Choice Models and the Hospitality Business Environment

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Choice Models and the Hospitality Business Environment

Abstract
[Excerpt] The purpose of this chapter was to introduce discrete choice analysis within the context of the hospitality industry. For a hospitality firm to be successful, it is necessary that sophisticated customer choice approaches, such as discrete choice modeling, become an essential component of the managerial decision-making framework. In this chapter, I have provided several examples of discrete choice studies conducted for a variety of hospitality and related applications. I have also discussed how the science of discrete choice modeling continues to evolve rapidly. I hope that researchers interested in hospitality and related services will find discrete choice modeling useful in their future research and applied projects. At the same time, I would like to note that similar to other modeling processes, choice modeling is subject to the "garbage in, garbage out" principle. It generates useful information only if the assumptions behind the selection of market drivers, the experimental design, and the data collection methods are sound.

To summarize, I believe that choice modeling can yield valuable insights for strategy development by revealing customer needs, by measuring the market share impact, by assessing overall brand equity, and by identifying switching barriers. Moreover, choice modeling can reveal any salient differences between managers' beliefs about customers' needs and wants and their actual needs and choices. For managers eager for reliable feedback on how customers view their offerings, choice modeling provides a rigorous way to turn customer-driven feedback into profitable and sustainable strategies for retaining or capturing market share and profitability.

Keywords
hospitality industry, discrete choice analysis, customer choice, management, decision-making

Disciplines
Hospitality Administration and Management

Comments
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While the business environment for the hospitality industry continues to be in a flux, the rapid proliferation of new products and services make it even harder for the firms to understand what customers really prefer and are willing to pay for. Making things even more challenging, potential goods, service, and experience features for market offerings in the hospitality industry have grown increasingly complex due to the advances in information technology (IT), which allows customers to compare and strategically assess the relative costs and benefits of different alternatives. For example, hotel customers can easily compare competitive offerings at online reservation channels such as Expedia, Orbitz, Kayak, Travelocity, etc. This increased market transparency creates both opportunities and risks for the service companies who must operate within this business environment. Therefore, as service providers face knowledgeable and sophisticated consumers, there is an increasing urgency to gain an understanding of the trade-offs associated with consumers' choices so that appropriate managerial decisions can be made.

The underlying problem in predicting customer choices resides in the fact that purchasing decisions are made on the basis of (potentially) many different criteria simultaneously, including brand, quality, performance, price, features, channel, and so on (McFadden, 1986). This problem is further confounded in “service” applications, where a customer may consider nontangible features and characteristics of the market offerings (e.g., service quality, safety, and trust; interactions between service providers and customers; and so on). For example, customers might choose a restaurant based on its cost, service quality, food quality, food variety, cuisine, and ambience. Similarly, customers might choose a hotel based on its location (close to airport, tourist location, and downtown), brand name, various facilities (swimming pool, golf course, spa and fitness centers), service quality, price, loyalty program, and quality ratings by past guests, among other things.

Furthermore, within the hospitality services, many determinants of customer choices (e.g., waiting time and product variety) are directly linked to operating decisions such as labor schedule, capacity planning, operating difficulties, and task priority policies. Given that
many hospitality services are “coproduced,” some drivers of customer choices are directly impacted by the actions of customers (e.g., waiting time is a function of employee productivity and customer arrival rate). Therefore, it is crucial to understand the relative importance of various components of service offerings on customer choices. Furthermore, hospitality firms are often organized in a structure where there are multiple decision makers (e.g., property owners, managers, and corporate brand standards), each with unique decision-making criteria and constraints. In such business environments, sometimes the objective assessment of customer choices is the only appropriate way to reconcile any differences in managerial priorities and practices.

During the last few years, research has redefined a sophisticated toolbox (discrete choice analysis [DCA]) for understanding the drivers of customer choices (e.g., Verma, 2007). Such tools and methodologies allow the prediction of market performance of new or existing service offerings with remarkable precision even for seemingly complex and erratic market conditions. For example, studies have demonstrated that the discrete choice framework is very effective in modeling the choice behavior of customers when exploring service designs (e.g., Easton & Pullman, 2001). Based on discrete choice data collected at the food court at a large international airport, Verma, Pullman, and Goodale (1999) developed a framework matching the needs of multiple market segments with service offerings. In another study, Verma, Thompson, Moore, and Louviere (2001) presented a nonlinear profit and market share optimization model linking customer preferences obtained from DCA with production cost and operating difficulty. Similarly Goodale, Verma, and Pullman (2003) developed a model for optimally scheduling labor shifts based on relative utilities for waiting times that were derived from customer choices.

Victorino, Verma, Plaschka, and Dev (2005) demonstrated how business and leisure travelers’ perceptions of technology-based innovations differ significantly in the hotel industry. Similarly, in a recent study, Dixon, Kimes, and Verma (2009) explored the relative preferences for technology-based innovations in restaurants using choice modeling. They identified significant differences in preferences due to customers’ past experiences. In another recent paper, MacDonald, Anderson, and Verma (2009) demonstrated how hotel pricing decisions can be made from customer choice models.

In summary, it is appropriate to state that discrete choice modeling is increasingly being used in many applications to predict customer choices in the hospitality industry. Therefore, the purpose of this chapter is to briefly summarize the science of customer choice modeling, highlight recent methodological advances, present examples from the hospitality industry, and discuss managerial implications.

**Discrete Choice Analysis: Background Information**

DCA provides a systematic way to identify the implied relative weights and attribute trade-offs revealed by the choices of decision makers (e.g., a customer or a manager). DCA has been used to model choice behavior in many business and social science fields. Introductions to and extensions of DCA can be found in sources such as Ben-Akiva and Lerman (1991); Hensher and Johnson; (1980); Louviere, Hensher, and Swait (2001); Louviere and Woodworth
(1983); and McFadden (1986). Thus, rather than repeat what is already well known, we only summarize the main ideas behind the approach in this chapter. Therefore, although the following subsections only provide a general overview of DCA, it should be noted that the approach can be adapted to fit many specific research situations and applications.

Information integration theory (IIT) in psychology (e.g., Anderson 1981, 1982) and random utility theory (RUT) in econometrics (e.g., Ben Akiva & Lerman, 1991; Louviere et al., 2001) provide the theoretical basis for DCA. In particular, research suggests that after acquiring information and learning about possible alternatives, decision makers define a set of determinant attributes to use to compare and evaluate alternatives. After comparing available alternatives with respect to each attribute, decision makers eliminate some alternatives and form a final choice set containing a few alternatives. They then form impressions of each alternative's position on the determinant attributes, value these attribute positions vis-à-vis one another (i.e., make trade-offs), and combine the attribute information to form overall impressions of each alternative.

Economic choice theory assumes that individuals' choice behavior is generated by maximization of preferences or utility.

It is now well known that the conditional probability of choosing an alternative from a given choice set can be expressed as a multinomial logit (MNL) model if the random components of utility (the errors in the valuation process) are IID Gumbel-distributed random variates (Ben-Akiva & Lerman, 1991; McFadden, 1986; Train, 2003). Other forms of choice models (e.g., nested logit models) can be derived by relaxing the IID error assumption, but for purposes of illustration and exposition, this paper focuses on the MNL model. The MNL model is expressed as

$$P_j(C_n) = \frac{e^{V_j \mu}}{\sum_{k=1}^{n} e^{V_k \mu}}$$

where $V_j$ represents the systematic component of utility of alternative $j$ in a choice set $C_n$, which includes $n$ alternatives. The parameter $\mu$ represents constant scale for underlying Gumbel distribution. Furthermore, $V_j$ can be written as

$$V_j = \sum_{a \in A} \beta_a X_{aj}$$

where $\beta_a$ is the relative utility associated with attribute $a$ of the alternative.

In practice, either actual transactional data captured in databases (known as revealed preference data) or experimental choice analysis (known as stated preference data) is used to estimate $\beta_a$ associated with equations 1 and 2 using maximum likelihood estimation techniques.

**Developing Choice Models From Revealed Preference Data**

To estimate choice models based on revealed preference data, a researcher needs to obtain a data matrix that represents actual choices made by the decision makers. Examples of such
databases include page views and hotel reservations made at online travel agent Web sites (e.g., Expedia, Travelocity, Orbitz, or Priceline); actual purchases of different cruise, golf, adventure, or dining packages; and sales for various products at retail stores. Furthermore, some additional characteristics of the decision criteria should also be captured such that the estimated choice models can link explanatory variables with observed choices. For example, based on observed hotel reservations, competitive product offerings, and information about unsuccessful bids at priceline.com, Anderson (2009) has developed a model for pricing hotels on opaque channels. In another paper, Dixon and Verma (2009a) explored the impact of the sequence of “pleasure and pain” in a service encounter on future customer choices. They use long-term ticket sales data (over 1 million individual transactions across a period of 6 years) from a large performing arts venue to calculate the probability of subscription ticket repurchase. They use the resulting choice model to optimize the mixed schedule of events offered by the organization. 

Similar to Anderson (2009) and Dixon and Verma (2009a), many other examples of the use of revealed preference models in hospitality and related services can be found particularly in the area of pricing and revenue management (RM). Mathematical economics literature also includes many examples of revealed preference models.

Developing Choice Models From Stated Preference Data

If the researcher does not have access to appropriate revealed preference data or if the available data set lacks appropriate statistical properties then choice models are estimated from stated preference methods—also known as experimental DCA. The experimental choice modeling approach requires that decision makers (e.g., customers, managers) make choices in simulated situations derived from realistic variations of expected market offerings. The process comprises typically three broad steps (e.g., Verma, Plaschka, & Louviere, 2002).

First, using qualitative assessment (e.g., customer interviews, case studies, industry data, and focus groups) and other information sources, a list of variables believed to influence customers’ buying decisions is compiled. For example, a residential developer might identify choice variables such as unit size (one bedroom, two bedrooms, three bedrooms), kitchen layouts (L-shaped, U-shaped, galley style, open-shaped with island), appliances (standard, designer, or professional designs), amenities (exercise facility, roof terraces, theater/entertainment suites, concierge/doorman), parking (number of parking places, valet or self-parking, washing/cleaning services), and “price” (per unit base, built out, location and amenity pricing).

Next, “choice” experiments are constructed, which ask respondents to select one out of two or more choice options available to them in a series of “choice sets.” For example, Victorino et al. (2005) presented descriptions of three hotels (economy, midrange, upscale) to respondents in a series of 16 choice sets; Verma et al. (1999) presented 12 experimental descriptions of four restaurants (a burger shop, a deli, a hot dog stand, and an Italian shop) to customers as choice sets; and Verma and Thompson (1996) presented 16 choice sets each including two descriptions of pizza delivery establishments to the customers. Within each set, the respondent was asked to choose one of the two (or more) presented services package or neither. Choice tasks can be constructed in many different variations as described in Louviere et al. (2001) and Train (2003). An example of a stated preference choice experiment is presented in Exhibit 7.1.
Exhibit 7.1  A Sample Stated Preference Choice Experiment

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hotel #1</th>
<th>Hotel #2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand name</td>
<td>XYZ</td>
<td>ZYX</td>
</tr>
<tr>
<td>Room rate (USD/night)</td>
<td>$150</td>
<td>$125</td>
</tr>
<tr>
<td>Star rating</td>
<td>4 Star</td>
<td>3.5 Star</td>
</tr>
<tr>
<td>Average Trip Advisor rating</td>
<td>3.75 out of 5</td>
<td>4.5 out of 5</td>
</tr>
<tr>
<td>Location</td>
<td>Downtown</td>
<td>Close to airport</td>
</tr>
<tr>
<td>Wireless Internet</td>
<td>Free</td>
<td>$10/day</td>
</tr>
<tr>
<td>Availability of spa</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Availability of children's program</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pets welcome?</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
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<tr>
<td>...</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

If Hotel #1 and Hotel #2 were your only alternatives, which one would you choose?

___ Hotel #1   ___ Hotel #2   ___ Neither

In the final phase, econometric models based on responses from a representative sample of customers (or potential future customers) are used to identify empirical key patterns in the survey responses, providing relative weighting for each explanatory variable (e.g., price, brand name, and service features). Managers can then select the optimal combination of variables in order to develop a profitable and sustainable value proposition that, under normal competitive constraints, will maximally leverage their available resources.

Recent Advances in Choice Modeling

Like any science, choice modeling continues to evolve as researchers in various academic and professional disciplines pursue projects with varied focus and emphases. I briefly describe four types of important advances next.

Multimedia Stated Preference Choice Experiments

Even a few years ago, a typical implementation of a stated preference choice modeling involved developing lengthy paper-pencil surveys in which a respondent was subjected to a
series of preconfigured choice scenarios. Choice sets were presented as static tables with little room for customization and adaptability for individual respondents. Recent advances in IT, including broadband Internet connections, digital imaging and video technologies, and computing speed, allow researchers to develop very realistic and highly customizable choice experiments specific to each respondent’s decision scenario. In a lot of our recent work across a wide range of industries (i.e., consumer durables, retail and shopping areas, hospitality and leisure destinations, financial services, industrial automation, medical solutions and systems, telecommunication), I have extensively used Web-based technologies (e.g., hyperlinked pictures, brand logos, and audio and video files) to realistically illustrate choice scenarios.

**Best-Worst Stated Preference Experiments**

The stated preference discrete choice examples discussed earlier assume that the respondents are selecting a bundle of product or service offerings. However, in many applications, the respondents need to prioritize a number of alternatives and not necessarily select an option (e.g., customer satisfaction ratings, rank ordering operational priorities, and relative preferences for new innovations). For such research problems, rating scales are commonly used to assess relative importance of various decision variables (e.g., rate customer satisfaction on a scale of 1 to 7). However, we also know that respondents are notorious for rating items very rapidly, using simplification heuristics to speed through the task (e.g., Cohen & Orme, 2004). Studies show that respondents use only a limited range of the scale points, resulting in many ties across items. Some respondents use just the top few boxes of a rating scale, and some refuse to register a top score for any item. Others conscientiously spread their ratings across the entire range.

While standardization of ratings (forcing the mean rating within each respondent to zero and the standard deviation to unity) has often been suggested as an appropriate remedy, this transformation removes the level differences between respondents and is often difficult for managers and policy makers to understand. Furthermore, when a respondent uses just a few scale points, the within-respondent standard deviation is very small, making the new standardized estimate very large. To improve the situation of low discrimination across items, some researchers use rankings. In a ranking task, respondents order the items from best to worst (with no ties). However, respondents often find it difficult to rank more than about seven items.

Researchers have experimented with many techniques to achieve the benefits of metric scaling while also encouraging respondents to discriminate among the items. Another common approach is the “constant sum,” or chip allocation scale. To use a constant sum scale, respondents allocate a certain number of points or chips across an array of items. As with rankings, constant sums are difficult to do with more than a small number of items.

Recently, Louviere and coworkers have developed a new choice-based approach known as best–worst or maximum difference choice analysis, which provides unbiased estimates of the relative preference ranking for a set of alternatives (Finn & Louviere, 1992). The best–worst choice approach requires subjects to identify alternatives in each experiment, which are respectively, “best” and “worst” on some latent dimension (e.g., attractiveness or satisfaction) (Finn & Louviere, 1992). I have found this approach to be particularly useful in the
Exhibit 7.2  A Sample Best-Worst Experiment

Listed below are several restaurant technology options. Please indicate the options that are MOST and LEAST attractive to you.

<table>
<thead>
<tr>
<th>Least Attractive Technology</th>
<th>Most Attractive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pagers for table management</td>
<td></td>
</tr>
<tr>
<td>Kiosk-based payment</td>
<td></td>
</tr>
<tr>
<td>Payment via SMS/text messaging</td>
<td></td>
</tr>
<tr>
<td>Online reservations</td>
<td></td>
</tr>
<tr>
<td>Handheld order taking</td>
<td></td>
</tr>
<tr>
<td>Virtual menu online</td>
<td></td>
</tr>
<tr>
<td>Internet-based ordering</td>
<td></td>
</tr>
</tbody>
</table>

service sector applications since often the decision makers (customers or managers) have to assess the relative attractiveness of alternatives, which are very different from each other. An example of a best-worst experiment within the hospitality context can be found in Dixon, Kimes, and Verma (2009), where we assess relative preferences for various restaurant technology innovations. Exhibit 7.2 shows an example of a best-worst experiment.

Advanced Analysis Procedures

While IT’s role in designing realistic experiments is impressive, even more impressive is the “behind the scenes” hard work of statisticians and management science researchers who have been developing advanced procedures for estimating and fine-tuning econometric models based on choice modeling. Advances in Bayesian statistics allow us to estimate choice models for each individual respondent and/or fine-tune market segment memberships. Several such statistical advances are described in a recent book by Train (2003). Innovative optimization procedures, such as chaos theory, neural networks, simulated annealing, genetic algorithm, and simulation modeling, are being used in various applications to identify optimal product-service design configurations and to link choice modeling outcomes with other managerial decision problems (e.g., Bonabeau, 2002). Other advances in choice experiment design include developing hierarchical choice experiments and partial profile designs. While use of such procedures increase complexity in designing choice studies, data analysis, and econometric models estimation, they also allow researchers to reduce the choice-task complexity for respondents by only showing a few market drivers within each choice set at one time.

Fusion of Revealed and Stated Preference Data

During the last few years, firms have invested heavily in customer relationship management (CRM) systems and IT that capture many different types of actual transactions. Such
implementation generates a huge amount of customer transaction data (e.g., airline or hotel check-in records, reservation patterns, use of various facilities, credit card usage patterns, frequent user/loyalty card records, and wireless voice and data records), which can be used to monitor customer preferences over a long period of time. Effective use of such transactional data can allow organizations to customize product-service offerings to usage patterns of individual customers thereby increasing satisfaction, retention, and loyalty (Loveman, 2003). As mentioned earlier, Anderson (2009) described an excellent example of use of transactional data for pricing hotel rooms for an opaque channel.

While the use of transactional and data mining techniques can be extremely helpful in isolating trends based on past choices, such approaches can only have limited use when making predictions about really new product-service features. Hence, experimental choice modeling results combined with econometric models developed from existing transactional databases can realistically estimate the impact of new innovation within a specific business context. The reader, however, should note that extreme care needs to be taken in such data merging techniques, in order to isolate any statistical differences due to use of multimethods. Otherwise, the resulting models might be confounded with random errors.

Within the hospitality context, I have not seen much use of choice models based on both transactional and stated preference data sets. In a recent paper, MacDonald et al. (2009) described the strengths and benefits of combining two types of data sources when developing hotel pricing models. In another study, Dixon and Verma (2009b) demonstrated how past ticket sales data could be combined with experimental stated preference models to optimize performing art events that are of interest to both loyal and new customers.

Managerial Insights From Discrete Choice Modeling

In a series of recent articles, my coauthors and I have described a number of managerial insights that emerged from customer choice modeling studies (e.g., Verma, 2007; Verma & Plaschka, 2003; Verma et al., 2002). Therefore, here I highlight and summarize some of the valuable managerial implications that I have observed in our recent studies particularly related to the hospitality industry.

The statistical models developed from customer choice studies can be easily incorporated into decision support systems (DSS) (see Exhibit 7.3). While design of experimental choice experiments and estimation of models requires sophisticated training and skills, implementation of the estimated model(s) in spreadsheet-based DSS is fairly easy. Once the DSS is available, a manager only has to input the attributes of their own and competitor products to predict expected market shares. The DSS essentially approximates the dynamic nature of the market, allowing managers to evaluate multiple businesses, operating and marketing strategies, and the effects of changing strategies in the competitive marketplace. In addition, the predictive power of customer choice models can be further improved by market segmentation techniques, such as latent segment or Bayesian analysis.

The relative weights of various explanatory variables (β or utility) can be used to identify the homogeneities in a firm's user base and assess how they impact the current and future value of firm offerings. The choice models can also identify key features that drive market
Exhibit 7.3 Types of Decision Support Systems Based on Discrete Choice Analysis

![Diagram showing types of decision support systems based on discrete choice analysis](Image)

share in different customer preference clusters. An example of multiple customer preference clusters (gourmet buyers, tough sells, and bargain hunters) and corresponding relative utilities for various choice drivers (price, brand name, feature, service) was presented in Verma (2007). The gourmet buyers have relatively higher utilities for all of the choice drivers except price. The tough sells consider each of the four choice drivers to be relatively equally important whereas bargain hunters seem to be most price sensitive. Identifying such preference differences across customer groups can help a firm develop a more effective marketing campaign for each cluster. A similar example for financial services was presented in Verma, Iqbal, and Plaschka (2004).

The relative weights can be used to calculate two very useful “what-if” analyses for combinations of service offerings known as customer desirability. The desirability can be presented in the format of a relative index between 0 and 100. A desirability index of zero represents the least desirable service of all possible combinations. Similarly a desirability index of 100 represents the most desirable service combination. The estimated weights for various service components can also be used to calculate customers’ willingness to pay for a specific market offering. An illustrative decision-support simulation used to calculate desirability index and willingness to pay for two hospitality situations can be downloaded from the Web site of the Cornell Center for Hospitality Research (http://www.hoteischool.cornell.edu/research/chr/pubs/search.html; search for “Verma” under author index).

In addition to identifying the overall relative impact of customer preferences, choice modeling results can also be used to assess the relative impact of changing the value of one or more variables on overall market share. For example, the models can assess how the market share of one firm will be affected by a change in one or more choice drivers by the competition. Iqbal, Verma, and Baran (2003) and Verma et al. (2001) have presented market share simulations for online financial services and hospitality industry.

By assessing the relative weights of various explanatory variables to identify “order-winning features,” a firm can further optimize its service offerings. This analysis enables the firm to focus on a selected few choice drivers when developing new products/services or
changing selected features of existing offerings. This has clear implications for new service development as well as for the development of service extensions and derivatives. For example, Victorino et al. (2005) tested the relative value of various types of new service development ideas for business and leisure customers.

Assessment of brand equity (as related to customer choices) is another potentially important analysis that can be conducted from the choice modeling results. For example, Verma, Kimes, and Dixon (in press) demonstrated the relative impact of brand equity in customer choices for membership dining programs.

Furthermore, I believe that robust and reliable estimates of switching inertia can be easily derived from by designing customer choice experiments when respondents have to choose between "current" and "new" service providers (e.g., Li, Madhok, Plaschka, & Verma, 2006). Such choice experiments can be customized for each individual by first asking the respondent to describe the value levels for each market driver of their current service providers (e.g., the travel service they used for their most recent business trip). Subsequently, we pair the currently used service with experimentally designed profiles of "alternative" service providers to generate a series of choice experiments. Generally speaking, the switching barrier, or inertia, is the tendency for customers to stay with their current service provider despite the availability of other "better" offerings. This might be caused by one or a combination of factors, such as customer habit or preference for status quo ("don't like to switch"), satisfaction with current service offerings, lack of real or perceived alternatives, alternative offers lack credibility, and so on. Although in free markets we always assume that customers can choose their preferred vendor, we often observe in service oriented markets that customers do not switch providers even if they freely can choose to do so because of switching inertia (e.g., customers rarely change bank accounts because of one bad experience or marginal increase in fees!). Consequently, a new service provider has to overcome existing customer inertia and must offer a substantially stronger service bundle simultaneously to win a customer's business or must offer a highly customizable service bundle to gain dominance in a market.

Customer choice modeling results can also be used for developing effective implementation guidelines or for prioritizing various initiatives so as to maximize the net gain from any chosen strategic plan. By understanding consumer choices, managers can effectively develop and position service offerings to better suit market needs. In addition, mathematical models representing consumer choice can be linked to several operating decisions (e.g., labor scheduling, special activities planning, and service offerings) and optimal service configurations can be identified for further improvement. The reader is referred to Goodale et al. (2003) and Verma et al. (2001), which provide examples of discrete choice experiments linked with operating characteristics (labor scheduling and operating cost/difficulty) in services.

In addition to the applications previously described, choice models and associated DSS also can be used as education and training tools and to help managers better align their decisions with what customers want and are willing to pay for. Often managers of large service organizations (e.g., hotels, resorts, financial services, and health care organizations) are too busy managing day-to-day operations; hence, a gap may exist between the managers' perceptions of customer needs and customers' actual needs. Comparing two choice models—one representing customer choices and another one representing the managers' beliefs about customer choices—can identify such a "perception choice" gap (e.g., Verma & Thompson, 1999).
Conclusion

The purpose of this chapter was to introduce discrete choice analysis within the context of the hospitality industry. For a hospitality firm to be successful, it is necessary that sophisticated customer choice approaches, such as discrete choice modeling, become an essential component of the managerial decision-making framework. In this chapter, I have provided several examples of discrete choice studies conducted for a variety of hospitality and related applications. I have also discussed how the science of discrete choice modeling continues to evolve rapidly. I hope that researchers interested in hospitality and related services will find discrete choice modeling useful in their future research and applied projects. At the same time, I would like to note that similar to other modeling processes, choice modeling is subject to the "garbage in, garbage out" principle. It generates useful information only if the assumptions behind the selection of market drivers, the experimental design, and the data collection methods are sound.

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