in a tweet during the summit, “We have powerful data locked in different places, so it is not usable.” Whether talking about user generated content, or the power of back-office, utility, and operational data, making data more usable is essential. As one tweeter suggested, “Start with the decisions not with the data.” This solid advice is reflected in the research on data featured in this report.

Who Will Be The Data Innovators?

The innovators of the future will continue to unlock the benefit of data for delivering on the hospitality value proposition. At the start of the keynote panel on data, we posed this question to the audience, Who will be the data innovators? We offered the audience two choices, insiders, such as hospitality brands (e.g., hotels and restaurants), or outsiders, such as technology companies, vendors, and suppliers. A total of 82 individuals texted their answer to our poll question. As their responses show, 76 percent believe data innovation will come from outside the industry.

We were struck by that finding, but we also remain unsure of what this suggests for the future of service innovation in hospitality. One interpretation of the survey poll might be that the industry will stick to its service operations expertise and focus on important decisions, while leaving the development of tools and analytics to vendors with strong analytic and statistical expertise in this domain. If that is the case, then strategic partnerships will be critical for the future of data innovation. A less positive interpretation is that the industry lacks the skill and talent to innovate with data, and that this deficiency may lead to a shifting of customer ownership and raise the possibility of dependence on vendors for critical guest and operational intelligence.
Optimization and Data Analytics
This first report of the four in this series explores the value of data and data analytics to address optimization issues, whether optimizing rates, booking channels, or even energy costs. The impact of online travel and the growing use of data analytics are explored in the research summaries to follow. During the CHRS, data presentations explored the role of big data, the growing importance of data capture and understanding, and the role of data analytic techniques to provide more optimal approaches to data mining and knowledge creation. The appendix at the end of this report provides the presentation titles and authors so you can see the full range of content explored during the summit.

In this report we highlight the following seven data-based research presentation from the summit:

- “Optimizing Hotel Booking Choices on OTA Websites,” by Jean-Pierre van der Rest, Paolo Cordella, Gerard Loosshilder, and Zvi Schwartz (page 4);
- “Applied Analytics for Hospitality Energy Efficiency and Associated Core Operations Transformation,” by Har Amrit Pal Singh Dhillon, Saju Ramachandran, and Parminder Singh (page 8);
- “How Recognizing Visitor Intent Fuels Customer-Focused Experiences,” by Matthew Butler and Lane Cochrane (page 14);
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- “How Hotels’ Organizational Learning Depends on Two Different Learning Curves,” by Jie Zhang, Nitin Joglekar, and Rohit Verma (page 28).

With the rise of internet-based search and booking as major innovations, Matthew Butler and Lane Cochrane in their paper “How Recognizing Visitor Intent Fuels Customer-Focused Experiences,” examine behavioral click-stream data as a way of forecasting online user intent. To better understand the benefits of qualitative data, the paper by HyunJeong Han and colleagues, “Solving the Online Review Puzzle,” shows how the use of software tools facilitates insights from the large volume of unstructured customer commentary available online.

Optimization is the focus of three papers. The paper by Jean-Pierre van der Rest and his colleagues, “Optimizing Hotel Booking Choices on OTA Websites,” considers the value of placement in the customer booking decision. He shows that hotels with lower placement positions gain little awareness, traffic, or conversion from advertising. Turning to rate optimization, Jian Wang, in the paper “Optimizing Hotel Group Room Rates,” works on the group pricing problem, revealing that early requests are more price sensitive than late ones. The paper concludes by suggesting that future work is needed to optimize rates for all groups and meeting space. The research of Har Amrit Pal Singh Dhillon and co-authors in their work, “Applied Analytics for Hospitality Energy Efficiency and Associated Core Operations Transformation,” illustrate how data analytics help practitioners to understand how to optimize efficiency of their energy resources. Whether handling a costly critical resource, a pricing decision, or customer choice, these papers use data to assist with optimization.

We conclude the summaries with research that explores how to understand knowledge and learning. Scott Erickson and Helen Rothberg, in their paper “Data, Knowledge, and Intelligence in Hospitality Industries,” compare hospitality to other industries such as banking and software, observing that big data and competitive information are low in the hospitality industry when compared to the banking and software industries. They suggest that the dispersed locations of hospitality firms, and low employee buy-in may be the primary challenges in knowledge use within the industry. Our group of papers concludes with the work of Jie Zhang and colleagues in the paper “How Hotels’ Organizational Learning Depends on Two Different Learning Curves,” which explores both organizational and customer learning over time. Interestingly learning effects are dampened as volume and variety of a hotel concept increases, and economies of scale did not have a significant effect. Overall this paper reveals the difficulties of learning in complex hotel organizations.

We thank these authors for their original presentation and their additional work on developing these papers.—Cathy Enz and Rohit Verma, co-chairs
Hotel industry operators are well aware of the principle that the top of the screen is the best placement for their properties for online travel agency (OTA) or search engine results. To that end, hoteliers apply search engine optimization (SEO) strategies, as well as purchase advertisements and position as part of their search engine marketing (SEM) program. Studies have supported that approach for promoting bookings. For instance, Brian Ferguson of Expedia.com cites a study that found that “95 percent of bookings occur with first-page placement, and almost half (47%) of these bookings are made with hotels in the top six positions.”\(^1\) Likewise, a study by Group M UK and Nielsen regarding Google and Bing searches found that users clicked on one of the top-three results 68 percent of the time, with 48 percent clicking on the result listed first, 12 percent on the second, and 8 percent on the third.\(^2\)


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Not every hotel can be at the top of the screen, however. Consequently, the industry could benefit from a systematic estimation of the value of a top placement. That knowledge might contribute to a determination of whether a hotel would be better off investing in a better placement, or whether the hotel could offset lower positioning with other tactics, for example, lowering the room rate or offering a package. To address those issues, this study uses conjoint analysis and simulation to estimate the monetary value of high placement in search results.

**Hypotheses**

The researchers postulate a positive, nonlinear relationship between the hotel’s position on the booking site and the customer’s propensity to book. Formally, the hypothesis is:

H1: The propensity to book a hotel room night is lower when a hotel advertisement is placed lower on the landing page of an OTA website’s customer search result, and the reverse is also true, with the booking likelihood higher when the position is higher.

To test this hypothesis the researchers estimate the impact of the search result order in the form of the monetary equivalence of the gap between each position, starting with positions 1 and 2, and moving down the screen.

Substantial money is on the line here, as slot fees could be based on a fixed fee or a percentage of the room price that would increase with higher positions. Booking.com, for instance, charges base commissions of 13 to 17 percent of room rate, plus “extra” percentages to move up.

Because the commission paid is tied to the room price, one can express the monetary equivalence of the screen position in terms of the room rate. Establishing an equivalence would enable hotels to explore the tradeoff between the room rate they quote and the fee paid for improved placement. Thus, the second hypothesis is:

H2: Hotels differ in how much their search result position is worth in terms of room-rate-induced propensity to book.

**Methodology**

To test H1, the authors created a fictitious online booking site that would replicate typical common booking behavior of OTAs. An online panel of 1,492 Dutch respondents selected by GMI (Global Marketing Institute) were asked to choose hotels based on a hypothetical trip that specified the city to be visited, the date, and number of nights. With that input the respondents were shown a “search response” that included 50 hotels. Needless to say, this booking page showed only the top hotels on the first screen, and respondents would have to scroll down to see other properties. The hotels’ attributes were manipulated according to conjoint analysis procedures so that the researchers would learn the effects of hotel brand and type, distance to the center, review scores, price, and position on the page.

Respondents were asked to search for a hotel in four rounds, during which the details regarding the hotels offered and their position on the page varied based on an orthogonal research design. Subjects were asked to treat each round as if the search were completely new.

The propensity for booking a hotel was considered as a function of its position on the landing page. The null hypothesis (H1) was that each hotel has an equal probability of being chosen. In reality, the probability of being chosen was a function of placement, review score, and price, all of which varied in accordance with the experimental research design and can be isolated in the analysis.

Using hierarchical Bayes (HB) estimation, choice probabilities were derived using a multinomial logit model to estimate the propensity of a particular subject to choose a particular hotel.

\[
P_k = \frac{\exp (x_i^k \beta)}{\sum \exp (x_j^k \beta)}
\]

where \( k \) is the choice set of all possible hotels, \( P_k \) is the probability of individual \( i \) to choose the \( k \)th hotel; and \( x_i^k \) = a vector including the attributes to the \( j \)th hotel.

Categorical parameters were estimated for the main effect of factors. To assess the effect of the placement of a hotel on the search page, 16 dummy codes were created to represent the effect of being placed in positions 1 through 15 and 15+.

To study the value of search engine positioning (H2), one should assess the value of the hotel placement in the context of the rest of the hotel’s characteristics. For this simulation, numerous scenarios were created to represent potential search pages,

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\[3\] Precise figures are not available, but these figures come from various sources on guestcentricite.com, quora.com, and skift.com.

The results confirm earlier insights that there is value in being first on the initial search page. As shown in Exhibit 1, guests’ propensity to book drops steeply until position 6, where the rate of change is reduced and tails off to near zero, about at position 12. Looking at Exhibit 2, one can conclude that the first position is superior in terms of probability of booking and should be pursued, but if it is unaffordable due to commission fees, hotels should attempt a listing at position 6 or higher, although the drop is precipitous from position 1 to 6.1

To test Hypothesis 2, which suggests a tradeoff between paying the OTA a commission fee for a higher placement or accepting lower placement and making up for that by reducing room rate, the researchers used a simulator to compare 21 hypothetical hotels with various characteristics (see Exhibit 3). Adjusting hotel chain and base room rate (attribute 1), hotel style (attribute 2), and the distance to the city center (attribute 3), the study ran scenarios in which the placement of each hotel on the initial search page was systematically changed from number 1 through number 21. Then the study determined the monetary equivalence of placement improvement (or demotion) was estimated as the effect of a price increase or decrease compared to a base price. This calculation estimated the amount that a room rate would need to change when the hotel changes its placement on the search page to maintain the same booking likelihood. This allows generalization of the results and an assessment of differences in how much a search result position was worth in terms of room-rate-induced propensity to book.

Results

The results confirm earlier insights that there is value in being first on the initial search page. As shown in Exhibit 1, guests’ propensity to book drops steeply until position 6, where the rate of change is reduced and tails off to near zero, about at position 12. Looking at Exhibit 2, one can conclude that the first position is superior in terms of probability of booking and should be pursued, but if it is unaffordable due to commission fees, hotels should attempt a listing at position 6 or higher, although the drop is precipitous from position 1 to 6.1

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5 Booking likelihood in this study was lower than, for instance, Goodwin, op.cit.
Based on this analysis, the monetary equivalent of being number 2 instead of number 1 ranges between 9 percent and 25 percent of the room rate. This suggests that hotels in position 2 that wish to maintain a similar booking performance as would occur had they been in first place, need to reduce their room rates by anywhere between 9 and 25 percent. A MANOVA test shows that the hotel chain and its base price is a key driver to moderate the effect of placement. The analysis further indicates that relatively expensive chains (e.g., Sofitel, Hilton) wishing to compensate for dropping their placement from number 1 to number 2 would have to reduce their price to a greater degree than the cheaper ones (e.g., Parkhotel, Caesar). That being the case, upper end properties might be more inclined to pay the commission fee for the top spot rather than trim rates. Even for specific properties within hotel chains, the recommendation on which direction to follow might vary. As the cost of maintaining the same level of probability of booking for that hotel is higher (in terms of reducing room rate), the hotel has stronger incentive to pay the OTA’s premium to be placed higher. Hotel chains could base their decisions on whether to pay for the top spot on the specifics relating to the unit. The decision can be based on simulations similar to the one demonstrated in this paper.

Note: The website enabled filtering (i.e., Price and Total Review Score) and sorting (i.e., Price and Total Review Score).

Exhibit 3

Hotel attributes

| Overview 1 Discrete attributes | | | |
| Attribute 1 | Attribute 2 | Attribute 3 | Attribute 4 |
| Hotel chain (including base room price) | Hotel Style | Distance | Call to action |
| This is the chain that the hotel is part of; a mix of international chains and local names | This is the type of hotel. Each type had a unique description on the product page | This is the distance from the city center in the subject’s city of choice | This is the presence of a call to action on the booking page to activate the visitor |
| Holiday Inn (€ 199) | Romantic | 500m | Present with a hotel |
| Best Western (€ 159) | Spa | 1km | Absent |
| Sofitel (€ 349) | Gastronomy | 15km | |
| Hilton (€ 219) | Luxury | 3.5km | |
| Park Hotel (€ 129) | Design | 5+km | |
| Metropole (€ 189) | | | |
| Caesar Hotel (€ 149) | | | |

| Overview 2 Semi-continuous attributes | | |
| Attribute 5 | Attribute 6 | Attribute 7 | Attribute 8 | Attribute 9 |
| Hotel room price per night | Customer rating for cleanliness | Customer rating for staff helpfulness | Customer rating for quality of facility | Rank order position of the hotel on the initial search screen |
| Every hotel chain had a base room price (see table 1) and the actual room price varied around the base price with three steps up (~ +40%, +25% and +12%) and down (~ -40%, -25% and -12%); seven price levels in total | We had 12 customer ratings for cleanliness of the hotel room which were chosen randomly and assigned based on the experimental research design; 12 levels in total | We had 12 customer ratings for hotel staff helpfulness which were chosen randomly and assigned based on the experimental research design; 12 levels in total | We had 12 customer ratings for quality of the hotel facility which were chosen randomly and assigned based on the experimental research design; 12 levels in total | There are 50 entries on the search page. The rank order position of hotels on the search page is assigned based on the experimental research design |

Note: The results of the MANOVA show that monetary value significantly varies across hotel brands (and their base prices), F= 8.49, df=6, p = .001, and the slopes in figure 2 are also significantly different across the seven hotels, F= 4.00, df=34, p = .000.
In general, the findings call for a strategy that is based on the tradeoff of position cost against room rate. If the room rate reduction required to compensate for going from number 1 to number 2 is lower than 15 percent, then the hotel would reduce the room rate. If the required rate reduction to compensate for going from position 1 to position 2 is higher than 20 percent, the better plan would be to pay the commission fee. Interestingly, the study does not support paying for slots that are much lower than about number 6 on the results page.

Discussion

In summary, the study supports previous findings that the propensity to book a hotel diminishes as the hotel’s listing information or advertisement is placed lower on an OTA or search engine results page. The impact varies somewhat by the type of hotel. The study points to the need for a fact-based strategy for establishing and negotiating commission fees associated with placement slots.

The considerable commercial value of the slots on the search page progressively degraded from top to bottom in this study. At position number 12 the likelihood of selection is extremely low and is not meaningfully different from zero.

Ironically, there is little value in slotting advertisements in lower positions, because they will not gain much awareness, traffic, or conversion. This presents a challenge to designers who need to do more to entice visitors to scroll down and add more value to slots below position 12.

This study did not simulate a booking site that contains sort and filter functions. Further research might examine whether these functions can help overcome the display limitations and the need for extensive scrolling. Although the study demonstrates the high value of the top slot, it also finds that a hotel can compensate for lower positioning by a reduction of room price (or perhaps other features). The value of other slots, notably 2 through 6, 7 through 12, and beyond, are also quantifiable. Operators of OTAs can use this knowledge to develop a differentiated strategy where higher priced chains and units with less favorable conditions such as far from a city center, have more incentive to pay a higher slot fee. Hotel chains can decide which properties should pay a higher slot fee, and which properties should manipulate other factors or encourage direct booking on Brand.com.

Applied Analytics for Hospitality Energy Efficiency and Associated Core Operations Transformation

Har Amrit Pal Singh Dhillon, Saju Ramachandran, Parminder Singh

Energy prices have been remarkably volatile in recent years, and energy remains a considerable expense for hotels and restaurants. Controlling energy use and costs is worthwhile both for economic reasons and also from a sustainability standpoint. Hospitality firms must plan and optimize energy consumption costs without compromising on business outcomes, services, or guest comfort. Retrofits are one way to reduce energy use, but the capital intensity of that approach opens the door to finding ways to conserve energy with existing equipment.

As explained in this study, analytics and data mining have the ability to enhance energy efficiency in the hospitality sector and thereby conserve capital. An analytic approach can help such organizations to intelligently and systematically manage, plan, and optimize their energy consumption and transform associated core operations. Increasing adoption of building management systems, along with room management, metering, and asset management systems, results in generating considerable data. Analyzing those data can help hospitality managers to control costs, ensure a better guest experience, and prevent equipment breakdowns.
This paper outlines several analytics-based approaches to generating energy savings by tightening operations and staff behavior in hotels and restaurants, thereby reducing leakages and waste. Based on their experience across multiple types of hotels and restaurants with many different formats, service levels, menus, and schedules, the researchers have identified significant opportunities to analyze periodic patterns of energy consumption, as well as weather, occupancy, and guest counts, among other measures. This analysis is based on the concept of “service windows,” each of which represent a discrete, identifiable period with its own energy consumption profile that recurs day after day.

This paper discusses various data mining-based research methods and presents a use case for analytics for energy efficiency and associated core operations transformation.

Research Methods

The analysis applies energy, operational, and business data received from the various sub-systems, including energy management systems (EMS), utility billing systems, property management systems (PMS), building management systems (BMS), and POS systems. These data can be intelligently correlated to generate opportunities for energy savings, energy forecasting, and improved site and network operations and efficiency of asset use. The applicable data mining and analytical methods are listed below, followed by their application.

- **Regression**—Hotel energy consumption model;
- **Statistical comparison**—Network wide thermal profile analysis and compliance;
- **Correlation and state prediction**—Asset reliability and performance analysis;
- **Clustering**—Energy consumption analysis across the hospitality industry and benchmarking;
- **Time series analysis**—Service window framework applied in QSR & operational transformation; and
- **Control chart**—Food safety compliance analysis for a QSR.

Main Results

(1) **Regression.** The researchers built a hotel energy consumption model for a hotel (Exhibit 4). This accurate predictive energy consumption model included heating degree-days (HDD), cooling degree-days (CDD), and occupancy as the independent variables. Using historical energy consumption as the dependent variable, the resulting equation could be used to predict the energy consumption. As shown in Exhibit 4, the equation demonstrated the greater effect of heating or cooling demand, as compared to occupancy (green bars). The model shows a good correlation with temperature and occupancy, in the sense that an increase in occupancy shows enhanced energy performance. Using the analytical model, it becomes possible to continually review the performance of the property and take corrective actions.

(2) **Time-series analysis to develop a service-window framework.** Although quick-service restaurant managers

7 The analytical equation was \( y = [46657.74 + (504.9 \times \text{HDD/day}) + (285.4 \times \text{CDD/day}) + (-202.3 \times \% \text{Occupancy})] \times \text{No. of Days} \).
do review their monthly utility bills, analyzing usage without connecting that usage to operations cannot give insights to the required operational transformation. Similar to an approach used for restaurant revenue management, the restaurant operating day can be divided into discrete service windows, which have fairly repetitive characteristics. As shown in Exhibit 5, a QSR’s service windows can be identified by energy data analysis, which shows eight periodic service windows that occur each weekday. Time series interval data regarding energy patterns can detect energy leakages through comparisons with specific restaurant operating schedules and load factors during each service window. These energy profiles are a result of such factors as the business volume, weather, equipment use, and the menu.

Variation in energy use in the service windows during business hours is due to guest count and sales. During off-times the service windows should have relatively consistent consumption. That is not the case in this graph, where the variation in energy use ranges from 80 to 53 percent of full load during non-service hours. This consumption variation is most likely due to operational scheduling, and one can achieve operational transformation by scheduling the equipment fire up and fire down according to the service window.

(3) Statistical comparison of network-wide thermal profile analysis. It is difficult to analyze the thermal profiles of various properties across a network. Therefore, enterprise-level analysis of temperature data helps identify sites with thermal profile issues, such as over heating or over cooling.

In the model depicted in Exhibit 6, yellow dots are the sites where there is a potential for heating set-point correction, light blue dots are the sites that might need cooling set-point correction, and pink dots are sites with consistently high temperature, which need to be checked for HVAC equipment issues. This analytical method allows for quick detection of non-conforming sites, subsequently helping management to take appropriate corrective actions that assist in stabilizing the network’s thermal profile.

(4) Correlation and state prediction based on asset reliability and performance analysis. Another important analytical method is asset performance analysis, based on an energy usage index (EUI), which helps monitor the reliability of the assets and in turn improve guest comfort. In the illustration in Exhibit 7, light blue + signs are high EUI assets with high compressor run hours but low average temperature, which means there is a sensor issue or RTU controls issue. That is, compressors are running consistently even though the space is overcooled. Red boxes in the bottom right of the model are low average EUI, with low or medium compressor run-hours but high average temperature. Again, there is a sensor issue or RTU controls issue, possibly including compressor failure because the compressors are not running even though the area is under cooled. Network wide analytics and correlation of EUI, RTU compressor run-hours, and average temperature in consumption...
Network thermal profile analysis

Exhibit 6

Asset performance analysis (based on energy usage index)

Exhibit 7
(5) **Clustering data for comparative energy analysis and benchmarking.** Hotel and restaurant operators with a large number of restaurants may find it difficult to detect energy leakages or deviations across their sites. Energy use depends on multiple factors like weather zone, occupancy, area of the facility, HVAC type, operating schedules, age of buildings, and hotel segment. One powerful method to analyze energy leakage and deviation is to segment or cluster the sites based on energy use and demographic variables.

Using the hierarchical method of clustering, in which items are grouped in ever larger groups according to the similarity or distance of their values, the values are gradually assembled until an optimal cluster solution is identified by gathering together relatively similar values (Exhibit 8). Clustering for nearly 90 U.S. hotels leads to the formation of nine groups, characterized by different segments and consumption levels. Once the clusters are established, each cluster has an average EUI as the benchmark. One can then identify hotels (or restaurants) that have energy usage that deviates noticeably from the cluster, which potentially have energy saving opportunities. Properties with an EUI higher than the cluster average potentially have energy leakages and should be given immediate attention.

(6) **Control chart for food safety compliance (based on temperature).** To ensure that a restaurant complies with food storage temperature norms, a control chart compiles temperature data over an interval of 2 minutes. The median temperature observed in an hour is then used for evaluating temperature policy adherence. The compliance report for a QSR’s walk-in freezer is illustrated in Exhibit 9. Using -18° to -22°C as the acceptable temperature range, the graph shows that policy breaches are highest in the employee-only hours (10:00 p.m. to 2:00 a.m.). The analysis also shows a relatively low percentage of compliance thru the day—from 5 to 40 percent. This points to equipment requiring some maintenance, but management must also address the periods of over cooling, which results in avoidable energy use.

**Implications for Future Research and Practice**

Many hotels and restaurants have energy management and building management systems that employ meters and sensors that log data related to energy consumption, temperature compliance, and asset performance. Each firm should establish a framework on how to analyze and employ the data sets thus generated to maintain a continuous program of improving operations and plugging leaks. These data must be analyzed using robust algorithms to further optimize the energy consumption.

The data mining tools discussed here, namely, regression, clustering, classification, time series analysis, and control charts, help to optimize energy use and limit leakage through model development, benchmarking, equipment cycling, and temperature compliance. The paper emphasizes the power of analyze-
ing energy and operational data in a way that helps hotel and restaurant operators to achieve savings with zero investment in equipment upgrades or retrofits.

In closing, the authors note the challenges of adopting these analytical methods, since the organization will need to overcome technical, operational, and organizational complexities to apply these analytics. The challenges include:

- **Disparate systems.** Every organization has a mélange of diverse systems;
- **Existing orientation.** Rather than an attitude of “fix the issue,” the organization should take an analytical and corrective approach that addresses ROI rather than retrofits;
- **Skill gaps.** Most organizations have staff with high engineering skill sets but statistical and analytical capability may be limited, as is access to the specialized tools outlined here; and
- **Data management.** Data must be stable and clean, so organizations must understand how to remove data inconsistencies. Handling large volumes of data can lead to inconsistent analytical results.

Overcoming those challenges will move an organization to more effective energy use with far less expense than total retrofits.
How Recognizing Visitor Intent Fuels Customer-focused Experiences

Matthew Butler and Lane Cochrane

With the rise of internet-based commerce, a broad research stream has been dedicated to modeling online search and purchase behavior.8 These modeling endeavors have taken a variety of approaches, including statistics9 and machine learning,10 but in general have implications for web personalization. Also known as website adaptation, web personalization is an umbrella term for several approaches to tailoring online experiences, including content personalization,11 chat,12 and re-targeting.13 From a machine learning perspective there have been two distinct tracks of research: (1) clustering of web user logs relating to unsupervised learning, and (2) predictive modeling relating to supervised learning.

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Much of the early work in web analytics research focused on unsupervised approaches that built user personas based on the web pages they visited.14 These clusters of personas could then later be used for predictive modeling purposes. However, when a meaningful label could be applied to user sessions, then a supervised learning approach can be applied. Typically, labels of this type are determined directly from the user logs. Certainly for online retailers the most valuable segment of users is those that are in the purchase phase. This has motivated the use of typical purchase funnel attributes as the target variables for supervised learning (i.e., purchased, visited, or abandoned the shopping cart). A plethora of research papers have modeled online purchasing behavior for the purpose of personalization.15 Regardless of approach or application, those papers share the same characteristic of modeling successful outcomes. That is, the labels denote the web session as either “made a purchase” or did not.

Modeling successful outcomes and taking a discriminative approach to categorizing user sessions is a straightforward modeling technique for aligning the analysis with business needs. This approach runs in contrast to unsupervised learning, where business intelligence comes only from interpreting the clusters, as the mathematics behind creating the clusters does not necessarily align to business needs. In that case the algorithm is optimizing a cost function typically independent from business objectives.

Though supervised learning has yielded some benefits it is still constrained to modeling behavioral data alone, while the context in which the data are generated, namely, the user’s state of mind, is not available. It can be difficult to interpret behavior without knowing the context, and for model building this leads to sub-optimal forecasts and ineffective personalization initiatives. This blind spot in the behavioral data is gaining more attention as recent studies in recommendation engines (arguably the most abundant form of web personalization) have been using context to improve the item set offered to users.16 From this research comes the focal point of the work described in this report, which aims to provide an alternative approach to modeling users on a website by incorporating context in the learning phase. The context is provided through stated user intent, thereby allowing the algorithms to differentiate the behavioral data based on users’ intentions and not just observed outcomes. Incorporating stated intent into the learning phase effectively removes the contextual blind spot stemming from the misalignment of business objectives and what can be inferred from observable variables in user logs.

The goals of this paper are to demonstrate that stated intent can be reliably predicted and to examine the advantages of knowing intent for website personalization.

Problem Definition and Approach

Working under the assumption that the ability to forecast user intent improves personalization, the researchers built and validated a model of stated intent, starting with a dataset that combines behavioral data with stated user intent. The process of doing so was performed by running a survey on a business to consumer e-commerce website that collected user feedback at the end of a session. Contained in the feedback survey is a question regarding the user’s intent for the session. Information from the questionnaire can be augmented with the user’s click stream data to create a dataset applicable for supervised learning.

In considering whether stated intent can be reliably predicted from observable variables, the researchers analyzed the following variables: environment characteristics (e.g., browser, time of day, location), the sequence of URLs visited by the user, and the amount of time spent on each URL. The target variable is user intent, which is determined from the survey’s purpose-of-visit question. The original seven levels on the survey were concatenated into three meta purposes of visit: namely, research, support, and purchase. The dataset contained the full click streams of over 60,000 different visitors along with their associated survey responses. However, distribution for visitor intent is unbalanced: only 11 percent said they intended to purchase, approximately half (46%) of visitors had support-related queries, and the remaining 43 percent professed research-related intent.

Since no known studies have attempted to predict stated visitor intent using behavioral click-stream data, this study constitutes a feasibility assessment regarding such a determination. For this purpose the researchers made a simplifying assumption in which they observed the whole user session at one time and therefore removed any sequential estimation component which would be required for in-session predictions. Having no precedent, the researchers conducted the feasibility study using the following four supervised machine learning approaches: function approximation, decision trees, instance-based learning, and Bayesian approaches. As shown in Exhibit 10, the data set is a mix of categorical data (e.g., URLs, browser, location) and numeric attributes (e.g., time, path length).

Experiment Results

For each algorithm the researchers report overall classification accuracy (Exhibit 11). For the top performing algorithm (NBstack), they also show the full confusion matrix and a rejection curve (Exhibit 12). The rejection curve demonstrates the relationship between the confidence of the algorithm and accuracy.


15 Magdalini and Vazirgiannis. op.cit.

The baseline accuracy is 45.88 percent, which represents a majority class classifier that predicts the intent of support for all sessions. From the zero-intelligence baseline, each of the algorithms is able to achieve an improvement in classification accuracy that is statistically significant \((p \leq 0.01)\). The rejection curve in Exhibit 12 is well-behaved and monotonically decreasing, which demonstrates that as the algorithm becomes more confident about a prediction it is more likely to be correct.

The rejection curve is the trade-off between confidence and coverage, but its shape denotes an information-rich input dataset. If the curve is flat or more chaotic, then the relationship between the input attribute space and the output dependent variable would be weak.

The confusion matrix table in Exhibit 12 displays the prediction results for each class of intentions. Most correct classifications are found in the research and support intentions, whereas intent to purchase was generally misclassified. This class imbalance problem is well documented in the machine learning literature.\(^{17}\) The algorithms under study are optimizing an error criterion which lends itself to poor prediction on minority classes. The precision for purchase was 12.13 percent and recall was 12.06 percent, which is only marginally greater than what would be achieved with a zero-intelligence approach. As discussed below, to improve predictions on this class a different approach will have to be taken, such as supervised sampling or anomaly detection.

**Intent for Personalization**

Having established that intent can be reliably predicted, the next step is to use intent to enrich and simplify online personalization. Finding ways to simplify personalization is crucial. Over 90 percent of companies state that personalization is important, but a mere 4 percent feel that they are able to deliver it.\(^{18}\) The potential for content management systems, live assistance, and marketing campaigns is immense, but the majority of digital marketers do not know how to begin (72%, according to one study).\(^{19}\) We believe that these barriers to personalization are in part created by the focus on “who” a user is as opposed to “why” that person is on the website. Someone who is at an initial research stage will have different requirements than someone shopping to buy immediately. The specific demographics of each of those web visitors is moot, compared to their purpose of visit. For marketers, one can easily map out relevant content, suggestions, and support, when sessions are described based on intent as opposed to profile. Personalization strategies become

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\(^{19}\) Ibid.
The results from the feasibility study clearly show a significant improvement to proactive chat can be facilitated by shifting the distribution of chats being offered to purchase intenders from the other two groups. The study demonstrates an anomaly detection approach to finding purchasers, due to the low accuracy percentage of other approaches. Exhibit 14 shows the distribution of chat offers for a proactive chat system both with and without using a model of intent to decide which users get offered a chat session. The model not using intent is a rule-based approach based on such typical measures as time spent and URLs visited. Exhibit 15 provides further details on the chat experiment, including the percentage of chats offered and the realized-assisted sales.

Triggering proactive chat based on a model trained with user intent yields a chat offer distribution more skewed to purchasers. This heavily skewed distribution in turn yields an increase in chat-assisted conversion and in chat acceptances. However, due to the higher propensity of purchasers to convert, the increase in sales is close to 12 times the increase in chats. In sum, this approach yields a 58-percent increase in sales with only a modest 4.84-percent increase in chats.

**Conclusions and Implications**

The results from the feasibility study clearly show a significant increase over existing benchmarks in classification accuracy in predicting stated intent. This demonstrates that intent can be inferred from click streams. The results also highlighted the susceptibility of the algorithms used in the study to the class imbalance problem, which diminishes the ability to identify the relatively small percentage of users who intend to purchase. However, the chat example, where an anomaly detection approach was used to recognize purchase intenders, demonstrated a significant increase in the model’s ability to find purchase intenders, which translated into significant gains in chat-assisted conversions. The gains in chat-assisted conversion served as evidence as to how intent improves web personalization initiatives above what can be achieved with behavioral data alone. Future work concerns the refinement of the approaches and the introduction of additional variables to the models such as scrolling and other actions.
Solving the Online Review Puzzle: When Scoring 5 Out of 5 Isn’t Perfect

HyunJeong (Spring) Han, Srinagesh Gavirneni, Shawn Mankad, Joel Goh, Rohit Verma

Although the hotel industry has long sought customer feedback to improve its operations, no channel has matched the internet for the sheer volume of comments and ratings. While ratings can provide an overall indication of a guest’s opinion, posted commentaries potentially provide a rich vein of feedback. Unfortunately, information in the commentaries is voluminous and unstructured, and is therefore not amenable to analysis using the existing methods that have been designed for quantitative data.

This paper demonstrates the use of automated software tools that have been designed to analyze large volumes of text. Using TripAdvisor commentaries on hotels in Moscow, Russia, this paper shows how to delve into the text of consumer reviews using methods that go beyond word count and overall sentiment of the review text.\(^{20}\) The only major study that employs advanced text-mining methods for services was by Ghose et al.\(^{21}\) Using nouns and noun phrases, they ranked hotels by combining data from text-mining consumer reviews with location information and crowd-sourced user-contributed opinions. In contrast to that study, this paper analyzes the full text of the review by means of probabilistic topic clustering.\(^{22}\) This analytical method addresses the two main difficulties of extracting information from the textual content of consumer reviews, namely, the unstructured nature of guest comments, and the (typically) large quantity of data. These two factors make manual coding of the data an unsuitable process.

The researchers extracted information from TripAdvisor reviews of Moscow’s hotels by using modern text analytic algorithms to convert the unstructured textual data to a structured form for statistical analysis. In sum, the results show that the users’ comments do not always align completely with their numerical satisfaction scores, although reviews that give high ratings also contain greater positive sentiment than those with


lower ratings. In particular, the authors find that the numerical customer ratings do not tell the whole story and that the information embedded in the text can bring additional insights for how hotels can improve their operations. Notably, the reviews of some hotels that were given a “perfect” score of 5 also contain some negative sentiments, a situation which implies that the review text can be further used to improve hotel operations. The analysis shows emotional density of the reviews, based on specific words and number of exclamation marks. Moreover, customer feelings are strongest at either extreme of the numerical ratings. Finally, the reviews can be stratified based on the quality of writing (below high school, high school, college, graduate level). Generally speaking, the higher the review’s numerical rating, the higher the writing quality.

Because each review may refer to several different aspects of a hotel’s operations, the analysis uses topic modeling, an established technique from natural language processing, to extract components of the experience the customers are focusing on. What the researchers found is that reviews with high numerical ratings refer to a relatively large number of minor issues, whereas reviews with low ratings focus on a smaller number of major issues.

Data and Methods
The analysis looked at TripAdvisor reviews for Moscow’s hotels posted in English from January 2012 through December 2013, recording the date, customer satisfaction rating, full text of the review, and type of reviewer (using such categories as business, family, solo, or couple). About 60 percent of the reviews during that period were written in English, which resulted in a total of 7,347 for analysis. The reviews were largely favorable, as 2,582 had a numerical rating of 5 and another 2,815 had a numerical rating of 4.

For the purpose of this analysis, hotels were grouped into thirds according to their mean customer satisfaction score, and each set of reviews was analyzed for three critical areas: (1) style of writing, (2) sentiment, and (3) content.

Sentiment Analysis
The word count and sentiment provide the most basic summary statistics. These are worth noting, since research has shown that they are associated with customer decision making and product sales.23 Sentiment is gauged according to words found in validated databases (called dictionaries). Dictionaries by Liu and Nielsen have words scored from -5 (strongly negative) to +5 (strongly positive), denoting their sentiment strength.24 For instance, “breathtaking” is scored as a 5, “amazing” is scored as a 4, “impress” is a 3, “like” is a 2, and “agree” is a 1. The sentiment measure is constructed using words with non-zero scores.

Style of writing. Writing style is determined by document length, number of exclamation marks, and estimated reading comprehension level. Reading level is estimated using the Flesch-Kincaid Grade Level, which uses such factors as sentence length and average number of syllables per word to indicate comprehension difficulty.25

Topic modeling. Topic modeling refers to a class of algorithms that use a probabilistic framework to summarize large archives of text by discovering hidden topics, or themes that occur within a set of documents.26 Taking note that certain words are more likely to be used with a particular topic, documents are composed of a probabilistic mixture of topics. Thus, the underlying statistical problem is to use the given text data to infer the topics (distributions of words) and decompose each document into a mixture of topics. Extensive work in computer science and applied statistics has led to fast and scalable estimation algorithms capable of handling millions of documents.27

The topic modeling analysis involves two probability distributions: focus, which expresses the proportion of each topic found within each review,28 and words related to a topic, that is, which words are more likely to be used with each topic. Typically, the analyst inspects the most frequent words to assign a label or meaning to each topic. Topics were modeled separately for each comprehension-level tier and each numerical rating.

Results

Sentiment Analysis:
Even 5-Rated Hotels Have Negative Review Content
Not surprisingly, a review’s sentiment is positively correlated with the numerical rating (Exhibit 16), but even 5-point reviews contain at least some (moderate) negative sentiment. Exhibit 17 contains some illustrative excerpts from a few 5-rated reviews.

Writing Styles:
Best and Worst Experiences Bring Out More Emotions
The analysis found a correlation between writing comprehension level and the hotel ratings. Middle and high-rated hotels have a greater number of high school and college level reviews.

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26 Blei and Lafferty, op.cit.
27 Blei, op.cit. Software and guidelines are from: Gruen B. and Hornik, op.cit.
compared to low-rated hotels (significant at $p < .01$). Similarly, emotional content also varied across the three tiers, as the lowest tier of reviews contained on average 1.8 negative and 0.6 positive emotional terms, in addition to an average of 0.96 exclamation marks. The middle-tier reviews contain on average 1.0 negative and 1.9 positive emotional terms, along with an average of 0.58 exclamation marks. For top rated hotels those figures were 0.4 negative terms, 3.2 positive terms, and 0.66 exclamation marks.

**Topic Modeling: Identifying Themes in Reviews**

The analysis identified 25 topics used to describe the low-rated hotels, and 20 topics each for the mid and high-rated hotels. The most frequent words across all categories include such items as room condition, front-desk service, proximity to public transportation and tourist attractions, and amenities, including free internet and breakfast (see Exhibit 18). Each rating tier also had its own special set of descriptors. In low-rated hotels, keywords included “smell,” “cold,” “secure,” and “just need place,” showing that customers’ basic expectations were not met.

- “A 10 minute walk to Red Square (says the receptionist)—count on 20 unless you speak and read Russian.”
- “The breakfast was worth the high price because everything, everywhere in Moscow is high priced.”
- “My sole complaint, poor TV reception, was fixed within a few hours.”
- “Only not so good, smoking in some areas, but in Russia everybody smokes; you need to be sure if you don’t smoke you need to ask for the non-smoking section everywhere you go.”
- “Though both the food quality and range are fine, it certainly loses out to our St. Petersburg hotels (Domina Prestige, Taleon Imperial, and Grand Hotel Europe).”
- “For supermarkets, we had a hard time finding one. Finally, found one at the former Hotel Moscow, near the Russian State Museum on the Red Square (it’s called the Domain Market or something?). The other nearby one is underneath the classy TSUM Department store, but it’s very expensive and you will be shocked!”

**Exhibit 16**

Review sentiment stratified by satisfaction score

**Exhibit 17**

Negative excerpts from high scoring reviews
due to noise levels, odor, or temperature. In contrast, high-rated hotels’ keywords included “pool,” “lounge,” “buffet,” “perfect or best view,” and “star,” indicating that these customers crave an overall experience and are less transactional.

Final Observations
Despite the importance of customer feedback in the hotel industry’s continuous improvement process, a comprehensive characterization of the customer experience is difficult to achieve. This study demonstrates how the text contained in online reviews offers an opportunity for a detailed view of customers’ comments regarding their hotel stay. Using a large dataset from TripAdvisor relating to hotels in Moscow, the study shows the value of software tools that quantify consumer review sentiments, identify the emotional content, and extract the main topics of discussion.
Conceptualization and Methodology
This paper proposes that knowledge-management intangibles which are valued by originating firms would also be valued by competitors, who are seeking competitive intelligence. That is chiefly true in industries such as pharmaceuticals and software where knowledge or data creation are the key to the business.

The study reports two variations on Tobin’s q, which compares a firm’s market capitalization with replacement cost of assets. Market cap to book value of assets is commonly used instead of replacement cost, because replacement cost is difficult to gauge. This study uses market cap to book value and also market cap to assets, which leaves out the liability adjustment found in book value. Book value of assets reports those tangible assets actually owned by the organization (assets less liabilities). Data were taken from the Institutional Brokers’ Estimate System (I/B/E/S) and include all firms with at least $1 billion in revenues listed on North American exchanges from 2005 through 2009. The study thus had 7,000 observations from over 2,000 companies, categorized by industry using SIC numbers.

In addition to measuring knowledge and intangibles the study applies data from a benchmarking study conducted by Fuld & Company, a well-established competitive intelligence (CI) consultancy. Data include over 1,000 self-reports from competitive intelligence practitioners concerning the maturity and proficiency of their operations from 2005 through 2009 on a scale of 0 to 4.5. The CI Index is a different reading of the same data, a combination of the level and number reports. Each practitioner’s expertise level is added across all responses (two 4s, one 3, and one 1 would result in a score of 12 on the index).

Finally, the study presents the volume of “big data” stored by companies in several industries, drawn from a study by McKinsey Global Services. Stored data is a proxy for big data and business analytics potential. As number of firms varies

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Intangibles metrics for selected industries

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<tbody>
<tr>
<td>7900: Amusement &amp; Recreation Services</td>
<td>2.71</td>
<td>0.91</td>
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<td>105</td>
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<td>7011: Hotels &amp; Motels</td>
<td>4.20</td>
<td>1.05</td>
<td>1.09</td>
<td>1</td>
<td>1</td>
<td></td>
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<tr>
<td>5812: Eating Places</td>
<td>3.56</td>
<td>1.56</td>
<td>1.55</td>
<td>3.5</td>
<td>6</td>
<td></td>
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<tr>
<td>7372: Software</td>
<td>3.89</td>
<td>2.14</td>
<td>0.64</td>
<td>4.5</td>
<td>113</td>
<td>715*</td>
<td>1,792*</td>
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<tr>
<td>602: Banking</td>
<td>1.61</td>
<td>0.14</td>
<td>0.07</td>
<td>4.5</td>
<td>50</td>
<td>619</td>
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<tr>
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<td>1.02</td>
<td>1.16</td>
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*Communications and Media

considerably by industry in the McKinsey report, stored data per firm is probably the more insightful of the indicators.

**Results and Discussion**

Other than banking, the industries are about equivalent with regard to their capitalization to asset ratios (see Exhibit 19). For the full database that ratio is 1.02. Hotels and gaming are quite close to that, and restaurants are a touch higher, suggesting higher levels of knowledge or intangibles being applied. Looking at capitalization to book value, the data reflect the hotel industry’s high asset concentration, which affects comparison with other businesses. Asset concentration also drives a low revenue to asset ratio for hotels. Looking at two other asset intensive industries, software is an industry with high intangibles (on both measures), while banking is quite low. Software has done more with intangibles relative to its large tangible asset base while banking has not. Big data is unambiguously low in the hospitality industries compared to banking and software. The authors suggest that this difference occurs principally because services don’t have the same level of supply chain, operational, or transactional data constantly coming in as does manufacturing. Finally, competitive information is relatively low in the hospitality industries, again compared with the aggressive software and banking sectors.

To assess the hospitality industry’s use of data and information, the researchers apply Kurtz and Snowden’s “sense-making” framework, which looks to categorize the organization and distribution of knowledge in different scenarios, as summarized by Simard. 31

- Known (common: data and information),
- Knowable (complicated: explicit knowledge),
- Complex (partially knowable: tacit knowledge), and
- Chaos (unknowable: intuition).

This framework highlights the challenge of making data and information (including big data) useful when it is turned into knowledge through analysis. Explicit knowledge is easily transferred between individuals and locations, providing opportunities for knowledge management. Tacit knowledge can be turned into explicit knowledge but may need to be shared person-to-person. Thus, tacit knowledge doesn’t always have the same impact because it must be made manifest. In hospitality industries, knowledge management involves both explicit and tacit knowledge, but a chief challenge of knowledge management.

management is the industry’s many dispersed locations and the difficulty in gaining employee buy-in and use throughout far-flung operations.

In addition to dispersion, the hospitality industry must also motivate contributors to share their knowledge and users to apply any new suggestions. A great deal of this knowledge is operational. There is distinct value there, but the tacit or intuitive insights leading to higher level tactical or strategic knowledge development and application aren’t apparent. The industry’s relatively low competitive intelligence scores start with the realization that one doesn’t need an advanced competitive intelligence operation to understand what competitors may be doing. After all, walking through their facility, joining their loyalty programs, or hiring mystery shoppers can provide just about full information on competitors’ activities. Beyond that, the detailed analysis required for competitive information is not especially rewarding, given that the data are mostly available for observation.

Based on this analysis the researchers see value in careful investment in analyzing big data, the price of which is gradually dropping. As time goes on, hospitality firms will find new and more valuable applications of these data. Knowledge management must link numerous units, but a challenge arises in encouraging employees to use the systems, since many view themselves as temporarily in the industry. The industry could develop a system of motivators and reward to encourage both contributions and withdrawals to the industry’s usable knowledge.

Acknowledgment: The authors gratefully acknowledge Fuld & Company for providing some of the data used in this study.

Optimizing Hotel Group Room Rates

Jian Wang

This paper examines the challenge of applying revenue management (RM) to group business, which can be a large contributor to many hotels’ revenue streams. The paper moves beyond the simple question of whether to accept a group request, and examines how to price such a request by offering an example based on the proprietary GroupREV application. Most studies relating to this topic have assumed that the group room rates are already determined, and that the decision to accept the group’s business would be based on displacement-cost analysis. In that scenario, group requests can be accepted as long as the displaced transient revenue opportunity is less than what would be gained from the group revenue opportunity.\(^{32}\)

Displacement cost analysis is usually performed on top of hotels’ existing transient RM systems. This analysis does not help with the determination of the optimal group rate, however. Instead, it only helps to ascertain the minimum acceptable rate.

The difference between the minimum rate to satisfy displacement and the optimal rate that the group is willing to pay represents a large and important revenue opportunity. At the same time, determining the correct rate for a particular group proposal is critical for winning the deal. The calculation of an appropriate group rate is complicated by the relatively long booking windows associated with group business, given the greater statistical uncertainty over time. The only paper on this topic, produced by Hormby et al., described the implementation by Marriott International of a group pricing system, which they called Group Pricing Optimizer (GPO). That system integrated the processes of segmenting markets, estimating a price response model, and recommending an optimal group rate along with negotiating range.

In contrast, the approach described in this paper optimizes the room rates for a single group request, using a heuristic approach which includes the steps of segmentation, reference rate forecasting, price sensitivity estimation, room rate optimization, and recommendation. In particular, this approach takes into account the fact that hotels already have a revenue management system. The case study demonstrates this methodology.

**Group Revenue Management and the Group Pricing Problem**

In addition to their long booking window, group bookings typically come with a contractual obligation specifying financial penalties if delinquent, may require additional space such as meeting rooms, and have less consistent patterns than do transient business. In part that inconsistency is a function of the fact that transient travelers choose the room they’ll book, whereas group travelers generally are picking up rooms in the hotel that is hosting the meeting, as chosen by the meeting planner.

Another consideration for group business is that group pricing is more risky than transient pricing. It’s especially important to get group pricing correct. If a hotel misprices a transient room, there’s a loss of a few room-nights, perhaps, but mispricing group business (and losing the sale) can cost many room-nights (as well as function proceeds).

**Assumptions**

Group business can be divided into three types: groups that use both rooms and meeting space, groups that use guest rooms only, and those that use meeting space only. This paper focuses on how to optimally price the two group types that book guest rooms. In this paper, price sensitivity is specifically defined as the winning likelihood, that is, the likelihood that a group will book the requested rooms at the room rate quoted. The methodology assumes satisfaction of the following hypotheses:

- The arrivals of group requests are independent and stochastic.
- Price sensitivity is only dependent on the variables of group market (that is, group type), group (or deal) size (i.e., the number of rooms), room type, days left (i.e., the number of days between booking date and arrival date), arrival season, and length of stay.
- Price sensitivity changes negatively over price. That is, fixing all other factors, the likelihood of winning a group will diminish as the quoted room rate increases.
- Groups can be segmented by price sensitivity. The segmentation will be complete and exclusive, such that the groups within the same segment have similar price sensitivity and the groups in different segments have distinctly different price sensitivities. In addition, the acceptance of a group request is also subject to the availability of rooms, which is influenced by the bookings of transient travelers and other groups.

**Heuristic Approach**

A group not only competes with all transient guests and other groups for the same guest rooms but may also compete with other groups for the same meeting space. Ideally, the optimization of room rates for all group and transient business should be solved simultaneously, but that is not possible in the current environment, particularly given that hotels already have revenue management systems in place. That is the reason for proposing the heuristic approach that aims to optimize the room rates for each individual group. This approach allows hotels to keep their existing transient RM systems intact while optimizing the group rates.

This approach starts by segmenting groups according to their rate ratio, which is the group rate divided by the reference rate, followed by the forecasting of reference rates. The analysis estimates a price sensitivity model for each group segment and optimizes the resulting rate ratio. Then, the optimal room rates are recommended for each group request. The processes in this approach are outlined as follows.

**Segmenting Groups**

The segmentation of groups is performed using CHAID (Chi-squared Automatic Interaction Detection). Independent variables are group market, group size, room type, days left, arrival season, and length of stay. The dependent variable reflects the groups’ price sensitivity. Like that of Hormby and colleagues,
this analysis uses the variable of win rate, indicating whether a group’s business was won or lost.\textsuperscript{35} This paper proposes a rate ratio as the dependent variable, which is defined as the ratio of group rates over reference rates. Group rates here include the quoted rates for lost deals and rates paid for won deals. Reference rates represent a base rate around which historical won rates used to vary and future won rates might vary. Rate ratios thus defined can be understood as the normalized group rates with respect to the won rates in market. In practice, hotels may classify groups roughly based on their business knowledge. For example, groups are often pre-classified into a number of group market segments such as government, national associations, corporate meetings, and local social events. To incorporate this business knowledge, segmentation will be performed underneath each individual group market.

**Forecasting Reference Rates**
Reference rate forecast at an arrival date \( t \) can be estimated with a reference rate forecast

\[
\hat{r} = A_t \cdot R_t \cdot (1 + T_t)
\]

where the term of \( R_t \) denotes the seasonality of won group rates, \( T_t \) the projected trend, and \( A_t \) the average of de-seasonalized won group rates.\textsuperscript{36} These terms can be estimated by building a regression model and weighted averaging.

**Estimating Price Sensitivity**
For each group segment, the price sensitivity at a rate ratio \( \chi \) can be expressed as:

\[
\text{Winning Likelihood } (x) = \frac{\exp(\beta_0 + \beta_1 \cdot x)}{1 + \exp(\beta_0 + \beta_1 \cdot x)}
\]

where the unknown parameters \( \beta_0 \) and \( \beta_1 \) can be estimated by building a logistic regression model with the observations of the number of won deals, and the total number of quotes.

**Optimizing Rate Ratio**
Given any group segment, the optimal rate ratio \( \chi^* \) can be optimized by solving the following optimization model:

\[
\text{Expected Revenue } (x^*) = \max_{x \in \chi} \text{Winning Likelihood } (x) \cdot x
\]

where \( \chi \) denotes the range of admissible rate ratios for the segment. Phillips applied a variation of this model.\textsuperscript{37}

The closing of a group deal results from a negotiation process. Regardless of the optimization results, hotels do not want their group sales staffs to quote rates that are too low or too high. As a result, floor rate ratio and ceiling rate ratio are preferred for creating a range within which the sales team can negotiate as necessary. A floor rate ratio can be estimated in part as the max of the break-even point at which the group revenue gained becomes no less than the transient revenue lost, based on displacement cost analysis. The selection of the actual floor ratio can be subjective, but should reflect a pricing strategy. The higher the ratio, the more aggressive the strategy. The ceiling rate ratio can be driven by a benchmark strategy, in which a relatively high rate ratio is the starting point for negotiations. This rate is also subjective, but again is part of the hotel’s strategy, depending on how aggressive or conservative the sales staff might be. A conservative approach, for instance, might involve choosing the 5th percentile of won rate ratios as the floor and the 95th percentile as the ceiling rate ratio.

**Recommendation of Optimal Room Rates**
After the optimal, floor, and ceiling rate ratios are estimated, the determination of optimal, floor, and ceiling rates for a group request will be straightforward. For an incoming quote those rates can be derived as the products of the corresponding optimal, floor, and ceiling ratios, by the reference rate forecast at the time at which the group desires to arrive.


\textsuperscript{36} Holt-Winter multiplicative method.

and the median win rate ratio. The segmentation segregates requests for short lengths of stay (segment 1 and 2), and further splits the longer stays between large group requests (segment 5), small group requests booking early (segment 4), and small group requests booking late (segment 3). Group requests for longer stays (3 and more days) and smaller groups (30 and less rooms in average) are further segmented between late and early requests.

Although the specific analysis is proprietary, a sample outcome is shown in Exhibit 22, which summarizes the estimates of floor, ceiling, and optimal rate ratios. The optimization indicates that early requests (segment 4) are more price sensitive than late ones (segment 3). As a result, a higher rate ratio is optimized (126.9% as opposed to 84.2%). This is consistent with business intuition that price should increase as we get closer to the day of arrival. In addition, Segment 5, which includes larger groups for longer lengths of stay, is deemed more sensitive to price, and the optimization recommends lowering the rate ratios to 61.3 percent. The market for large corporate groups is known to be highly competitive, and so the recommendation thus derived reflects the business sense. A similar intuition acknowledges that requests for short lengths of stay are also more competitive, which is in line with the results for segment 1 (77.5%) and segment 2 (88.5%).

Conclusions
Mathematically speaking, the group room rates thus “optimized” are in fact sub-optimal. They are an approximation of the global optimization for the mix of group and transient. In consideration of the fact that group business is highly negotiated, such “optimal” rates appear to be superior to the rates that are determined based purely on business rules in many hotels. As an effort to further improve this approach, research is underway to optimize the rates for all groups simultaneously, where group demand forecasting and meeting space will be considered in the model. Furthermore, the global optimization of the mix of group and transient will be investigated.
Studies of innovation in service firms suggest that implementation of those innovative ideas rests in large part on a learning curve for the organization—a learning curve that is subdivided to include both employees and customers. Models of service innovations conceptualize the implementation of product innovation as an evolutionary process that sees improved performance over time through organizational learning.

In the process of organizational learning, organizations encode knowledge and experience into routines with a goal of increasing performance. Numerous studies have shown that learning by doing increases a firm’s performance over time, but the context and contingencies of that learning remain open to examination. The contingencies of organizational learning are the focus of this study.

Organizational learning for service firms is complicated by the fact that the service providers and the customers jointly co-produce a service and each group has a learning curve. This study examines the link between organizational learning and innovation by considering the basic factors of service production, including the service concept, people, experience, and institutional context. The study’s goal is to understand the role of organizational learning during the implementation of service innovation.

Research Question, Framework, and Hypotheses

This study goes beyond simply measuring the experience–performance relationship and instead seeks to determine the elements controlling the context and learning mechanisms to achieve desired performance outcomes. The primary research question is: How do learning effects vary depending on the service context? Two active organizational context factors are immediately apparent: (1) the configuration of service

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Our primary research question is:  

Research Question, Framework and Hypotheses

To identify two active organizational context factors (Argote and Miron-Spektor, 2011; Damanpour, 1996, 1991) from service operations literature: (1) the configuration of service co-production between the service provider and customers; and (2) the volume and variety characteristics of the service concept. The model tested here conceptualizes an interaction of these two fundamental characteristics of service operations with operating experience to influence performance at the operating unit level. Exhibit 23 depicts the framework and associated hypotheses.

In summary, the hypotheses depicted in the model are as follows:

- **H1a**: There is a positive relationship between operating experience (EXP) and performance.
- **H1b**: There is a diminishing return in performance from experience.

H1a and H1b test the positive link between experience and performance, together with the potential diminishing return as learning advances. There is empirical evidence of both effects, and thus it is expected that the coefficients will change when the contextual factors are included in the model.  

- **H2a**: Increase in the cost efficiency of service provider (ODF) increases performance.
- **H2b**: There is a positive interaction effect between experience and ODF.
- **H3a**: Increase in the cost efficiency of customers (CDF) decreases performance.
- **H3b**: There is a negative interaction effect between experience and CDF.
- **H4a**: There is a positive relationship between service volume and performance.
- **H4b**: There is a negative interaction effect between service volume and performance.
- **H5a**: There is a positive relationship between service variety and performance.
- **H5b**: There is a negative interaction effect between service volume and service variety.

H2a&b and H3a&b account for the co-produced nature of service operation, given that both the service provider and the customer participate in the service production process.

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45 For example, Chase, R.B., Tansik, D.A., 1983. The customer contact model for organization design. Management Science 29, 1037–1050; and Sampson and Froehle, op.cit.


Variability introduced by the customer has long been recognized as a barrier to consistent service quality at sustainable cost. Service organizations typically address this issue by setting priorities according to the levels of customer influence in different areas of the service operations. For example, researchers and practitioners alike have recommended using service blueprinting as a service design and quality management tool based on the varying levels of customer influence in a service process. The underlying learning process is affected by the differential mix of service efforts from the service provider and the customers.

H4a  There is a negative relationship between service variety and performance.

H4b  There is a negative interaction effect between experience and service variety.

H5a  There is a positive relationship between service volume and performance.

H5b  There is a negative interaction effect between experience and service volume.

Finally, H4a&b and H5a&b aim to provide empirical understanding of how learning is moderated by the characteristics of the service concept. The dominant design of a service concept varies in its configuration of volume and variety across individual operating units. The configuration is aimed at targeting customers’ needs in a particular hotel. For example, some customers enjoy a variety of high-touch services, while others prefer no frills. Organizational learning will be different for services designed to satisfy such varying demands.

Research Method

The study tests these hypotheses using operating data from 822 U.S. hotel properties over an 11-year period (2001–2011). The data are drawn from the PKF Hospitality Research (PKF-HR) database of revenue and expense items, in accordance with Uniform System of Accounts for the Lodging Industry (USALI). The dataset used in this study focuses on the following operating expense categories: labor costs, utilities, material expenses, and maintenance costs. The analysis controls for differences in hotel size and complexity by including operating profit margin, capital, and size of operations. Exhibit 24 reports the sample characteristics, as compared with the national statistics.

The U.S. hotel industry has a long tradition of organizational learning to sustain competitiveness, but its high turnover (60% by one estimate) makes knowledge creation, retention, and transfer difficult. The study adopts the conventional form of learning curve:

\[ y = ax^b \]

where \( y \) is the performance measure, \( x \) is the cumulative experience and \( b \) is a parameter capturing the rate of change in performance. Log-linear transformation results in an additive form. The researchers follow Ingram and Simons and measure performance by operating profit margin of individual hotel sites normalized by labor cost, that is, annual gross operating profit margin divided by total labor expense (log transformed).

The characteristics of a service concept are developed from the hotel property types because each property type offers a specific set of amenities and service levels to satisfy their target customers. The independent variables are operating expenses and revenue per available room.

<table>
<thead>
<tr>
<th>Sample 2011 Data</th>
<th>American Hotel &amp; Lodging Association (2011 National Data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of properties</td>
<td>822</td>
</tr>
<tr>
<td>Revenue per available room</td>
<td>$85.65</td>
</tr>
<tr>
<td>Average Daily Rate (ADR)</td>
<td>$96.41</td>
</tr>
<tr>
<td>Average Occupancy</td>
<td>68.15%</td>
</tr>
<tr>
<td>ADR&lt;$30</td>
<td>0.61%</td>
</tr>
<tr>
<td>ADR $30-$44.99</td>
<td>9.00%</td>
</tr>
<tr>
<td>ADR $45-$59.99</td>
<td>16.79%</td>
</tr>
<tr>
<td>ADR $60-$85</td>
<td>25.43%</td>
</tr>
<tr>
<td>ADR Over $85</td>
<td>48.18%</td>
</tr>
</tbody>
</table>


Using the approach described in Zhang et al., the study derives a two-factor measure of production-cost efficiency from operating expenses: an operations-driven factor (ODF) and customer-driven factor (CDF). These two expense-based factors are developed using accounts specified in the USALI. The operations-driven factor weighs more on utilities (electricity and water) and maintenance expenses, since these expenses are generally under the control of management regardless of the number of rooms occupied. On the other hand, the customer-driven factor reflects guest occupancy levels, because it weighs most heavily on supplies used in rooms and food and beverage departments, which typically vary with occupancy.

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### Results

Although the passage of time has an influence on organizational learning, we see no effect on customer learning over time (Exhibit 25). The results are consistent across the five models, and we interpret the results from the full model, Model 4 ($R^2 = 0.526$) as follows.

Although the positive link between experience and performance is verified in the non-contingent Model 3, with slight diminishing returns, the interaction effects overwhelm the main effect of experience in Model 4. The evidence suggests that mechanisms other than the passage of time contribute to the experience–performance link depicted by the learning curve.

Performance benefits from service concepts with high volume or variety (H4a, H5a). However, the learning effects are dampened as volume and variety increase (H4b, H5b).

Learning by the service provider (ODF) increases performance (H2a), and the increase in operating experience further strengthens the effect (H2b). The opposite effects (H3ab) are found for the customers (CDF).

### Control variables

Operating units with more assets achieve higher profitability per labor dollar. High labor expenses hurt profitability, and the economies of scale effect is not supported.
Discussion and Conclusion

On balance we found that organizational learning does occur over time, but this is because employee-driven factors improve, and not because customers “learn” how to do their part in service co-production. The data confirm the difficulties of learning in complex hotel organizations.

**Variegated rates of service learning.** Services that are more intensive and variable create higher barriers for learning, as suggested in the taxonomy in Exhibit 26. The positive main effects of the service concept characteristics coupled with the negative coefficients for their interactions with experience underscore the complex relationship between learning and innovation. Although new services with higher intensity and variety directly boost performance, they also result in higher barriers for learning. For example, technology innovations such as a customer relationship management system hold promise to personalize customer experience, but such an innovation’s successful implementation is often elusive. Future research should benefit from investigating issues related to balancing the innovativeness of design choices and their ease of learning.

**The co-production learning paradox.** The positive link between experience and performance holds for service providers but not for customers. This is depicted in the main effects for ODF and CDF and their interactions with experience, which display coefficients with opposite signs. Consistent with other studies, the service provider’s efficiency increases as experience increases over time. Part of this improvement is job-related experience and part of it is direct training programs.

Neither of those apply to customers, in part because hotels constantly host new customers. Thus, since there’s no formal “customer training,” we cannot expect the same learning effects for customers as for employees. Further, individual customers’ exposure to service processes varies significantly in frequency and duration. Future research that develops measures of customer exposure to innovation and studies of related behavior will allow better assessment of the contingent learning effects for services. When implementing service innovation, managers need to be mindful of the contingent nature of learning. Mapping out the characteristics of service offerings is the first step toward benchmarking performance. In addition to planning for staff training, the implementation of any service innovation should include ways to “educate” or inform customers on the new process, to ensure that both co-producers are capable of realizing the full potential of the service concept.
Maximizing Revenue in the Ever-Changing Search World – Hummingbird, Social Impact, and More...

Anil Aggarwal, Chief Executive Officer, Milestone Internet Marketing, Inc.

This session goes through the journey of the consumer seeking to book a hotel room. We discuss how hoteliers can set their digital marketing plans and priorities to map to the various online touch points that a consumer goes through. The session will cover the key recent developments in the digital marketing world, and how hoteliers can maximize revenue and positioning in this ever-changing realm.

In Hotel Reviews Numbers Do Lie—Pay Attention to the Text

Spring Han, Assistant Professor, Faculty of Management, Higher School of Economics; Co-authors and presenters: Srinagesh Gavirneni, Shawn Mankad, Rohit Verma

It has been established that online reviews have a direct impact on decision-making and product sales. Yet, most extant works utilize only the numerical rating or sentiment. We apply text analytics to reviews for hotels from a leading review website for prescriptive, content-driven insights for key service operational areas.

The Growing Impact of Online Reputation Management across the Hotel Enterprise

RJ Friedlander, Co-founder and Chief Executive Officer, ReviewPro

The rise of social and mobile technologies have given every guest a voice, and the guest intelligence that comes from online reputation (ORM) data and analytics is changing the way savvy hotel executives manage their organizations. The experience of thousands of leading hotels around the world provides a unique perspective into how ORM has evolved from a standalone activity into an integrated process that affects most areas of the hotel enterprise.

Attribution Modeling in Hospitality Industry: State-of-the-Art and Beyond

P.K. Kannan, Ralph J. Tyser Professor of Marketing Science, University of Maryland; Co-author and presenter: Hongshuang (Alice) Li

Focus on how big data of the customer journey to hotel websites can be used to attribute credit for the customer touch points that result in bookings. Results from a recent implementation and implications for media mix allocation will be discussed. Attribution modeling is absolutely essential for today’s hospitality industry. Analyzing big data can make your marketing more efficient and effective.

Big Data in the Hotel Business—Let’s Bring the Dots Together

Michael Toedt, Managing Partner and CEO, Toedt, Dr. Selk & Coll.

Big data will change how companies work and interact in the future. The increase in profitability by using big data of up to 60% forecasted by McKinsey is a benchmark, but should be even higher for hotels.

Mobile and Big Data’s Potential for Human Capital Development

David Topolewski, Chief Executive Officer & Mobile Learning Evangelist, Qooco

We’ll discuss the use of mobile services to train hotel employees better in communication, on-property upselling, and vocational skills, thereby boosting productivity, guest satisfaction, and RevPAR. Combined with cloud services, mobile learning generates data, and allows for benchmarking and empowering hotel employees and management with performance monitoring. Benchmark the competencies of employees to upsell and deliver superior service to guests, and the implications for financial returns. Understand how to bridge the gap between the brand promise and brand delivery of great services to guests.

260-Billion-Dollar Opportunity for Automated Dynamic Pricing for US Restaurants

Pawan Marwaha MMH ’06, Co-founder and Chief Grabber, RezGuru by TableGrabber; Co-author and presenter: Sonia Marwaha

We digitize restaurants with a Global Distribution System (GDS) along with an automated dynamic pricing tool to optimize their revenues. Our algorithm analyzes historical trends along with various macro and micro data points, to predict demand and allow restaurants to better plan their manpower, inventory, and pricing to maximize their revenue potentials.

Understanding Customer Behavior on Direct Booking Engines

Michael Skinner, Lead Engineer and Chief Data Scientist, Duetto; Co-author and presenter: Duncan Hall

We explore how this data can be used to better understand prospective guests, focusing specifically on how this information can be used to estimate price elasticity. Lost business from direct booking engines is a powerful tool for understanding how different factors influence a prospective guest’s decision to book. The problem of estimating price elasticity is made much simpler, and hotels have direct control over strategies that make it simpler still.
Understanding the Unmanaged Business Traveler
Breffni Neone PhD '04, Associate Professor of Hospitality Management, The Pennsylvania State University; Co-author and presenter: Kelly McGuire MMH '01, PhD '07
The unmanaged business traveler is a highly valuable segment for most hotel companies. Understanding how these travelers use price and user-generated content to assess value and ultimately make a purchase decision will help hoteliers design pricing and positioning strategies to attract this profitable segment.

Data, Knowledge, and Intelligence in Hospitality Industries
Scott Erickson, Professor, Marketing and Law, Ithaca College, School of Business; Co-author and presenter: Helen Rothberg
Intangible assets can be a significant competitive advantage for firms. Drawing from our proprietary database, we present insights on development and protection of knowledge assets in hospitality, and competitive intelligence efforts to procure them. Given these metrics, we can draw even deeper insights concerning strategic use of such intangibles. Intangibles can be a critical strategic asset and can be effectively assessed, employed, and protected in hospitality industries. Deeper analysis of such intangibles can help to understand competitive conditions and lead to further strategic insights.

How Recognizing Visitor Intent Fuels Customer-Centric Experiences
Matthew Butler, PhD '13, Senior Data Scientist, iPerceptions; Co-author and presenter: Lane Cochrane
In the quest for customer-centric interactions, service companies are turning to marketing technologies to personalize the visitor experience. Equipped with intent, a powerful model of user behavior can be constructed to fuel personalization engines, ad retargeting, and live chat technology to create relevant customer-driven experiences. Behavior data alone is not enough to infer intent. Recognizing intent improves and streamlines personalized web experiences.

Upgrading Your Function Space with Better Analytics
Kate Keisling, Lead Consultant, Ideas—a SAS Company; Co-authors and presenters: Elizabeth Walsh, David Wilker
Attendees will benefit from IdeaS' three years of research and experimentation in the area of function space revenue management. Find out more about function space demand forecasting methods and which key performance indicators will help you to optimize your meetings & events profits.

Exploring Two New Customer Choice Models in Revenue Management
Jean-Pierre van der Rest, Professor of Strategic Pricing & Revenue Management, Hotelschool The Hague, Hospitality Business School
Two room rate pricing ideas are explored. How does the perceived value of cancellation, as well as the willingness to pay, change over the booking horizon? How does the relative position of a hotel's ad in the (OTA) travel website search engine results list impact consumer hotel choice decision-making?

Optimizing Hotel Group Room Rates
Jian Wang, Vice President and Chief Data Scientist, The Rainmaker Group
Group and transient both constitute the total business for many large hotels. Although revenue management has been successfully practiced in the hospitality industry for decades, the focus has been mainly on the pricing of transient rates. In this presentation, we introduce an approach to approximating the optimal group rates.

Price Optimization—Where Next?
Tim Unwin, Executive Vice President, RateGain
Price optimization has many flavors and is a key element in a variety of revenue management strategies. In "Price Optimization – Where Next," we examine how the analysis of competitor set data can be the foundation for a market-oriented pricing model, complementing the analysis of historical trends and other established methods.

Shaking the Money Tree: Big Data and Revenue Management in the 21st Century
Alex Dietz, Principal Industry Consultant, SAS Institute, Inc.
In the era of big data, revenue managers are rightfully questioning whether big data has real value to revenue management. We will explore the availability of big data in revenue management — and the importance of new analytic approaches — through work done by SAS, as well as through academic papers. The presentation will also explore the importance of combining new analytic approaches with big data in order to transform new information sources into value.
Applied Analytics for Hospitality Energy Efficiency & Associated Core Operations Transformation

HAPS Dhillon, Global Practice Head, Energy Management, Wipro EcoEnergy; Co-authors/Presenters: Saju Ramachandran, Parminder Singh

Energy is one of the top two or three costs for a hotel or restaurant, and also the fastest growing! The session will discuss and impart working knowledge of proven analytical methods and frameworks for launching a data-driven, continuous improvement program for reducing energy waste and transforming operations.

Lean Service Innovation and Profitability: A Panel Study in US Hotel Industry

Jie Zhang, Assistant Professor, Operations and Information Systems Management, The University of Vermont, School of Business Administration; Co-authors/Presenters: Nitin Joglekar, Rohit Verma

This study tests the theoretical framework which states that active organizational context interacts with experience and influences learning outcomes (Argote and Miron-Spektor, 2011). We find that organizational learning varies with contextual factors including the volume and variety of service provided, and the characteristics of the service provider and customers. The indirect paths of learning through the contextual factors (i.e., volume and variety of service provided, and characteristics of service provider and customers) dominate the direct learning effect, indicating important levers for managing learning in service.

How to Leverage Online Review Content to Enhance the “Search, Shop, Buy” Experience

Rob Castellucci, Senior Director, Key Account Management, TrustYou

Online reviews are pervasive in the hotel industry. How can these reviews be used proactively by hotel companies and online travel agencies alike to enhance the shopping experience?
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