DECISION SUPPORT FOR SUPPLIER SELECTION AND HOTEL REVENUE MANAGEMENT

By

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Abstract

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This dissertation focuses on the general theme of decision support for the area of hotel revenue management (RM), as well as supply chain management. In the first essay, I explore two research questions: How should the sophistication of hotel RM be measured? And what are the internal and external indirect drivers of the level of sophistication of hotel RM? The level of sophistication is based on decision tree tests, which include four steps: data capture, data foundation, rigor of analysis, and techniques used, including pricing, inventory allocation, and product configuration. Via an empirical analysis, I determine five positive drivers of hotel RM sophistication. My study provides hoteliers with guidelines for determining whether their RM system is at the right level of sophistication given their operating environment, and provides a roadmap for hotels to enhance RM sophistication through efforts to improve both internal and external drivers. The second essay discusses a supplier selection problem with business volume discounts. I develop a set of structural equations using predictive global sensitivity analysis, which can help managers make strategic order allocation decisions efficiently.

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This dissertation is dedicated to my parents, who have supported me unconditionally throughout this journey.

CHAPTER ONE

DRIVERS OF DEGREE OF SOPHISTICATION IN HOTEL REVENUE MANAGEMENT DECISION SUPPORT SYSTEMS

1.1 Introduction

Given the features of the hotel industry—high fixed costs, low marginal costs, and perishability of products and services—revenue management (RM) plays an increasingly critical role in determining hotels' financial success (Salerno, 2010). Modern hotel RM practices are evolving rapidly due to the increasingly competitive and rapidly changing business environment (Masiero et al., 2016). Consequently, hotel managers still face many challenges in RM (Cetin et al., 2016). Researchers in the hospitality field have been heavily involved in helping hoteliers overcome these challenges. The new challenges of revenue management in the hotel industry have also give rise to new academic interests. Among these, two revenue management-related issues seem quite dominant: (a) How should the sophistication of hotel RM be measured? and (b) What are the internal and external indirect drivers of the level of sophistication of hotel RM? This study focuses on examining these two questions. In this paper we first develop an internally valid measure of hotel RM sophistication. We then demonstrate the external validity of this measure by showing that external drivers of RM sophistication are associated with this measure. Thus, our validated measure is a foundation for future academic research: under what conditions is a more/less sophisticated RM system desirable. For example, under what operating conditions is more sophistication required to improve overall financial performance and market share? Our analysis of external driver impacts provides some preliminary insights for this theory development.

When measuring the sophistication of hotel RM, previous studies (Koupriouchina et al., 2014; Pereira, 2016) primarily focused on demand management, which refers to the overarching business logic behind optimizing prices and managing perishable asset inventory availability, such as forecasting room occupancy and customer demand. However, according to the RM sophistication framework proposed by Ng et al. (2017), three other components need to be incorporated when developing RM classification systems: data analysis/modeling, resource management, and data collection. Data analysis and modeling refers to the algorithmic implementation of demand management logic, while resource management refers to the non-technical side of demand management (e.g., designing rate classes for micro-markets, efficient engagement of customers, among others). Data collection refers to the IT infrastructure that supports the activities of the other components. In spite of their potential significance for RM, these three components have not been examined in studies of the RM sophistication of hotels. This study fills the literature gap by incorporating all four RM components in a decision tree to measure the sophistication of hotel RM.

Most previous studies (Oliveira et al., 2013) focus on the direct factors of hotel revenue management, such as cost control and predicting customer room choice, without examining the indirect factors that influence the sophistication of hotel RM. Although direct RM practices and factors can effectively enhance hotel RM sophistication, making efforts to improve indirect drivers are more cost-effective, easier to implement, and produce long-term change. These indirect factors can include both internal factors (which describe hotels' long-term properties and strategies and short-term operations) and external factors, such as a competitive environment.

These improvements in indirect drivers are generally easier to implement than changes to the system proper (i.e., the forecasting and optimization engines). Many of these indirect changes involve just being more thorough in sifting and winnowing through the large data warehouses that are offshoots of the primary system. Other indirect changes involve having better coordination between the parent company and franchise, or between sales agents and the parent company. Not only are these types of changes easier to implement, they often have a greater revenue impact than improving a forecasting or optimization algorithm. Bodea et al. (2009) note that in the hotel industry, conversion from the traditional forecasting system algorithms that assume independent market segment demand to algorithms that explicitly model correlations between segments is extremely difficult; many conversion projects have been problematic. Thus, paying significant attention to improving indirect drivers is important for maximizing the return on time spent improving the overall revenue management organization.

We extended Ng et al.'s (2017) study of a revenue management framework and drivers by adding an internal factor, utilization of electronic word-of-mouth (eWOM) in the hotel context, for three reasons. First, with the rapid development of information technology and social media, more customers book rooms and post reviews about their hotel stay experiences online. eWOM strongly influences customer demand and the financial performance of a hotel (Cantallops and Salvi, 2014). Second, utilizing eWOM through online management, such as designing online forums that encourage spreading positive eWOM and providing managers' responses to negative comments, significantly influences future customers' hotel booking intentions and behavior. Third, with the big data background, utilizing eWOM through data analytics of online customer reviews can help hotels better understand customers' expectation and needs, and thus improve their corresponding products and services (Xiang et al., 2015).

This study's primary contributions include the following. First, we incorporate all four components—data collection, data analysis, resource management, and demand management—in our use of a decision tree to measure the sophistication of hotel RM. Second, we develop and test hypotheses on the impact of six indirect internal and external factors of hotel RM sophistication, including eWOM utilization, customer segmentation, hotel size, differentiation strategy, organizational structure, and competitive environment.

The remainder of the manuscript is structured as follows. Section 1.2 reviews the relevant hotel RM literature and Section 1.3 develops the hypotheses. Section 1.4 introduces the methodology, while Section 1.5 analyzes the data. Section 1.6 presents the statistical results, which are discussed in Section 1.7. Theoretical and managerial implications are presented in Section 1.8, and Section 9 concludes the study and proposes future research directions.

1.2 Literature review of hotel RM research

RM is defined as selling the right inventory to the right customer at the right time and setting the right price (Smith et al., 1992). Many previous studies have focused on hotel RM practices (Arenoe et al., 2015); these studies can be categorized into five types.

A major RM component is pricing strategy (Feng and Xiao, 2000), and the first category of studies focuses on pricing decisions (Abrate and Viglia, 2016). These strategies appear especially beneficial to tap maximum willingness-to-pay amongst differing market segments (IDeaS, 2018), as well as balancing utilization and profitability of available capacity (Bitran and Caldentey, 2003). The optimal pricing strategy depends on the number of price points (Chatwin, 2000); number of price changes (Feng and Gallego, 1995); markdowns, markups, and promotions (Bitran and Mondschein, 1996); and joint pricing issues for multiple products (Bitran et al., 1998). For hotels, dynamic pricing strategies based on weekdays or weekends, length-of-stay, arrival dates, different seasons, and event periods are helpful for RM (Viglia et al., 2016; Koushik et al., 2012). Dynamic pricing strategies have reached a relatively mature level in the literature.

Almost all RM systems today use cross-elasticity price optimization as the key method. This is crucial for maximizing revenue under the most common conditions, where capacity is sufficient to meet demand. The overarching goal in these conditions is to get each customer segment (and, ideally, each individual customer (see Duetto, 2018) to pay an amount equal to their maximum willingness-to-pay. Key components of price optimization systems are: rate implementation and adjustments based on inventories, cross-elasticity demand function estimation through comparison with competitors' rates, price shop implementation to assess competitors' future rates, and cross-elasticity demand function optimization with respect to price (Cross et al., 2009).

Both strategic and tactical price decisions are examined in Abrate and Viglia's (2016) study, where three key factors are used to establish pricing: the tangible, reputational, and contextual attributes of hotels. A game theory approach is used to find the optimal equilibrium price when facing competitor hotels' pricing decisions (Arenoe et al., 2015). A dynamic approach is implemented to help hotels adjust their pricing based on time of booking and stay, change in occupancy rate, and competitors' pricing (Abrate and Viglia, 2016).

The second category of studies focuses on demand forecasting (Wu et al., 2017). Both future customer demand and room occupancy rates can be forecasted. A more detailed review of the literature shows that demand in each customer segment, hotel and room segment, and specific time ranges (e.g., before, during, and after events, weekdays versus weekends) have been forecasted in previous studies (Pereira, 2016). The forecasting methods include regressions, non-causal time series models, econometric methods, and artificial intelligence-based methods (Wu et al., 2017). Both pricing and demand forecasting have various influential factors to be considered, including seasonal factors, location, hotel properties (e.g., chain versus independent hotels), competitors' practices, event factors, exchange rates, and more (Corgel et al., 2013).

The third category of studies (Xu and Li, 2017) focuses on inventory allocation, which addresses the issue of what is the most profitable mix of demand for the given hotel capacity under conditions where capacity is insufficient to meet demand at a certain point in time (Choi and Kimes, 2002). The trend in hotel RM today is to jointly assess inventory allocation and pricing, and thus our pricing basis construct includes both pricing and inventory allocation concepts. Pricing and room allocation can be used as direct and indirect channels to maximize profits (Xu and Li, 2017). Hotel inventory allocation management includes overbooking and length-of-stay control.

The fourth category of studies focuses on revenue management related technical and managerial practices (Wang, 2012). Technical practices mainly include the design of revenue management systems (Gayar et al., 2011), which are comprehensive and have various modules. Managerial practices include customer relationship management (Wang, 2012) and specific actions practiced by hotels when considering the hotel features (e.g., luxury versus budget hotels), targeted customers, and the external environment, such as destination and customer culture (Panvisavas and Taylor, 2006).

The fifth category of studies focuses on the impact of hotel RM (Altin et al., 2017). The positive impacts include enhancing financial performance, strengthening customer relationships, and optimizing operations (Altin et al., 2017).

Our study crosses and connects with all five types of literature. Although previous studies have proposed RM techniques such as pricing and demand forecasting, the mechanisms for evaluating those techniques have rarely been examined. Whether hotels with those techniques are sophisticated in RM depends on the levels and details of their practices, which are the focus of this study's use of a decision tree to measure hotel RM sophistication. In addition, this study extends the fourth category of studies by examining the internal and external indirect actions that influence hotel RM. These actions may not be directly included in RM practices, however, implementing them can help hotels manage revenue. More sophisticated hotel RM can aid hotels in improving their financial performance and operations.

1.3 Hypotheses development

This section proposes six hypotheses related to the influential factors of hotel RM system sophistication. All six influential factors serve as indirect drivers of RM. Although they may not be directly related to RM practices, they can prompt better RM, or their presence can reward better RM. It is also possible that the presence of these drivers makes it less expensive to implement RM, or requires better RM to address the complexity. An examination of the indirect drivers of RM sophistication reveals that many revenue management practices are outside the scope of the system proper—the demand forecasting system and associated rate optimizer—but when fully developed can greatly improve the performance of the system. We categorize these six influential factors into two types: internal factors and external factors or competitive environment. The internal factors are subcategorized into two subtypes: factors related to short-term operations (i.e., eWOM utilization, customer segmentation definition) and factors related to long-term properties/strategies (i.e., hotel size, differentiation strategy, and organizational structure).

1.3.1 Internal operations drivers

With the rapid development of information technology and the associated greater popularity of customer online hotel reviews on booking or social media pages, eWOM, both in the form of online customer ratings and textual comments, has grown tremendously (Cantallops and Salvi, 2014). Better utilization of eWOM can enhance hotel RM sophistication through the following mechanisms. First, online review data has business value for understanding customer needs and perception. Hotel data and text mining of these online review data can help hotels better understand customers' stay experiences, and thus enhance the corresponding products and services (Xu and Li, 2016). This permits hotels to better meet customers' expectations and needs, and increase customer demand. Effective eWOM utilization makes it easier to discern subtle differences between market segments, thereby enabling the hotel to design unique and tailored packages for each segment.

Second, hotels can encourage satisfied customers to post online reviews and the positive eWOM reduces future customers' perceived risk, generating greater demand (Harrington, 2009). Providing economic benefits or building online forums can encourage the spread of positive eWOM. Hotels with positive eWOM can enjoy better reputations and be preferred by customers, increasing their willingness to pay (Öğüt and Onur Taş, 2012).

Third, when customers are dissatisfied and post negative online reviews, hoteliers can implement online management to alleviate the negative eWOM and respond quickly to explain reasons for service failures, commit to improving their product and services, and provide compensation (Gu and Ye, 2014). This can lead to retaining more customers and attracting new customers.

Fourth, the utilization of eWOM prompts better RM through the design and implementation of an RM system. Data collection and analytics provide sources for understanding hotel customers' booking behaviors, which facilitates the accuracy of demand forecasting (Kouprioúchina et al., 2014). Hotels can also adjust their room rates based on customer reviews, considering customers' willingness to pay a premium for hotels with higher customer ratings and customized products and services (Öğüt and Onur Taş, 2012). Based on this discussion, the first hypothesis is as follows:

***H1**: Hotel utilization of eWOM has a positive relationship with hotel RM sophistication.*

According to customer focus theory (Lohan et al., 2011), companies with clearly defined customer segments understand customer requirements, better utilize customer information, receive and utilize customer feedback, and improve relationships, motivating them to use RM systems. A larger value for the customer segmentation construct means it is easier to discern and differentiate smaller micromarkets. When this is improved, (a) the system proper's demand forecaster can be more accurate since confounding between predictor variables will be reduced, and (b) the system proper's rate optimizer will correspondingly drive higher revenues since there will be greater delineation of customer wants-needs.

Hotels with clear target customers can better understand the customers' needs and expectations, leading to customer satisfaction and loyalty. Thus, hotels can increase demand by attracting new customers and keeping existing ones (Ladhari and Michaud, 2015). In addition, hotels with better defined customer segments have a better understanding of customers' willingness-to-pay and can differentiate their products and services by understanding customers' staying behaviors and expectations. This understanding can help hotels be more profitable through adjusting their room rates and customized service prices (Chen et al., 2014). Moreover, a clear market segmentation strategy can help hotels become better known and have higher reputations in their segments, which facilitates building hotel brands and expanding market share (Chang and Ma, 2015). These all reflect RM techniques for enhancing hotel revenue. Therefore, we propose:

***H2**: Improved customer segmentation has a positive relationship with hotel RM sophistication.*

1.3.2 Internal strategies drivers

Hotel size is usually measured by the number of guest rooms or employees, and influences operating and managerial efficiency (Barros and Mascarenhas, 2005). Larger hotels can implement better RM with lower costs compared to smaller hotels because of the effect of economies of scale in implementing RM actions. Larger hotels have greater market share and easier access to advanced technology (Assaf et al., 2010). According to absorptive capacity theory (Zahra and George, 2002), larger companies have enhanced abilities to identify, assimilate, transform, and apply valuable external knowledge, and therefore to apply RM techniques. Optimization engines are more affordable for larger hotels or when spread across multiple properties.

In addition, larger hotels need superior RM to address their complexity. Advanced technologies such as large data warehouses of customer transactions or sophisticated client-server systems are crucial for managing demand using advanced RM systems (Guadix et al., 2010). When hotels offer more types of packages, such as business traveler and holiday packages offered by larger hotels, it is necessary for them to better manage loyalty programs, tour operator cooperation, and central locations (Assaf et al., 2010). This increases their range of price points, and thus requires them have more accurate demand forecasting and more sophisticated optimization approaches (Akaichi et al., 2015). Hence, the following hypothesis is proposed:

***H3**: Hotel size has a positive relationship with hotel RM sophistication.*

Differentiation strategies reflect the ways hotels differentiate their products and services to isolate themselves from competitors' pressures and thus improve their performance (Porter, 1980). Differentiation strategies benefit hotels by building a barrier to entry, and thus are a source of competitive advantage, in contrast to cost leadership, which aims to increase market share through lower costs and prices (Becerra et al., 2013). Hotels that use a differentiation strategy are more likely to sustain their performance over time than hotels that pursue a cost leadership strategy because a differentiation strategy focuses more on research and development, utilizing new technologies, brand and reputation building, and strong supplier and customer network connections (Banker et al., 2014). Having a differentiation strategy alleviates the pressure on hotels to reduce prices through a cost leadership strategy when they face fierce competition, as price competitions can easily result in a vicious cycle of price-cutting (Becerra et al., 2013). Hotels that are more highly differentiated are also viewed by customers as having higher perceived quality (Fernández and Marín, 1998).

A differentiation strategy in the hotel industry appears to necessitate a sophisticated RM system, as its goal is to attract a wider array of customers through the hotel's competitive differentiation advantage, increasing complexity (Ng, 2006). For example, these hotels need a detailed customer transaction database, which is fundamental in complex RM systems.

A differentiation strategy can reward better RM by encouraging hotels to implement competitive pricing, enhance service quality, and optimize advertising and promotion actions (Chen et al., 2016). Differentiation can also aid hotels in optimizing asset usage, seeking outsourcing, implementing cost leadership and design renovation (which all benefit resource management, helping hotels achieve higher revenue). This suggests the following hypothesis:

H4*: A differentiation strategy has a positive relationship with hotel RM sophistication.*

A more centralized organizational structure in hotels improves communication between employees, encourages employee involvement, raises employee morale and satisfaction, and reduces turnover and burnout (Chiang, 2010). A more centralized organizational structure facilitates employee training, which plays an important role in service attitude and proficiency, and influences customer perceptions (Han et al., 2016). This is turn generates more customer demand, which rewards RM.

In addition, a more centralized hotel organizational structure facilitates the strategic planning for implementing an RM system and enhancing financial performance (Aldehayyat, 2011). It also influences organizational culture and consequently RM practices (Botti et al., 2009). Organizational knowledge creation theory (Nonaka, 1994) indicates greater interaction and socialization are aided by a centralized organizational structure; this enhances the creation of organizational knowledge and RM implementation. The more centralized a hotel chain (a large umbrella organization of franchises/company-operated properties), the greater the opportunity for large data and experiential resource utilization to better define and delineate brands (e.g., market segments; Botti et al., 2009).

Furthermore, the hotel RM system having a strong and centralized core in their operations and evolution work better than those where franchises have considerable autonomy to override system processes, like competitive set determination, frequency and breadth of Internet price shops for competitors, and others (Altin, 2017). Centralization makes sense for these technologically advanced systems since there is a shortage of qualified personnel to properly design and maintain data intelligence, continuous competitor monitoring, and webpage customization. Keeping these subsystems as strong as possible will ultimately lead to improved performance from the primary system (forecaster and optimization systems). A greater degree of centralization also enables sales force effectiveness trackers to be utilized (Rainmaker, 2018). These systems monitor how well hotel sales agents are complying with system recommendations, especially in negotiating rates for groups and restricted rates. This increases the coordination of the system proper with agents that need to use the system in negotiations.

In the survey of this study, we use the degree of rigor in standard operating procedures as a proxy for the degree of centralization. Organizations that are highly centralized generally have more standard operating procedures and more structure (Child, 1972; Mintzberg, 1980). This is because they operate in a more top-down, command-and-control mode than decentralized organizations. Key decisions are made at the top of the organization, and then their implementation at lower levels (i.e., operating units) must be monitored to ensure compliance with top-level objectives. Highly structured standard operating procedures are a means of helping ensure compliance. Our organizational structure construct increases in value as the decision-making processes in a distributed organization become more centralized (e.g., a brand with many franchises, all with contractual obligations to a single parent company). Based on Table 1.1, the bulk of our respondents are in mid-to-large-sized properties and most of them are franchisees, so it is very likely that they are a part of a chain. Thus, the survey items in the online appendix for the organizational structure construct refer to degree of top-down control from the franchisor regarding personnel policies. Thus, this construct measures the degree to which the franchisor exerts control over the operations of the franchisee surveyed.

This degree of rigor is not equivalent to the degree of sophistication in the RM system. For instance, a brand can have a high degree of standard operating procedure structure and adherence and yet have a low level of system sophistication. This can occur in a variety of ways. First, even though the data systems and modeling capabilities might be present, the organization may fail to take full advantage of the granular data repository and therefore fail to discern changing patterns in market segment wants-needs. Second, the organization may fail to properly define their set of key competitors, a very difficult endeavor (see Koushik et al., 2012). The first example is an instance of modeling sophistication and data type granularity being high but product configuration (i.e., degree of product differentiation) being low, while the second example is an instance of the taxonomy construct of modeling sophistication being high but the subsequent data type being low. However, it is our conjecture that a higher degree of centralization increases the odds that the construct values in the taxonomy will also be high.

Based on the preceding discussion, the following hypothesis is proposed:

H5*: The centralization level of hotel organizational structure has a positive relationship with hotel RM sophistication.*

1.3.3 External drivers

According to competitive strategy theory (Rackoff et al., 1985), a more competitive environment suggests greater threats of new entrants and substitute products and stronger bargaining power of customers and suppliers, all of which push hotels to implement RM to deal with the fierce competition. Rigorous analysis and sophisticated demand management techniques need to be used in the RM system to develop more accurate forecasting when there are many competitors sharing the market. Given competitors' dynamic sales strategies for pursuing customer demand, more sophisticated RM practices are needed to adjust prices (Koushik et al., 2012). Fierce hotel competition can be caused by changes over time in the customer packages offered by competitors, as well as the cross-price elasticity relationship with competitors, which requires hotels to dynamically alter their room rates as a function of changes in the competitive environment (Koushik et al., 2012).

In addition, a fierce competitive environment induces hotels to manage their hospitality and tourism supply chains, which benefits their RM (Zhang et al., 2009) by diversifying market segments and enabling a clearer understanding of segment needs. It also encourages hotels to develop pricing strategy cooperation among tourism supply chain stakeholders as an efficient approach to managing hotel revenue under fierce competition (Guo et al., 2013).

Although our competitive environment construct is usually considered an exogenous factor, there are some activities that a hotel can undertake to (a) increase the level of competition in the environment, and (b) improve the performance of its system proper. One such activity is evolutionary price experiments (Duetto, 2018). If prices are changed incrementally over time in a structured, experimentally designed fashion, much information about the market segment's price and cross-elasticities can be uncovered, without the risk of making major price changes outside the scope of the database. The utilization of this indirect driver will ultimately improve forecasting accuracy, thus improving revenues. Therefore, this study proposes:

H6*: The competitive level of environment has a positive relationship with hotel RM sophistication.*

1.4 Measurements of RM sophistication

In this section, we propose a decision tree to measure hotel RM sophistication. We introduce the constructs in the decision tree, the flow and logic of the decision tree, and the procedure used to calculate RM sophistication scores. The scores are used as the dependent variable in structural equation modeling (SEM) in the next section, which conducts an external validation of our taxonomy—we test whether the expected relationships between various variables that describe a property's operating environment and the degree of RM sophistication hold.

According to the RM framework proposed by Ng et al. (2017), general RM sophistication has seven original indicators: pricing-basis, inventory allocation, product configuration, duration control, analytical approach, types of data, and data collection method. In a hotel context, pricing basis refers to how well room rates and rates for non-room amenities are linked to market willingness-to-pay and competitor behavior in terms of competitors' pricing and product configurations. Inventory allocation refers to how well a property reserves capacity for only the highest-paying customers in situations where capacity is not sufficient to handle all market segments. Product configuration refers to how well constructed all offerings are—price point, room layout-view, amenity bundling, cancellation restrictions—across the property over time. Duration control is largely irrelevant for hotels since they generally do not attempt to control customer stay lengths once customers are on the property. An analytical approach refers to the general ability to make good projections of demand and then optimize rates via some type of holistic procedure (e.g., dynamic programming, nonlinear programming). Types of data refers to a more fundamental understanding of product configuration; it is the ability to discern from the data repository the suites of needs-wants of various market segments. Data collection method refers to how automated the entire system is; the key to this is recording as many aspects of a customer transaction as possible. Some systems even automatically keep track of regrets (i.e., customers who evaluated their property via some online booking system but eventually booked elsewhere or not at all) (Duetto, 2018). Product configuration and pricing basis are how well these key data driven insights are executed in terms of service package construction and associated rate setting. Of the four final taxonomy categories, pricing-basis and inventory allocation fall under demand management; product configuration and duration control comprise resource management; analytical approach is the same as data analysis and modeling; and types of data and data collection method compose the data collection category.

Based on Ng et al. (2017), RM sophistication can be quantified using a decision tree. We modified the decision tree of general RM sophistication proposed by Ng et al. (2017, as can be found in Figure 1.1), to a new decision tree (as can be found in Figure 1.2) in the following aspects.

Figure 1.1 Decision tree for obtaining RM sophistication score for general industries in Ng et al.'s (2017) study

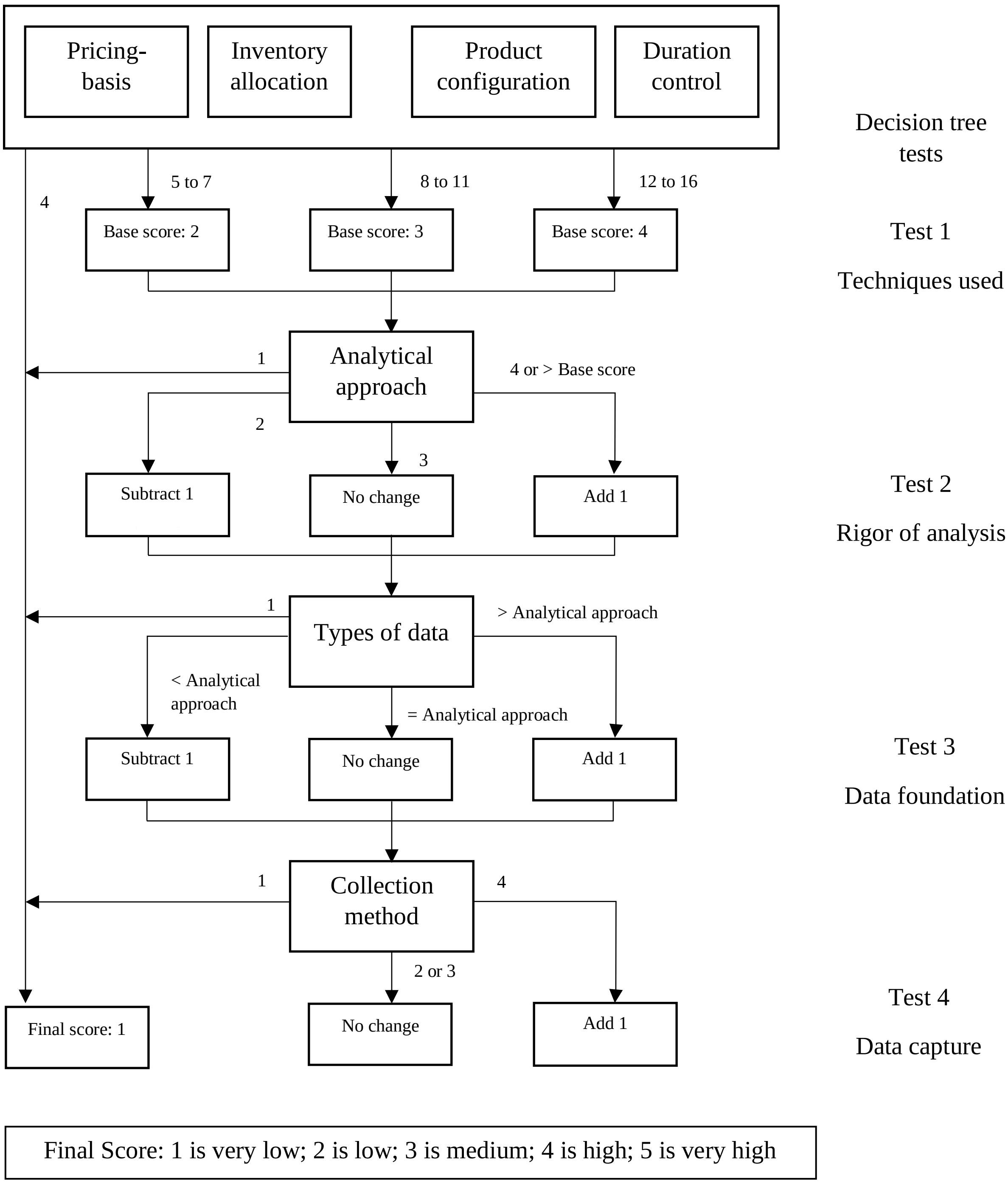
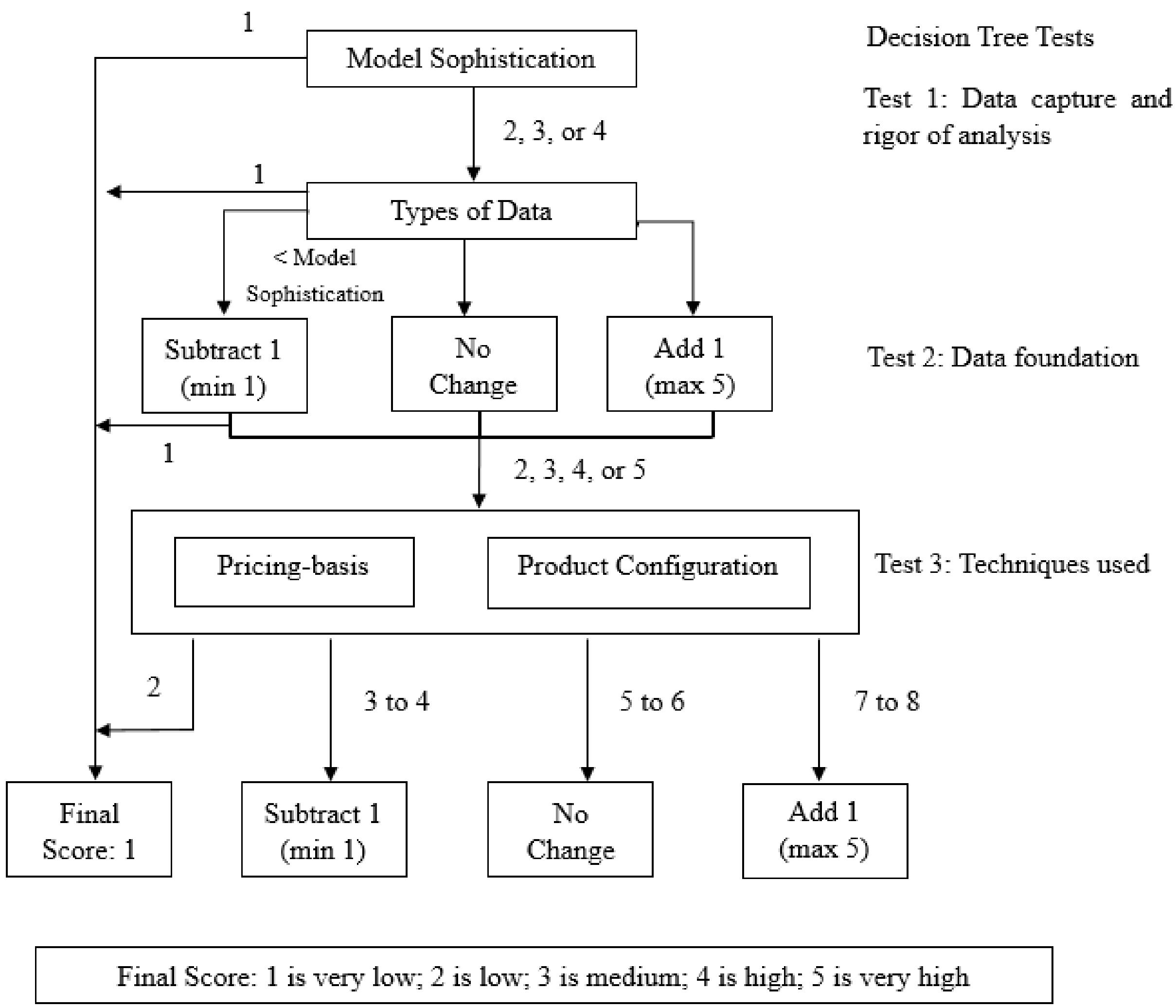


Figure 1.2 Decision tree for obtaining hotels' RM sophistication score in this study



First, we modified Ng et al.'s (2017) decision tree logic for measuring RM sophistication. The inversion of Ng et al.'s (2017) decision tree in our study is largely due to the single industry in our study compared to Ng et al.'s (2017) study, in which they attempted to create a general decision tree to measure RM across a wide range of industries. Relative to Ng et al.'s generic RM environment, our focused hotel study evaluates an environment with more commonality in strategies and information systems for pricing and product configuration. Therefore, the data platform is more critical in our study in determining degree of sophistication.

In practice, revenue management systems vary widely with regards to the granularity of data used (e.g., data type) in the analysis. Some reflect very detailed micromarket levels (e.g., the IDeaS system, 2018), whereas others are more aggregated, focusing simply on arrival days within season and length-of-stay (Koushik et al., 2012). However, system design choices between varying levels of granularity cannot happen unless (a) an automated data collection system exists (collection method) to allow a choice to be made, and (b) some sort of analytical framework (analytical approach) exists to perform the trade-offs that guide price updates. These are the main reasons that model sophistication is first in our decision tree, followed by data type.

Pricing basis-product configuration can be performed well only when the first two blocks in the tree are done well. Pricing basis-product configuration is essentially acting on the fact that hotels have (a) the essential automated data collection system and basic tools for evaluating trade-offs in place, and then (b) the desired level of granularity for the analysis. Pricing basis cannot be performed unless (a) and (b) are in place. This mechanism applies when evaluating an RM software system, which can be different from a pure conceptual model perspective.

In hotels, data collection, types of data, and analytical approaches serve as foundational RM practices. These can be objective (e.g., data related to demand and pricing) and subjective (e.g., online ratings and textual reviews) (Xu, 2018a). The different data types (e.g., objective-subjective, numbers-text), collection methods, data sources (online automatically, historical records, interviews), and analytical approaches (support systems, human-led) influence the level of technique used. Hotels implement corresponding RM techniques based on the analytical results of their collected data (Xiang et al., 2015). This rationale, suggesting a focus on data-based steps first and then technique, was used in the modified decision tree.

The second modification in our decision tree based on Ng et al. (2017) is that, according to the unique features of the hotel industry and the confirmatory factor analysis (CFA) results, our decision tree has four main constructs: pricing basis, product configuration, model sophistication, and data type. The amenity configuration is combined with the product configuration survey items in our study. This is because in practice the actual room type and associated rate are in effect analyzed together with the bundled amenities. Product configuration usually refers to the physical characteristics of a hotel room (e.g., view, size, number of beds, size of bathroom, handicapped equipped), whereas amenity configuration refers to all other features of a patron's stay that attract them to the hotel (e.g., ability to cancel anytime without penalty, discounts on local attractions, free meals—the features not related to the physical room type). For our taxonomy in Figure 1.2, we have combined product configuration with amenity configuration since hoteliers today focus on optimizing the total customer experience simultaneously (physical room and non-physical attributes) as their overarching objective (IDeaS, 2018; Duetto, 2018). Therefore, our combined construct measures the total customer experience to ensure the hotel's total profitability is considered when product-amenity change combinations and associated rate changes are contemplated (JDA, 2018; Rainmaker, 2018; Revenue Analytics, 2018). Some of the seven original constructs were combined to produce these final four.

In detail, the main modifications of the constructs were made based on two factors. First, data collection method and analytical approach were combined due to high correlation in our factor analysis. More fundamentally, though, these are combined since they are practically inseparable: a property cannot execute good demand forecasts that integrate a wide variety of information without a supporting automated data collection system. This combined construct is called model sophistication in Figure 1.2, Tables 1.4 and 1.5, and supported by CFA.

Second, the five other constructs were simplified into two. Pricing basis and inventory allocation were combined and called pricing basis, in large part because many systems in practice (Duetto, 2018; IDeaS, 2018) do not perform an inventory allocation once rate optimization is performed; this is because situations where demand exceeds capacity are quite rare today. However, some systems (Koushik et al., 2012) still have inventory allocation as a post-processor to price optimization. In addition, the trend in hotel RM today is to jointly assess inventory allocation and pricing. Thus, it makes sense to combine these two constructs, rather than keep them separate.

The duration control construct was also removed from the taxonomy, primarily because once a customer is at a hotel, the property is not likely to try to influence length of stay. The rationale for this is that the hotel industry is highly employee-customer interactive, providing many customized products and services, and many unstandardized services (such as catering). Service length is generally not a predictor of service quality or RM practices but is influenced by employee-customer interaction, resources, customization level, complexity level, and other factors (Akbaba, 2006; Hartline and Jones, 1996).

The original collection method construct has been combined with the analytical approach construct to form our new model sophistication construct. This was done because it would be impossible to implement an information system that performs structured trade-offs without the corresponding fundamental data collection system. To avoid confounding effects from these two constructs, we combined them into one. Two other constructs (product configuration and data type) map one-for-one onto the tree. While product configuration is broken into product configuration (three survey questions) and amenity configuration (three survey questions), these six questions are considered one unit in the decision tree calculations. Thus, we have collapsed Ng et al.'s (2017) original seven decision tree constructs to four.

The logic behind our decision tree involves viewing the progression of a RM information system from its most elemental aspects to more complex ones. A key idea here is that we focus on an information system. Thus, a "system" in which sales agents and senior management have a solid instinctual understanding of their internal capabilities, markets, and competition but lack sufficient data resources and analytical processes to (a) validate-refine these instincts, and (b) improve on these instincts through a data-driven process for product redesigns and associated prices is not considered as sophisticated as one where the data-analytical capability building blocks are in place but are not used in the best fashion. In essence, we rank the sophistication of RM information systems based on the philosophy of making data-driven decisions with sales agent/management judgmental overrides an enhancement to the system, such as when conditions are rapidly changing.

Figure 1.2 details the scoring algorithm for our decision tree. Referring to Ng et al. (2017), all four constructs used in the tree—model sophistication, data type, pricing basis, and product configuration—are rescaled from the original 1 to 5 scale to 1 to 4. As seen in Figure 1.2, the rescaling is based on manipulating the original five Likert scales in the survey, which then project onto the constructs with certain value ranges. In detail, we divided each response by five, multiplied by four, and rounded the results. The rescaling is performed because of the possible increment of one score being added in the following steps in the decision tree, which finally results in a possible value range from 1 to 5, where 1 indicates very low RM sophistication, and 5 represents very high RM sophistication.

The amenity configuration construct in Table 1.1 was a subset of the product configuration construct questions (available in the online appendix). The original idea was to create an amenity configuration construct that focused solely on services independent of the physical room type. Although the CFA results in Table 1.4 are good for both price configuration and amenity configuration, the resultant use of our decision tree to perform external validation of the taxonomy, the test of Figure 1.2, had better model fit results with the amenity configuration construct omitted; the model fit better with the original six survey items used for product configuration. This result is not surprising since (a) there were only six items in the product configuration construct; a split of this construct results in too few items for the two constructs, and (b) conceptually, it is difficult to separate the services for a customer from the physical room type—it is better to think of services and room type as a single "product" that can have many variations.

In detail, the mechanism of the decision tree used to evaluate RM system sophistication is as follows. Model sophistication is the first construct evaluated. If this construct is at its least sophisticated value of 1, then the final score automatically goes to 1 regardless of the other construct scores, since inconsequential database captures and basic forecasting-optimization functions cannot result in a sophisticated system. If, however, the sophistication score is 2, 3, or 4, then this score is carried forward to Test #2.

In Test #2, the data type score of 1-4 is considered. Here, the degree of understanding of markets and competition essentially modifies the Test #1 model sophistication baseline score. If the data type score is less than the model sophistication score, then the Test #1 score carried over is reduced by 1. If the data type score exceeds the model sophistication score, then the Test #1 score carried over is increased by 1. No change to the Test #1 carry over score is made if the data type score equals the model sophistication score. Thus, the baseline model sophistication carries over score is reduced if the fundamental understanding of markets-competition is not commensurate with the analytical complexity of the system and vice-versa. Therefore, the first two tests reflect our basic taxonomy framework that data granularity and associated forecaster-optimizer complexity is the foundation for the final sophistication score, and that the level of understanding of markets-competition augments that.

An augmented score from Test #2 of 1 again automatically makes the final score 1. Otherwise, the resultant scores (2, 3, 4, or 5) get carried over to Test #3. In Test #3, the pricing basis and product configuration score of 1-4 is added to produce a score ranging from 2 to 8. Just like the augmentation of the model sophistication score in Test #2, Test #3 augments the score carried over from Test #2. If the sum of pricing basis and product configuration is 2, then the final score is 1. If the sum is 3 or 4, then the Test #2 carry over is reduced by 1 to give the final score. If the sum is 5 or 6, then no adjustment is made to the Test #2 carryover to produce the final score. Finally, if the sum is 7 or 8, then the Test #2 carry over is increased by 1 to give the final score. Note that if that final score is 6, we automatically drop it to 5 so that the final system sophistication score is in the 1-5 range.

1.5 Data generation and preliminary analysis

This section introduces the survey design and data collection, and presents the descriptive statistics of hotels, respondents to the surveys, and variables in the surveys.

1.5.1 Survey design

We started with the realization that RM decision-making at most hotels is now a two-pronged approach, with system design and overall policy decisions made centrally, but with system overrides and local market knowledge integration at the individual property (Koushik et al., 2012). Given this, the unit of analysis is the individual property since these managers should understand (1) both the system-wide philosophies and practices and (2) local conditions that might require them to override system recommendations on occasion (Koushik et al., 2012; Pekgun et al., 2013). This generally occurs in situations where past patterns of customer behavior, in terms of wants-needs, willingness-to-pay, and competitor behavior, are not representative of the future. In such instances, it is important that property managers are constantly abreast of this disconnect between the past and the future so that recommended rates can be overridden appropriately. For instance, if a new special event, like a large convocation, is on the horizon, managers must override the system demand forecasts since this event will not have been accounted for in the database.

While the overall idea for survey items for the external factors and taxonomy constructs came from Ng et al. (2017), DeVellis's (2016) method was used to generate a list of items for each with the hotel industry in mind. The entire survey was pilot tested on 48 hospitality program undergraduates to check for clarity. These 48 undergraduates were split across two classes involving hospitality and wine business management, and a 100% response rate was obtained. The students' comments can be organized into these categories: (a) unfamiliar terminology, (b) passages cumbersome to process because they are too long, (c) vagueness in wording, (d) questions that telegraphed a desired answer, (e) overall survey too long, and (f) questionable relevance of certain items. We revised the instrument based on these comments and then sent it to two school of hospitality management academics for a further critique. After the resulting changes were made, the online survey was finalized in Qualtrics.

1.5.2 Data collection

The survey process followed the best practices of Dilman et al. (2014). Four follow-up email contacts were made to all frame members with one-week elapsed time between follow-ups. The final number of properties responding was 957 (a 64% response rate).

In detail, our sample frame was all properties in Canada and the United States and was obtained from the Dun and Bradstreet (2017) workbench tool. Our survey was sent out to a simple random sample from this frame, with a sample size of 1,480 unique properties. Since our goal is to obtain results that generalize across all hotel types, a simple random sample is statistically valid. We obtained a 64% response rate, and the results of that response rate, in terms of property characteristics, can be found in Table 1.1. In accordance with Dilman et al. (2014), we sent four reminder emails to all properties in the sample to maximize our response rate. We verified that we did not have non-response bias by first looking at a histogram of response times (the time from initial send until the survey was received). The histogram revealed three distinct clusters, with the first around day three to day six. After a break of two days where no responses were received, another cluster occurred from day 9 to day 13. Following a second break of three days, the final cluster peaked from days 20 to 31. Thus, in accordance with Armstrong and Overton (1977), we conducted equality of means tests for each survey question across the three clusters. The null hypothesis of all means being equal could not be rejected for any question, indicating the absence of nonresponse bias. Thus, we obtained a valid probability sample for our frame of all property types in Canada and the United States.

An examination of Table 1.1 reveals that this sample resulted in good variation across various hotel characteristics. For instance, there was a fairly even split between service levels: full service, limited service, and resort service. There was also a fairly uniform distribution of number of rooms, ranging from less than 50 to over 200. The vast majority of respondents were from three-and-four star hotels, which is the dominant category. Finally, we can find the function—that is, the job title—of each respondent was varied within our parameters of focusing on personnel with revenue management expertise (i.e., sales-marketing, along with general management and revenue management specialists). Thus, our final sample is a broad cross-section of hotel sizes and service types.

For each single property, when we were able to obtain more than one respondent, Krippendorff's alpha test (Hayes and Krippendorff, 2007) was run to check for response consistency among multiple managers within a single property. Out of the 957 unique properties surveyed, 839 only had one respondent, 99 had two respondents, and 19 had three respondents. The traditional value for Krippendorff's alpha to demonstrate adequate consistency is 0.8. Because all of our multiple respondent properties had an alpha below 0.65, and also because the limited number of multiple respondents lowers the construct reliability, we used a single measure for each property (generated by averaging each Likert question across the respondents) in our subsequent CFA and path modeling work.

1.5.3 Descriptive statistics

This subsection presents the descriptive statistics of the respondents and variables. Table 1.1 shows the profile of hotels used in this study. In addition, Table 1.1 presents and compares the average RM sophistication score of each type of hotels categorized by star levels, type of service, location, years, price, and size. We find using $p = 0.05$ that higher star level hotels have higher RM score than lower star level hotels. Similarly, higher-priced hotels generally have higher RM scores than lower-priced hotels, and hotels with more employees generally have higher RM scores than hotels having fewer employees. Regarding the type of service, full-service hotel has the highest RM score, with convention and resort hotels following, and the limited-service hotel and suite hotel have the lowest RM scores. Location, years since built, and number of rooms generally do not present differences in terms of their RM scores.

Table 1.1 The profile of hotels and their average revenue management sophistication score

Variable	Category	Range	Percentage	Mean	Standard Deviation
Star level	1	1	0.4%	3.00	0.00
	2	2	2.8%	3.14	0.36
	3	3	42.5%	3.90	0.84
	4	4	45.3%	4.01	0.80
	5	5	9.1%	4.35	0.82
Type of service	1	Full-service hotel	41.0%	4.07	0.76
	2	Limited-service hotel	26.2%	3.74	0.83
	3	Suite hotel	5.9%	3.63	0.82
	4	Convention hotel	4.8%	4.13	0.81
	5	Resort hotel	22.1%	4.13	0.87
Location	1	Downtown	38.6%	4.09	0.81
	2	City but not downtown	18.6%	3.90	0.81
	3	Near the airport	6.6%	3.79	0.86
	4	Suburb	11.7%	3.91	0.80
	5	Town or village	11.0%	3.93	0.95

	6	Parks or near attractions	13.4%	3.94	0.82
Years been built	1	<2	3.3%	3.75	0.44
	2	2-5	5.3%	4.20	0.89
	3	6-10	14.0%	4.05	0.88
	4	11-20	19.0%	4.01	0.85
	5	>20	58.5%	3.94	0.83
Average room rate	1	<50	1.2%	3.00	0.00
	2	50-75	1.2%	3.67	0.50
	3	75-115	11.0%	3.59	0.79
	4	115-150	23.3%	3.83	0.81
	5	>150	63.3%	4.11	0.82
Number of rooms	1	<50	4.9%	3.56	0.51
	2	50-100	14.6%	3.88	0.80
	3	100-150	18.3%	4.05	0.88
	4	150-200	18.7%	3.89	0.88
	5	>200	43.5%	4.04	0.81
Number of employees	1	<20	4.9%	3.60	0.67
	2	20-50	19.6%	3.71	0.81
	3	50-80	16.5%	3.87	0.79
	4	80-110	16.1%	3.97	0.84
	5	>110	42.8%	4.16	0.83

Table 1.1 also shows the profile of hotels used in this study. Most of the hotels are three or four-star level hotels, which is similar to the sample distribution in Xiang et al. (2015). Three or four-star level hotels are the hotels that most commonly use revenue management systems due to the availability of more resources compared with lower star level hotels (i.e., budget hotels), and because there are fewer five-star level hotels (i.e., luxury hotels). Thus, the fact that the vast

majority of respondents were from the three-and-four-star service level is representative of service levels in general. More full or limited service and resort hotels are analyzed in this study compared with suite or convention hotels, which is similar to the sample distribution as in Xu and Li (2016). Our sample exhibits a fairly uniform distribution of hotel locations, and most of the hotels were built more than five years' prior, suggesting they have resource availability and experience implementing RM. Most of the hotels have an average room rate of more than $75. Our respondents also represent a fairly uniform distribution across hotel size, as measured by the number of rooms, although the largest size (greater than 200 rooms) is a spike at 43% of the total sample. The number of employees is also fairly uniformly distributed, with most hotels having more than 110 employees. Thus, overall, our respondent set represents a wide variety of property service levels-sizes-types. We performed the means test for each type of hotel in each category to find the statistical difference of revenue management sophistication score between each type of hotel, as can be found in Table 1.1 as well.

Table 1.2 presents the profile of respondents in this study. Table 1.2 shows the demographic and job title information of the respondents. From Table 1.2, we can see that the demography of respondents is fairly well distributed, and there is a good proportion of respondents across the three job types that should be most knowledgeable about the property's RM system: the general manager (34%), sales/marketing personnel (40%), and RM specialists (13%). Thus, our respondent pool is knowledgeable about RM practices.

Table 1.2 The profile of respondents

Category	**Range**	**Percentage**
Gender	Male	49.3%
	Female	46.9%

	Prefer not to answer	3.8%
Age	18-20 years	0.0%
	21-30 years	11.0%
	31-40 years	20.9%
	41-50 years	29.1%
	51-60 years	24.7%
	Older than 60 years	9.2%
	Prefer not to answer	5.1%
Education	Some high school	0.3%
	High school graduate	2.4%
	Some vocational/technical training (after high school)	1.4%
	Completed vocational/technical training (after high school)	3.1%
	Some college	16.6%
	Completed an associate's degree	8.6%
	Completed a bachelor's degree	54.8%
	Some graduate school	2.8%
	Completed a master's degree.	6.2%
	Some graduate training beyond a master's degree	1.4%
	Completed a doctoral degree	0.0%
	Prefer not to answer	2.4%
Race	American Indian	1.0%
	Asian American	2.4%
	Asian	5.2%
	Pacific Islander	1.0%
	African American	1.4%
	White/Caucasian	71.0%
	Hispanic/Latino	3.8%
	European	1.7%
	Other	2.4%

	Prefer not to answer	9.8%
Income	Less than $25K	0.8%
	Between $25K and $50K	12.1%
	Between $50K and $75K	18.7%
	Between $75K and $100K	20.2%
	Between $100K and $125K	15.6%
	Between $125K and $150K	12.1%
	Between $150K and $175K	4.7%
	Between $175K and $200K	6.2%
	More than $200K	9.7%
Occupation	Accounting	0.4%
	CFO	2.0%
	Chef	0.8%
	Consulting	0.4%
	COO	2.8%
	Engineer	0.8%
	General manager	33.6%
	HR	0.8%
	Meeting planner	0.4%
	President/VP	4.3%
	Revenue management	13.4%
	Sales and (or) marketing	40.3%

Table 1.3 shows the descriptive statistics of the variables in this study, including the mean and spread of all construct scores. These constructs include (a) those that comprise the taxonomy proper (i.e., the components of the decision tree), and (b) those that form the set of indirect drivers of the taxonomy score (i.e., level of system sophistication). The coefficient of variation on the constructs generally hovers around 25%. Given that the middle construct scores are around the

high 3s, this coefficient of variation shows good variability in all constructs. Thus, the concepts underlying this study all vary significantly across the respondent pool.

Table 1.3 Descriptive statistics of variables

	Mean	Median	Standard Deviation	Minimum	Maximum
Contextual Factors and Tree Score					
Model Sophistication	4.06	4	0.64	1.67	5
Data Type	4.25	4	0.4739	2.75	5
Pricing-basis	4.43	4.6	0.5475	2	5
Product Configuration	3.77	4	0.9147	1	5
Amenity Configuration	3.22	3.25	0.8493	1	5
Tree Score	3.96	4	0.8526	1	5
Drivers					
eWOM	4.59	4.83	0.5171	3	5
Customer Segmentation	3.82	4	0.6886	1	5
Size	3.74	4	1.162	1	5
Strategy	3.5	3.33	0.8107	1	5
Organizational Structure	4.07	4	0.5995	2	5
Competitive Environment	3.71	4	0.8257	1	5

1.6 Results

This section presents the statistics and empirical results of the causal relationship in our model and the corresponding statistics of the model fit.

A two-step SEM procedure was performed for hypothesis testing and post-hoc analysis. For the first step, CFA was done for both taxonomy constructs and external contextual factors; indicators with statistically insignificant factor loadings were discarded. Tables 1.4 and 1.5 concern the reliability and validity of the taxonomy scoring system. Unidimensionality of constructs was checked by calculating each construct's comparative fit index (CFI) and standard root mean square residual (SRMR). Unidimensionality was achieved since all CFI values were above 0.9 and the SRMR scores were less than 0.1. Cronbach's alpha measures construct reliability and all scores were well above the 0.7 cut-off point. Discriminant validity was assessed using chi-square difference tests for all pairs of constructs; all were statistically significant, indicating discriminant validity was established. Similar procedures were done for external contextual factors. The reliability and validity of contextual factors (i.e., indirect drivers of revenue management) was established (see Tables 1.6 and 1.7).

Table 1.4 Unidimensionality and reliability of RM constructs

Construct	CFI	Standardized RMR	Cronbach's Alpha
Model Sophistication	0.910	0.0573	0.857
Data Type	0.991	0.0190	0.852
Pricing-basis	0.994	0.0147	0.863
Product Configuration	1.000	0.0000	0.738
Amenity Configuration	1.000	0.0000	0.804

Table 1.5 Chi-square difference tests for taxonomy constructs

Construct Pair		Difference	
		χ2	df
Model Sophistication	Data Type	966.2***	3
	Pricing-basis	1001.3***	3
	Product Configuration	485.5***	3
	Amenity Configuration	652.3***	3
Data Type	Pricing-basis	1725.8***	3
	Product Configuration	779.7***	3
	Amenity Configuration	864.5***	3

Pricing-basis	Product Configuration	706.0***	3
	Amenity Configuration	978.1***	3
Product Configuration	Amenity Configuration	26.1***	3

*** $p < 0.001$.

Table 1.6 Unidimensionality and reliability of the contextual factors

Construct	CFI	Standardized RMR	Cronbach's Alpha
eWOM	1.000	0.0000	0.740
Customer Segmentation	1.000	0.0000	0.745
Size	1.000	0.0000	0.750
Strategy	1.000	0.0000	0.772
Organizational Structure	1.000	0.0000	0.764
Competitive Environment	0.993	0.0216	0.751

Table 1.7 Chi-square difference tests for external contextual factors

Construct Pair		Difference	
		χ2	**df**
eWOM	Customer Segmentation	1024***	3
	Size	759.8***	3
	Strategy	1041.7***	3
	Organizational Structure	1070.7***	3
	Competitive Environment	1076.6***	3
Customer Segmentation	Size	630.0***	3
	Strategy	967***	3
	Organizational Structure	953.8***	3
	Competitive Environment	951.6***	3
Size	Strategy	748.7***	3
	Organizational Structure	701.1***	3
	Competitive Environment	448.4***	3

Strategy	Organizational Structure	1234.9***	3
	Competitive Environment	1051.3***	3
Organizational Structure	Competitive Environment	959***	3

*** $p < 0.001$.

The measurement model was validated and then in the second step, covariance structure analysis was used to assess external factor relationships and the calculated RM system sophistication decision tree score. The standardized regression weights are shown in Table 1.8. The goodness-of-fit indices for this model are: CFI = 0.997, RMSEA = 0.033, NFI = 0.994, RFI = 0.957, IFI = 0.997, indicating the structural model fits the data well. The model had an R^2 of 0.386, indicating significant explanatory power of the contextual factors for the sophistication decision tree score.

Table 1.8 Summary of hypotheses and standardized regression weights

Hypothesis		**Standardized Regression Weight**	**Result**
1:	Hotels' eWOM utilization increases RM sophistication.	0.384***	Supported
2:	Hotels' better-defined customer segmentation increases RM sophistication.	0.098**	Supported
3:	Larger hotel size increases RM sophistication.	0.039	Rejected
4:	Hotels' differentiation strategy increases RM sophistication.	0.163***	Supported
5:	A more centralized organizational structure of hotel increases RM sophistication.	0.148***	Supported
6:	Higher competitive environment increases hotel RM sophistication.	0.157***	Supported

** $p < 0.01$; *** $p < 0.001$.

To test the robustness of our statistical results and decision tree, we used the decision tree proposed in Ng et al. (2017), which has a reverse structure (techniques used first and data capture last). The goodness-of-fit indices for the reverse decision tree model are: CFI = 0.997, RMSEA = 0.033, NFI = 0.993, RFI = 0.948, IFI = 0.997. The model had an R^2 of 0.243. We find our decision tree model has a better fit than the reverse decision tree model as evidenced by the higher NFI, RFI, and R squared values. Thus, statistically, our taxonomy fits better than Ng et al.'s (2017). In addition, as we pointed out, our taxonomy ordering is more in line with how the building blocks of an RM information system in the hotel industry would be layered: a system cannot really exist without some sort of micromarket delineation in the database, coupled with some level of analytical (trade-off capability and projection capability) sophistication. With these foundations in place, the impact of the system can be improved by using these foundations to (a) discover granular price and cross-elasticities at detailed micromarket levels, (b) use (a) to dynamically optimize prices, and (c) use the granular transaction databases to evolve product offerings. Thus, our taxonomy has more face validity, and our hypothesis test results have more relevance in hotel industry.

1.7 Discussions

Overall, the results provide two main differences from the previous study on RM sophistication indicators (Ng et al., 2017) using the hotel context. The first main difference is the finding of a new specific indicator of RM sophistication for the hotel industry (eWOM utilization). The results support H1; hotel eWOM utilization enhances RM sophistication. This new indicator reflects the significant influence of eWOM on hotel demand and prices due to substantial customer demand driven by online sources; customers refer to previous reviews to learn more about the hotel's attributes and reduce perceived risk when booking due to physical distance. With the rapid development of IT, more customers post online reviews after their booking and hotel stay. These include ratings, overall satisfaction, satisfaction with specific hotel attributes, and customer textual reviews. Better utilization of online customer reviews can enhance hotel reputation, spread positive eWOM, remedy service failures via online responses, enhance future customers' booking behaviors, and benefit hotel RM systems (Cantallops and Salvi, 2014). Utilization of eWOM can also allow properties to collect and analyze online review data. These data create a direct channel for acquisition of hotel stay perceptions and improvement of the corresponding product, services, and RM systems.

The second main difference is that hotel property size does not have a significantly positive influence on a hotel's RM system sophistication (H3 is not supported). One explanation is that hotel size does not totally indicate a property's operational mode. For example, some chain hotel properties, although smaller than independent hotels, adopt a RM system and provide the standard employee training on RM due to franchising (Xu, 2018b). Second, hotel size is stable over time due to the fixed location and huge initial investment. However, RM practices can be enhanced across time periods, making hotel size a non-significant indicator of RM sophistication.

The results support H2, indicating better defined customer segmentation increases RM sophistication. Customer segmentation can be implemented by categorizing customers through demographic information, travel group composition, and travel purpose (e.g., leisure/business travelers) (Chu and Choi, 2000; Xu, 2018a). Customer segmentation can facilitate a better understanding of prospective customers' expectations, needs, and demand; thus, RM systems are implemented to better serve customers, enhance satisfaction, and improve financial performance. Hotels implementing customer segmentation can better understand target customers, adjust their pricing strategy, and enhance the corresponding products and service qualities to better serve customers (Xu, 2018b).

A differentiation strategy requires more sophisticated RM practices, supporting H4. A hotel differentiation strategy aims to create different stay packages (e.g., rate-room type-stay length-non-room services such as conference rooms/restaurants/spa/outside attractions) for different customer segments (Chen and Xie, 2013). Differentiation enhances a hotel's competitive advantage and is contributed to, in part, by RM sophistication (Algieri et al., 2018).

A more centralized organizational structure has a positive impact on RM practice sophistication, supporting H5. The key reason is that state-of-the-art decision support technology and associated expert support staff are more readily available if affiliated with a chain. Today, the most common type of RM system implementation is distributed with a centralized decision support system serving multiple properties (Altin et al., 2017) and residing at either corporate headquarters or a third party vendor. Ongoing enhancements to the system are made centrally, incorporating best practices via the centrally-located and scarce experts. However, local market knowledge of each property is essential so that (a) bounds on rates are consistent with the property's customer service value proposition relative to local competitors, and (b) system-generated rates can be adjusted in anticipation of local market shifts-anticipated competitor reactions that are not currently modeled. A centralized organizational structure can enhance the work engagement of employees and motivate the organization to enhance revenue (Lu et al., 2016). This structure can concentrate employees' opinions and formulate and implement strategy in a relatively short time. When implementing a new revenue system or adjusting its functions, a more centralized approach can enhance the speed of the hotel's response to environment changes and alleviate inconsistencies between the opinions of policy makers and practitioners.

A competitive environment enhances a hotel’s RM system sophistication, supporting H6. Increased competition motivates hotels to improve RM due to eagerness to increase market share, enhance customer demand, and survive. Hotels in more competitive environments also adjust their rates more frequently based on competitors’ pricing and benchmarking practices (Min and Min, 1997). Hotels in this environment are under more pressure to demonstrate a competitive advantage, which can be enhanced through RM sophistication (e.g., accurate demand forecasting, optimal pricing strategy) (Algieri et al., 2018).

1.8 Implications

This study provides theoretical building blocks for further analyses, which to some degree will be normative. It (a) develops a taxonomy to measure the degree of hotel RM system sophistication and (b) determines exogenous drivers of sophistication. The ultimate practical use of the results is testing how a hotel’s deviations from the predicted level of system sophistication impacts profitability.

1.8.1 Theoretical implications

Ng et al.’s (2017) taxonomy is now tailored to the hotel industry with several distinct differences. First, the construct items were regenerated from a hotel context. Second, construct validation indicated that (a) duration control is irrelevant; (b) pricing-basis and inventory allocation should be combined, a result expected in a hotel setting where inventory allocation is often ignored after rate optimization (Pekgun et al., 2013; Wynn, 2018) or is integrated as a post-processor into the rate optimization system (Koushik et al., 2012); and (c) analytical approach and collection method should be combined, which makes sense given that sophisticated hotel systems require major data collection automation to go along with centralized systems (Altin et al., 2017). Third, the prioritization of rigor of analysis and techniques used were switched in the scoring calculus. The primary emphasis on rigor of analysis was due to significant variations in the combination of techniques used in hotel systems. Also, a system cannot even begin to become sophisticated until some basic trade-off and projection features exist.

Tests of external drivers of system sophistication are also unique. First, the construct items were generated from a hotel context. Second, the additional construct, eWOM, reflects the importance of capturing and analyzing text data from customer reviews in hotel systems (Noone, 2016). Indeed, the IDeaS hotel RM system automatically captures and processes this information (Noone, 2016). This additional construct was a significant predictor of system sophistication. Third, the results indicate that property size has no influence on sophistication. Given that the majority of systems are centralized client-server types where even smaller affiliated properties have access to the latest modeling-analysis approaches and best practices, this finding makes sense. Fourth, unlike Ng et al.'s (2017) findings, strategy type played a significant role in determining system RM sophistication—a differentiation strategy is likely to result in more RM sophistication. In this study, we use the strategic framework of differentiation versus cost leadership, which is different from the framework used in Ng et al.'s (2017) study (i.e., prospector, analyzer, and defender), and this can be one of the main reasons causing the different findings. The differentiation strategy more precisely captures the trend in RM systems toward isolating finer differences between customer segments, and then creating a wider variety of products to meet these smaller differences. A hotel does not have to be an innovator in the Miles and Snow (1978) typology to do this well. They could also fall under the analyzer strategy in the Miles and Snow (1978) typology and do just as well at making these distinctions. Even a defender could be adhering to a strategy that already had a significant amount of differentiation. Thus, it seems reasonable that strategy was an insignificant variable in Ng et al.'s (2017) study because the different strategy variable settings they used (i.e., Miles-Snow [1978] strategies) do not isolate varying levels of strategic differentiation. Because differentiation seems to be the key factor associated with varying degrees of RM sophistication, it is not surprising that strategy was insignificant in Ng et al.'s (2017) study. Because we explicitly use differentiation is our analysis, we are able to demonstrate strategic significance.

1.8.2 Managerial implications

RM systems can enhance hotels' financial performance (Guadix et al., 2010). To enhance RM sophistication, hotels can use the corresponding implications in two ways. The first is directly improving RM actions—including the four aspects of data collection, data analysis/modeling, demand management, and resource management. Hotels should utilize the availability of big data, such as online customer reviews, and keep accurate records of past customer demand, room occupancy, and business operations, which serve as a foundation for analyzing those data to better understand customer needs and forecast future customer demand. The specific method of data analytics depends on the data and hotel setting (Pereira, 2016). Based on the data analytics, hotels can implement technical actions such as dynamic pricing, inventory allocation, and product configuration.

However, an advanced RM system needs a special analyst or consultant and employees who take actions, and also requires the use of tangible and intangible resources. Considering the resource-based theory of competitive advantage (Grant, 1999), hotels should identify and classify their resources to determine how to employ each type of resource to improve their capability to form a competitive advantage. This indicates that many times hotels may have limited resources to directly design and enhance RM systems.

Hotels can also consider using indirect approaches to enhance RM sophistication, namely, by improving the drivers of RM decision support system sophistication. When aiming to enhance RM, hotels should first consider building internal long-term features, such as a centralized organizational structure and differentiation strategy. A centralized organizational structure with clear policies, documentation of operations, and professional employee training can benefit a hotel's RM actions. Hotels can also implement a differentiation strategy, which differentiates their products and services compared to their competitors, to attract greater customer demand, meet the needs of customers with certain preferences and higher expectations, and gain a competitive advantage.

When long-term properties are not easy to change in the short term, hotels should consider implementing operations such as utilizing eWOM and clearly defining customer segmentation to enhance RM. Hotel utilization of eWOM should include viewing online customer reviews as a resource to better understand customer expectations, needs, satisfaction, and stay experiences. Text and data mining approaches can be utilized to analyze customer opinions from online reviews (Xu, 2018b). Hotels should utilize eWOM to attract future customers; actions include providing more motivation for customers to write online reviews by offering vouchers, opening more channels (such as hotels' own online discussion bulletins to spread positive eWOM), and implementing service recovery actions (providing detailed responses, commitment to improve, and compensation to alleviate negative eWOM) (Gu and Ye, 2014). Regarding segmentation, hotels can use various approaches, such as online surveys and customer comment cards for feedback to segment and target customers (Xu, 2018a). Hotels can segment customers according to their travel purpose and demographic information, allowing them to develop corresponding customized products and services, and implement price differentiation strategies for various customer types.

The external driver of RM in this study is a fierce competitive environment, which provides both challenges and opportunities in implementing more sophisticated RM. Hotels should view the fierce competition not merely as “evil”, but also as motivation, requiring them to use benchmarking strategies to learn from successful hotels and implement corresponding improvements, referring to competitors’ room rates, and seeking collaborative advertising. All these provide more opportunities for hotels to implement RM through optimal pricing and more accurate demand forecasting. Hotels should implement the above actions in real time, adjust the actions dynamically, and quickly respond to internal and external environment changes.

1.9 Concluding remarks

This study integrates four components of RM: demand management, resource management, data analysis and modeling, and data collection to propose a measurement of RM sophistication in hotels. The level of sophistication is based on four steps in decision tree tests: data capture, data foundation, rigor of analysis, and techniques used, including pricing, inventory allocation, and product configuration. Through surveys from hotel managers, five driving factors were identified as influencing the sophistication of RM systems: eWOM utilization, customer segmentation, organizational structure, differentiation strategy, and competitive environment. These five drivers all have a positive impact on RM system sophistication. The results have implications for hoteliers, suggesting better ways to develop their RM systems and utilize these internal and external drivers to enhance sophistication and financial performance.

Future studies can extend this research in the following ways. First, studies should examine and compare the drivers of the sophistication of RM systems for different types of hotels such as chain/independent, full-service/limited-service, conference/resort, or for businesses in other hospitality and travel industries. Second, studies should examine RM sophistication using a dynamic approach, considering changes in environment, customer perception, and properties of hotels within a timeline. Third, the cost of RM actions can be considered to determine the optimal sophistication of RM decision support systems.

Appendix A: Survey Construct Map (Prior to Combining Constructs)

Latent Variables (Constructs)	Indicating Questions
Size	Section I: Question 1 and 2
Lifecycle	Section I: Question 3
Competitive Environment	Section II: Question 1-5
Customer Segmentation	Section II: Question 6-10
Perishability	Section II: Question 11-16
Demand Uncertainty	Section II: Question 17-21
Organizational Structure	Section II: Question 22-26
Strategy	Section II: Question 27-31
eWOM	Section II: Question 32-36
Pricing-basis	Section III: Question 1-5
Inventory Allocation	Section III: Question 6-10
Product Configuration	Section III: Question 11-16
Duration Control	Section III: Question 17-21
Analytical Approach	Section III: Question 22-27
Types of Data	Section III: Question 28-33
Collection Method	Section III: Question 34-38
Respondents' Demographic Data	Last Section All Questions
Hotel's Background Information	Section I: Question 3-7

Appendix B: Survey to Hotel Property Management

Section I. About Your Hotel

The following items are related to your hotel's basic information. Please read each statement carefully and indicate the option that fits in your hotel's case.

Your Hotel ….	**Less than 50**	**Between 50 and 100**	**Between 100 and 150**	**Between 150 and 200**	**More than 200**
1. Has how many number of guest rooms?	☐	☐	☐	☐	☐
	Less than 20	**Between 20 and 50**	**Between 50 and 80**	**Between 80 and 110**	**More than 110**
2. Has how many number of employees	☐	☐	☐	☐	☐
	Less than 2 years	Between 2 and 5 years	Between 5 and 10 Years	Between 10 and 20 Years	More than 20 Years
3. Has built for	☐	☐	☐	☐	☐
	1 star	2 stars	3 stars	4 stars	5 stars
4. Has star level	☐	☐	☐	☐	☐
	Under $50	Between $50 and $75	Between $75 and $115	Between $115 and $150	More than $150
5. Has the average daily room rate	☐	☐	☐	☐	☐

	Full-service hotel	Limited-service hotel	Suite hotel	Convention hotel	Resort hotel
6. Has mainly been considered as	☐	☐	☐	☐	☐

Section II. About Your Hotel's Market

The following items are related to your hotel's market basic information. Please read each statement carefully and indicate your agreement or disagreement by marking the appropriate response category.

	Strongly Disagree	**Disagree**	**Neither Disagree Nor Agree**	**Agree**	**Strongly Agree**
1. Customer preferences or required features for the hotel room and services change very quickly	☐	☐	☐	☐	☐
2. Other hotels' products and services change very quickly in our market	☐	☐	☐	☐	☐
3. Promotion and deal wars happen frequently in our market	☐	☐	☐	☐	☐
4. Price competition happens frequently in our market	☐	☐	☐	☐	☐
5. Competitor hotels compete for product and service quality in our market	☐	☐	☐	☐	☐
6. Customers often reserve the room ahead through reservation systems instead of Walk ins.	☐	☐	☐	☐	☐
7. It is easy to limit the number of customers who can reserve the room at a discount rate.	☐	☐	☐	☐	☐
8. It is easy to categorize customers into leisure travelers and business travelers	☐	☐	☐	☐	☐
9. It is easy to categorize customers into different travel modes such as family travelers, solo travelers, couple travelers, and group of friends.	☐	☐	☐	☐	☐
10. It is easy to find out the main trip purpose of travelers staying in the hotel.	☐	☐	☐	☐	☐
11. Our hotel has many demands from festivals, conferences, and other events.	☐	☐	☐	☐	☐

12. Our hotel has many demands from travel agents.	☐	☐	☐	☐	☐
13. It is difficult to match our guest room and service availability with customer demand.	☐	☐	☐	☐	☐
14. When the room reservation is cancelled, it is hard to sell the room again.	☐	☐	☐	☐	☐
15. The products such as food and beverages can not be keep for long time if not sold.	☐	☐	☐	☐	☐
16. We lose much potential profits if the rooms can not be sold.	☐	☐	☐	☐	☐
17. It is very expensive to update our guest rooms to increase capacity.	☐	☐	☐	☐	☐
18. The demand of guest rooms has a strong seasonal variation.	☐	☐	☐	☐	☐
19. The demand of guest rooms in the weekdays and weekends are significant different.	☐	☐	☐	☐	☐
20. The demand of guest rooms is influenced much by external factors such as economy cycle, political issues, environment, and etc.	☐	☐	☐	☐	☐
21. The demand of guest rooms is hard to be forecasted.	☐	☐	☐	☐	☐
22. In the hotel, very few actions are taken without the approval of a supervisor.	☐	☐	☐	☐	☐
23. Duties and authority of employees are documented in policies, procedures, or job descriptions.	☐	☐	☐	☐	☐
24. Standard service procedure and guidelines are available for most work situation	☐	☐	☐	☐	☐
25. Our hotel has a clear standard of employees training.	☐	☐	☐	☐	☐
26. Our hotel has a clear organizational structure of employees.	☐	☐	☐	☐	☐
27. Our hotel tries to attract demand from customers with different demographics.	☐	☐	☐	☐	☐
28. Lowering cost is not the only objective of our hotel's operating process.	☐	☐	☐	☐	☐
29. Our hotel tries to provide customized products and services.	☐	☐	☐	☐	☐
30. Our hotel has some products, services, or environment that most of the other hotels don't offer.	☐	☐	☐	☐	☐

31. Our hotel tries to attract demand from all types of customers instead of a certain customer segmentation.	☐	☐	☐	☐	☐
32. Our hotel reviews customer online reviews toward the hotel periodically.	☐	☐	☐	☐	☐
33. Our hotel has our own online forum, website, or comments card to provide customers post reviews toward the hotel.	☐	☐	☐	☐	☐
34. Our hotel replies customers' online reviews or feedback periodically.	☐	☐	☐	☐	☐
35. Our hotel uses customer review as a marketing tool to advertise.	☐	☐	☐	☐	☐
36. Customers' online reviews provide an important way for our hotel to improve the products and services.	☐	☐	☐	☐	☐

Section III. Your Hotel's Revenue Management Implementation

The following items are related to your hotel's revenue management implementation. Please read each statement carefully and indicate your disagreement or agreement by marking the appropriate response category.

	Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree
1. Your hotel often changes room rates in response to other hotels' price movements.	☐	☐	☐	☐	☐
2. Your hotel often changes room rates according to the demand.	☐	☐	☐	☐	☐
3. Your hotel often changes room rates according to the time such as weekends, festivals, events, vacation seasons.	☐	☐	☐	☐	☐
4. We often review the market and discuss the needs of price changes.	☐	☐	☐	☐	☐
5. We price guest room differently according to the reservation time.	☐	☐	☐	☐	☐
6. When the demand is high, we reserve guest rooms or service capacity for customers willing to pay a premium.	☐	☐	☐	☐	☐

7. We offer a "last minute" discount for guest rooms online that otherwise be unsold.	☐	☐	☐	☐	☐
8. We offer a discount for guest rooms during the late night for walk-in customers since it is highly likely these guest rooms will not be sold otherwise.	☐	☐	☐	☐	☐
9. Rules have been established regarding how our prices or available offerings should change according to the expected demand.	☐	☐	☐	☐	☐
10. We charge higher prices or change our available offerings during times of high demand.	☐	☐	☐	☐	☐
11. We have various types of guest rooms to charge differently instead of only having one or two types of standard rooms.	☐	☐	☐	☐	☐
12. Our hotel provide full services to customers.	☐	☐	☐	☐	☐
13. We provide many different products and services compared with other hotels.	☐	☐	☐	☐	☐
14. We often create package offers such as including rooms and meals.	☐	☐	☐	☐	☐
15. We target specific rooms or services to certain customer segments.	☐	☐	☐	☐	☐
16. We provide different amenities and services to different types of hotel rooms.	☐	☐	☐	☐	☐
17. We monitor the extent to which hotel employees follow established operating and services processes.	☐	☐	☐	☐	☐
18. We regularly regulate and redesign service process to enhance service speed and customer turnover.	☐	☐	☐	☐	☐
19. We forecast customer arrivals and differentiate reservation and stopping-by customers, and length of stay.	☐	☐	☐	☐	☐
20. We charge booking fees or hold customers' credit card information to guarantee their reservation.	☐	☐	☐	☐	☐
21. We charge customers extra fee for late check out.	☐	☐	☐	☐	☐
22. We often use computer modeling or simulation tools to analyze data.	☐	☐	☐	☐	☐
23. We often use mathematical analysis or other formulae to analyze data.	☐	☐	☐	☐	☐

24. We often refer to the historic trend to make demand forecast.	☐	☐	☐	☐	☐
25. We often use scenario modeling (“what if” analysis) to make decision.	☐	☐	☐	☐	☐
26. We often distribute surveys to customers to ask them staying experience.	☐	☐	☐	☐	☐
27. We often use quantitative methodologies to analyze data.	☐	☐	☐	☐	☐
28. We often compare our hotel’s performance with other hotels’, or do benchmarking.	☐	☐	☐	☐	☐
29. We know the size of our target markets and information about customer demographics.	☐	☐	☐	☐	☐
30. We know the reason why customers prefer to stay in our hotel.	☐	☐	☐	☐	☐
31. We know customers’ willingness to pay for our guest room and / or services.	☐	☐	☐	☐	☐
32. We know competitor hotels’ products or services, pricing, strategies, and strengths.	☐	☐	☐	☐	☐
33. We know customers perception about their staying experience.	☐	☐	☐	☐	☐
34. Many of our sales data are automatically recorded using computers.	☐	☐	☐	☐	☐
35. Our hotel use professional software and or systems such as ERP to record data.	☐	☐	☐	☐	☐
36. Manual staff input is NOT the main way to record data.	☐	☐	☐	☐	☐
37. Our decision making relies on data records rather than manager experience.	☐	☐	☐	☐	☐
38. Past data such as sales data is a valuable resource for our hotels to make future decisions and develop.	☐	☐	☐	☐	☐

About you (Demographic information)

Gender (please circle): Male, Female

Age: (____________)

Marital status (please circle): ☐ Single ☐ Widowed ☐ Divorced ☐ Married ☐ Live together

Occupation: (____________)

Position / Title : (____________)

Educational level (please circle): Less than high school Bachelor's degree

High school graduate/ G.E.D.

Graduate work

Associate degree/Certificate

Graduate degree

Some college or technical school

Other (_______)

Ethnicity (please circle): American Indian/Alaska Native Asian American/Pacific Islander

Asian

Black/African American

Caucasian/White

Hispanic/Latino

European

Other (please specify:__________)

Annual income: (____________)

How much do you consider yourself a decision maker in your hotel on a scale from 1 (not at all) to 7 (very much)?

Please circle: 1, 2, 3, 4, 5, 6, 7

How much do you consider yourself be familiar with your hotel's operating process on a scale from 1 (not at all) to 7 (very much)?

Please circle: 1, 2, 3, 4, 5, 6, 7

Your nationality: _________________

Thanks for your participation!

References

Abrate, G., Viglia, G., 2016. Strategic and tactical price decisions in hotel revenue management. *Tourism Management* 55, 123-132.

Akaichi, F., Nayga, R.M., Gil, J.M., 2015. Effect of price-discount distribution in multi-unit price promotions on consumers' willingness to pay, sales value, and retailers' revenue. *Agribusiness* 31 (1), 14-32.

Akbaba, A., 2006. Measuring service quality in the hotel industry: A study in a business hotel in Turkey. *International Journal of Hospitality Management* 25 (2), 170-192.

Aldehayyat, J.S., 2011. Organisational characteristics and the practice of strategic planning in Jordanian hotels. *International Journal of Hospitality Management* 30 (1), 192 – 199.

Algieri, B., Aquino, A., Succurro, M., 2018. International competitive advantages in tourism: An eclectic view. *Tourism Management Perspectives* 25, 41-52.

Altin, M., 2017. A taxonomy of hotel revenue management implementation strategies. *Journal of Revenue and Pricing Management* 16 (3), 246-264. https://doi.org/10.1057/s41272-017-0077-1

Altin, M., Schwartz, Z. Uysal, M., 2017. 'Where you do it matters': the impact of hotels' revenue management implementation strategies on performance. *International Journal of Hospitality Management* 47, 46-52.

Amway, D., 2018. Interview transcript with Don Amway, a general manager with the Newman Group that owns-operates several properties in southern Oregon.

Arenoe, B., van der Rest, J.P.I., Kattuman, P., 2015. Game theoretic pricing models in hotel revenue management: An equilibrium choice-based conjoint analysis approach. *Tourism Management* 51, 96-102.

Armstrong, J., Overton, T., (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research* 14 (3), 396-402.

Assaf, A., Barros, C.P., Josiassen, A., 2010. Hotel efficiency: A bootstrapped metafrontier approach. *International Journal of Hospitality Management* 29 (3), 468-475.

Banker, R.D., Mashruwala, R., Tripathy, A., 2014. Does a differentiation strategy lead to more sustainable financial performance than a cost leadership strategy? *Management Decision* 52 (5), 872-896.

Barros, C.P., Mascarenhas, M.J., 2005. Technical and allocative efficiency in a chain of small hotels. *International Journal of Hospitality Management* 24 (3), 415-436.

Becerra, M., Santaló, J., Silva, R., (2013). Being better vs. being different: Differentiation, competition, and pricing strategies in the Spanish hotel industry. *Tourism Management* 34, 71-79.

Bitran, G., Caldentey, R., 2003. An overview of pricing models for revenue management. *Manufacturing & Service Operations Management* 5 (3), 203-229.

Bitran, G., Caldentey, R., Mondschein, S., 1998. Coordinating clearance markdown sales of seasonal products in the retail chains. *Operations Research* 46 (5), 609-624

Bitran, G.R., Mondschein, S.V., 1996. Mailing decisions in the catalog sales industry. *Management Science* 42 (9), 1364-1381.

Bodea, T., Ferguson, M., Garrow, L., 2009. Data set-choice-based revenue management: Data from a major hotel chain. *Manufacturing & Service Operations Management* 11 (2), 356-361.

Botti, L., Briec, W., Cliquet, G., 2009. Plural forms versus franchise and company-owned systems: A DEA approach of hotel chain performance. *Omega* 37, 566-578.

Cantallops, A.S., Salvi, F., 2014. New consumer behavior: A review of research on eWOM and hotels. *International Journal of Hospitality Management* 36, 41-51.

Cetin, G., Demirçiftçi, T., Bilgihan, A., 2016. Meeting revenue management challenges: Knowledge, skills and abilities. *International Journal of Hospitality Management* 57, 132-142.

Chang, H.P., Ma, C.C., 2015. Managing the service brand value of the hotel industry in an emerging market. *International Journal of Hospitality Management* 47, 1-13.

Chatwin, R.E., 2000. Optimal dynamic pricing of perishable products with stochastic demand and a finite set of prices. *European Journal of Operations Research* 125 (1), 149-174.

Chen, C.C., Xie, K.L., 2013. Differentiation of cancellation policies in the US hotel industry. *International Journal of Hospitality Management* 34, 66-72.

Chen, C.M., Chang, K.L., Langelett, G., 2014. How demand uncertainty and market concentration affect long-term price instability. *International Journal of Hospitality Management* 37, 146-149.

Chen, C.M., Lin, Y.C, Chi, Y.P., Wu, S.C., 2016. Do competitive strategy effects vary across hotel industry cycles? *International Journal of Hospitality Management* 54, 104-106.

Chiang, C.F., 2010. Perceived organizational change in the hotel industry: An implication of change schema. *International Journal of Hospitality Management* 29 (1), 157-167.

Child, J., 1972. Organizational structure, environment and performance: The role of strategic choice. *Sociology* 6 (1), 1-22.

Choi, S., Kimes, S.E., 2002. Electronic distribution channels' effect on hotel revenue management. *Cornell Hotel and Restaurant Administration Quarterly* 43 (3), 23-31.

Chu, R.K., Choi, T., 2000. An importance-performance analysis of hotel selection factors in the Hong Kong hotel industry: a comparison of business and leisure travellers. *Tourism Management* 21 (4), 363-377.

Corgel, J., Lane, J., Walls, A., 2013. How currency exchange rates affect the demand for US hotel rooms. *International Journal of Hospitality Management* 35, 78-88.

Cross, R.G., Higbie, J.A., Cross, D.Q., 2009. Revenue management's renaissance: A rebirth of the art and science of profitable revenue generation. *Cornell Hospitality Quarterly* 50 (1), 56-81.

DeVellis, R., 2016. Scale Development: Theory and Applications. 4th Ed. Sage, Thousand Oaks, CA.

Dilman, D., Smyth, J., Christian, L., 2014. Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method. 4th Ed. Wiley, New York.

Duetto, 2018. http://duettocloud.com. Last accessed: June 29, 2018

Dun and Bradstreet Workbench, 2017. www.dnb.com.

Feng, Y., Gallego, G., 1995. Optimal starting times for end-of season sales and optimal stopping times for promotional fares. *Management Science* 41 (8), 1371-1391.

Feng, Y., Xiao, B., 2000. A continuous-time yield management model with multiple prices and reversible price changes. *Management Science* 46 (5), 644-657.

Fernández, N., Marin, P.L., 1998. Market power and multimarket contact: Some evidence from the Spanish hotel industry. *The Journal of Industrial Economics* 46(3), 301-315.

Garrow, L., 2009. Online travel data: A goldmine of new opportunities. *Journal of Revenue and Pricing Management* 8 (2/3), 247-254. https://doi.org/10.1057/rpm.2008.55

Gayar, F. E. N., Saleh, M., Atiya, A., El-Shishiny, H., Alkes Youhanna Fayez Zakhary, A., Abdel Aziz Mohammed Habib, H., 2011. An integrated framework for advanced hotel revenue management. *International Journal of Contemporary Hospitality Management* 23(1), 84-98.

Grant, R.M., 1999. The resource-based theory of competitive advantage: implications for strategy formulation. *In Knowledge and Strategy*, pp. 3-23.

Gu, B., Ye, Q. 2014. First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management*, *23*(4), 570-582.

Guadix, J., Cortes, P., Onieva, L., Muñuzuri, J., 2010. Technology revenue management system for customer groups in hotels. *Journal of Business Research* 63 (5), 519-527.

Guo, X., Ling, L., Dong, Y., Liang, L. 2013. Cooperation contract in tourism supply chains: The optimal pricing strategy of hotels for cooperative third party strategic websites. *Annals of* Tourism Research 41, 20-41.

Han, S.J., Bonn, M.A., Cho, M., 2016. The relationship between customer incivility, restaurant frontline service employee burnout and turnover intention. International Journal of Hospitality Management 52, 97-106.

Harrington, J., 2009. Games, Strategies and Decision Making. Worth Publishers. Chapter 15.

Hartline, M.D., Jones, K.C., 1996. Employee performance cues in a hotel service environment: Influence on perceived service quality, value, and word-of-mouth intentions. *Journal of Business Research* 35 (3), 207-215.

Hayes, A., Krippendorff, K., 2007. Answering the call for a standard reliability measure for coding data. *Communication Methods and Measures* 1, 77-89.

IDeaS, 2018. https://ideas.com. Last accessed: June 29, 2018

JDA Software, 2018. https://jda.com. Last accessed: June 29, 2018

Koupriouchina, L., van der Rest, J. P., Schwartz, Z., (2014). On revenue management and the use of occupancy forecasting error measures. *International Journal of Hospitality Management* 41, 104-114.

Koushik, D., Higbie, J., Eister, C., 2012. Retail price optimization at InterContinental Hotels. *Interfaces* 42 (1), 45-57.

Ladhari, R., Michaud, M., 2015. eWOM effects on hotel booking intentions, attitudes, trust, and website perceptions. *International Journal of Hospitality Management* 46, 36-45.

Lohan, G., Conboy, K., Lang, M., 2011. Examining customer focus in IT project management: Findings from Irish and Norwegian case studies. *Scandinavian Journal of Information Systems* 23 (2), 29-58.

Lu, L., Lu, A.C.C., Gursoy, D., Neale, N. R., 2016. Work engagement, job satisfaction, and turnover intentions: A comparison between supervisors and line-level employees. *International Journal of Contemporary Hospitality Management* 28 (4), 737-761.

Masiero, L., Pan, B., Heo, C.Y., 2016. Asymmetric preference in hotel room choice and implications on revenue management. *International Journal of Hospitality Management* 56, 18-27.

Miles, R., Snow, C. 1978. Organization Strategy, Structure, and Processes. McGraw-Hill, New York.

Min, H., Min, H., 1997. Benchmarking the quality of hotel services: managerial perspectives. *International Journal of Quality & Reliability Management* 14 (6), 582-597.

Mintzberg, H., 1980. Structure in 5's: A synthesis of the research on organization design. *Management Science* 26 (3), 322-341.

Ng, F., Rouse, P., Harrison, J., 2017. Classifying revenue management: A taxonomy to assess business practice. *Decision Sciences* 48 (3), 489-522.

Ng, I. C. L., 2006. Differentiation, self-selection and revenue management. *Journal of Revenue and Pricing Management* 5 (1), 2-9.

Nonaka, I., 1994. A dynamic theory of organizational knowledge creation. *Organization Science* 5 (1), 14–37.

Noone, B., 2016. Pricing for hotel revenue management: Evolution in an era of price transparency. *Journal of Revenue and Pricing Management* 15 (3/4), 264-269.

Öğüt, H., Onur Taş, B.K., 2012. The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal* 32 (2), 197-214.

Oliveira, R., Pedro, M.I., Marques, R.C., 2013. Efficiency performance of the Algarve hotels using a revenue function. *International Journal of Hospitality Management* 35, 59-67.

Panvisavas, V., Stephen Taylor, J., 2006. The use of management contracts by international hotel firms in Thailand. *International Journal of Contemporary Hospitality Management* 18 (3), 231-245.

Pekgun, P., Menich, R., Acharyu, S., Finch, P. Deschamps, F., Mallery, K., Van Sistine, J., Christianson, K., Fuller, J., 2013. Carlson Rezidor hotel group maximizes revenue through improved demand management and price optimization. *Interfaces* 43 (1), 21-36.

Pereira, L.N., 2016. An introduction to helpful forecasting methods for hotel revenue management. *International Journal of Hospitality Management* 58, 13-23.

Porter, M.E., 1980. Competitive Strategy. Free Press, New York.

Rackoff, N., Wiseman, C., Ullrich, W.A., 1985. Information systems for competitive advantage: Implementation of a planning process. *MIS Quarterly* 9 (4), 285-294.

Rainmaker, 2018. https://www.letitrain.com. Last accessed: June 29, 2018

Revenue Analytics, 2018. http://www.revenueanalytics.com. Last accessed: June 29, 2018

Salerno, N., 2010. Hotel revenue management is now more important than ever. Retrieved from: http://www.hospitalitynet.org/news/4048278.html. Accessed

Smith, B.C., Leimkuhler, J.F., Darrow, R.M., 1992. Yield management at American Airlines. *Interfaces* 22 (1), 8-31.

Viglia, G., Mauri, A., Carricano, M., 2016. The exploration of hotel reference prices under dynamic pricing scenarios and different forms of competition. *International Journal of Hospitality Management* 52, 46-55.

Wang, X.L., 2012. Relationship or revenue: Potential management conflicts between customer relationship management and hotel revenue management. *International Journal of Hospitality Management* 31 (3), 864-874.

Wu, D.C., Song, H., Shen, S., 2017. New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management* 29 (1), 507-529.

Wynn, C., 2018. Interview transcript with Cassi Wynn, head of revenue management at a company in eastern Washington, USA, who owns several RedLion and Hampton Inn hotels.

Xiang, Z., Schwartz, Z., Gerdes Jr, J.H., Uysal, M., 2015. What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management* 44, 120-130.

Xu, X., Li, Y., 2016. The antecedents of customer satisfaction and dissatisfaction toward various types of hotels: a text mining approach. *International Journal of Hospitality Management* 55, 57-69.

Xu, X., Li, Y., 2017. Maximising hotel profits with pricing and room allocation strategies. *International Journal of Services and Operations Management* 28 (1), 46-63.

Xu, X., 2018a. Does traveler satisfaction differ in various travel group compositions? Evidence from online reviews. *International Journal of Contemporary Hospitality Management* 30 (3), 1663-1685.

Xu, X., 2018b. Examining the relevance of online customer textual reviews on hotels' product and service attributes. *Journal of Hospitality & Tourism Research* 1096348018764573.

Zahra, S.A., George, G., 2002. Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review* 27 (2), 185-203.

Zhang, X., Song, H., Huang, G.Q., 2009. Tourism supply chain management: A new research agenda. *Tourism Management* 30 (3), 345-358.

CHAPTER TWO

SELECTING AMONG SUPPLIERS WHO OFFER BUSINESS VOLUME DISCOUNTS

2.1 Introduction

Supplier selection is a complicated decision-making problem, especially when business volume discounts (BVDs) are present. Managers must make sustainable and profitable decisions in an ever-changing global market. Being able to identify the best suppliers and to allocate order quantities promptly is essential to taking advantages of BVDs.

Mathematical optimization models might be attractive to researchers, but managers might prefer a more intuitive and quick approach in searching for the best potential suppliers. We present an alternative way to solve the supplier selection problem by utilizing predictive global sensitivity analysis (Kouvelis, Munson, & Yang, 2013; Wagner, 1995) to create structural equations that can help managers with their decision making process.

In predictive global sensitivity analysis, an optimization model is solved multiple times with a wide range of input variable values. Summary independent variables are developed and then regressed against the output variable of interest. Combinations or those variables are entered into a stepwise regression model to capture the most influential input variables and the combinations of them. These variables are formulated into structural equations that can be calculated relatively easily. Our study creates a two-stage process. First, the structural equation based on a logistic regression model helps managers identify which suppliers are good candidates for positive allocation. Second, an equation based on a linear regression model predicts the percentage allocation to each supplier for each product. These equations are easy to set up in spreadsheets and can be calculated instantaneously.

The remainder of this paper is organized as follows. In Section 2, we review relevant literature on supplier selection models with quantity discounts and predictive global sensitivity analysis. In Section 3, we set up the mixed integer programming (MIP) model for the business volume discount (BVD) problem. Section 4 presents the predictive global sensitivity analysis model and the process of selecting individual variables. We develop two structural equations in Section 5. In Section 6, we validate both equations with a holdout dataset. Section 7 concludes the study and identifies limitations and future research directions.

2.2 Literature review

2.2.1 Supplier selection models with quantity discounts

When a customer wants to buy a variety of products from a set of suppliers who offer business volume discounts on all units, it is referred to as a basic total quantity discount (TQD) problem. The TQD problem is NP-hard, but it could be solved by a series of cost minimization flow problems using branch-and-bound, linear programming based branch-and-bound, and branch-and-cut techniques (Goossens, Maas, Spieksma, & van de Klundert, 2007). Manerba & Mansini, 2012 propose a hybrid algorithm to solve the capacitated TQD problem. Metaheuristics have been introduced to solve the capacitated TQD problem as well (Manerba & Mansini, 2014). The existing literature on quantity discounts from the buyer's perspective is extensive and focuses particularly on creating mixed integer programming (MIP) models for capacitated supplier selection and order allocations (Munson & Jackson, 2015). For instance, a multi-objective MIP solution methodology has been developed for a vendor selection problem in a business volume discount environment (Dahel, 2003). It has been demonstrated that a linear MIP model could solve both the all-units discount and the incremental discount cases (Chaudhry, Forst, & Zydiak, 1993; Stadtler, 2007). An analytical hierarchy process and a multi-objective MIP have been used to determine the order allocations with various types of sourcing and pricing (Xia & Wu, 2007). A number of studies have utilized mixed integer programming for the supplier selection problem with uncertain demand and quantity discounts (G. Zhang & Ma, 2009; J. Zhang & Chen, 2013).

2.2.2 Predictive global sensitivity analysis

It is now well established from a variety of studies that global sensitivity analysis provides a practical way to capture the sensitivity of optimal values in classic optimization models (Wagner, 1995). Using predictive global sensitivity analysis, researchers have been able to create structural equations that capture the trade-offs of strategic global facility networks (Kouvelis, Munson, et al., 2013) and monitor the positions of operational hedging (Lee & Munson, 2015). For a deterministic supplier selection problem with business volume discounts, we propose to use predicted global sensitivity analysis to create structural equations. The goal of this study is to provide an approach that is easy to replicate and that can assist managers to make strategic order allocation decisions in a timely fashion.

2.3 Business volume discount optimization model

2.3.1 Problem statement

When facing a set of suppliers who offer competitive BVDs, managers are interested in selecting the best ones and deciding the associated order quantities efficiently. Theoretically, managers can utilize an appropriate vendor selection model to solve the problem, but it takes time and effort to set up the model. The complicated model may be intimidating to managers as well. To alleviate the manager’s stress in the decision-making process, we create a group of user-friendly structural equations applying the predictive global sensitivity analysis technique.

We utilize a vendor selection model in a BVD environment, which is a mixed-integer programming model with deterministic capacity, product price, business volume and corresponding discount rates for suppliers, and demand for customers. We assume that each supplier offers a BVD among all the items that are purchased by the customer based on the total dollar amount spent with that supplier. The decision variables are the customer's order quantity for each product from each supplier. Our model is designed for a single-period use because we believe that the managers only need to make strategic decisions on this level at most several times a year.

2.3.2 Business volume discount optimization model (Dahel, 2003)

Indices

i = Product index, $i = 1, \dots, I$

j = Supplier index, $j = 1, \dots, J$

r = Discount level index, $r = 1, \dots, R$

Parameters

P_{ij} = Original unit price for product i from supplier j

β_{jr} = Discount rate if the original total dollar amount V_j from supplier j falls into discount interval $r = 1, \dots, R$

u_{jr} = Business volume breakpoint of discount bracket r for supplier j

M = A very large number

D_i = Demand of product i

K_{ij} = Capacity of supplier j for product i

Decision variables

x_{ij} = Order quantity for product i from supplier j

v_{jr} = Original dollar amount purchased if V_j lies in discount bracket j, for $j = 1, \dots, J$

Y_{jr} = Binary variable that equals 1 if V_j lies in discount bracket j, for $j = 1, \ldots, J$; otherwise, 0.

The objective function

$$Minimize \sum_{j=1}^{J} \sum_{r=1}^{R} (1 - \beta_{jr}) v_{jr} \tag{1}$$

Subject to

$$V_j = \sum_{i=1}^{I} P_{ij} x_{ij} \ \ \forall j \tag{2}$$

$$V_j = \sum_{r=1}^{R} v_{jr} \quad \forall j \tag{3}$$

$$V_j \geq u_{jr} Y_{jr} \qquad \forall r, j \tag{4}$$

$$v_{jr} \leq M Y_{jr} \qquad \forall r, j \tag{5}$$

$$\sum_{j=1}^{J} x_{ij} = D_i \quad \forall i \tag{6}$$

$$\sum_{r \in R} Y_{jr} = 1 \ \ \forall j \tag{7}$$

$$0 \leq x_{ij} \leq K_{ij} \ \ \forall i, j \tag{8}$$

$$Y_{jr} = \{0,1\} \qquad \forall r, j \tag{9}$$

The objective function minimizes the total purchasing cost with BVDs. Constraints (2) and (3) determine the business volume from supplier j. Constraints (4) and (5) locate the business volume with discount at the correct bracket of the discount scheme for each supplier. Constraint (6) ensures that each product's demand is satisfied. Constraint (7) guarantees that only one level of discount will be used for each supplier. Constraints (8) and (9) confirm our decision variables to be non-negative.

2.4 Predictive global sensitivity analysis

2.4.1 General steps for creating structural equations

We build a group of structural equations by utilizing predictive global sensitivity analysis. These equations provide an alternative for the complicated mathematical optimization model described in the previous section. The equations are easy to update and offer an accurate estimation of the order quantities from a set of suppliers. These structural equations facilitate managers to make purchasing decisions promptly with confidence.

We generate the dataset for predictive global sensitivity analysis by running a vendor selection optimization model many times. We insert a wide range of input parameters with the goal of covering a wide variety of BVD settings. We obtain the order quantities of each product from each supplier as a part of our dataset. We use the proportion of the order quantity to the product demand as the dependent variable for future analysis. We choose and combine some of the model parameters as the independent variables in the structural equations. Managers can update the independent variables directly without knowing every detail of the input parameters.

It is an art to create relevant independent variables. Managers should apply their business and industrial expertise in selecting the most influential ones. Previous studies (Kouvelis, Li, & Ding, 2013; Wagner, 1995) have suggested that to capture the non-linearalities and interaction effects, the structural equations should include the polynomial terms and cross-terms of the selected independent variables. Since the decision-making process divides into two stages naturally, we construct two structural equations to capture the characteristics of each move. In the first stage, managers need to identify the most appealing clusters of suppliers. In the second stage, they decide the order quantities from the desired suppliers. We apply a logistic regression model and a linear regression model in each stage, respectively.

To construct the first structural equation, we propose a set of potential independent variables and create four polynomial terms, x^{-2}, x^{-1}, x, and x^2, for each one. We choose each pair of the independent variables and construct 10 terms in the form of $x^{-2}y^{-1}$, $x^{-2}y$, $x^{-1}y^{-2}$, $x^{-1}y^{-1}$, $x^{-1}y$, $x^{-1}y^2$, xy^{-2}, xy^{-1}, xy, and xy^2. We include both the polynomial and the interaction terms in a stepwise logistic regression with $\alpha = 0.05$ as entry and $\alpha = 0.10$ as removal to select the best set of the independent variables. We retain the ones that ensure the logistic regression passing the Hosmer and Lemeshow goodness-of-fit test ($p \geq 0.05$), which prove an adequate fit of the model.

In building the second structural equation, we use a similar procedure. We choose a group of possible independent variables and run one-at-a-time regressions (Wagner, 1995). We also test the polynomial fit, x^{-2}, x^{-1}, x, and x^2, for each independent variable. We perform stepwise linear regressions with $\alpha = 0.05$ as entry and $\alpha = 0.10$ as removal to discover the independent variables with the best polynomial fit. We keep the variables with the highest adjusted R^2 in the model because they are usually the driving force for changes in the dependent variable. Then we combine the selected independent variables as the interaction terms. We make each pair in the form of $x^{-2}y^{-1}$, $x^{-2}y$, $x^{-1}y^{-2}$, $x^{-1}y^{-1}$, $x^{-1}y$, $x^{-1}y^2$, xy^{-2}, xy^{-1}, xy, and xy^2. We include both the polynomial terms chosen from the latest step and the interaction terms into a large-scaled stepwise regression. The variables that survive the stepwise regression and yield the largest adjusted R^2 value build into our final structural equations.

2.4.2 Dependent and independent variables

We chose the order quantity to the total demand ratio of a product as the dependent variable. When updating the structural equation, managers can observe immediately the best candidates for suppliers and the proportion of demand they should purchase from them.

Order Quantity to Demand:

$$QD_{ij} = \frac{x_{ij}}{D_i} \tag{10}$$

Equations (11)–(20) represent the independent variables that we developed.

Capacity to Demand:

$$KD_{ij} = \frac{K_{ij}}{D_i} \tag{11}$$

Competitor Average Capacity to Demand:

$$KAVGD_{ij} = \frac{\sum_{p \neq j} K_{ip}/(J-1)}{D_i} \tag{12}$$

Price Premium:

$$PAVG_{ij} = \frac{P_{ij}}{\sum_{j \in J_i} \frac{P_{ij}}{J}} \tag{13}$$

Price to Minimum Competitor Price:

$$PMIN_{ij} = \frac{P_{ij}}{\min P_{iJ}} \tag{14}$$

Highest Discount Rate:

$$B_j = \max_j \beta_{jr} \tag{15}$$

Discount Rate to Maximum Discount Rate:

$$BMAX_j = \frac{\beta_{jr}}{\max_j \beta_{jr}} \tag{16}$$

Discount Rate to Average Discount Rate:

$$BAVG_j = \frac{\beta_{jr}}{\sum_j \beta_{jr}/J} \tag{17}$$

Highest Breakpoint to Total Cost:

$$UMAX_j = \frac{\max u_{jr}}{\sum_{i \in I_j} \min(K_{ij}, D_i) \times P_{ij}} \tag{18}$$

Price to Minimum Net Price:

$$NETPMIN_{ij} = \frac{P_{ij} \times (1 - \beta_{jr})}{\min_j \left(P_{ij} \times (1 - \beta_{jr})\right)} \tag{19}$$

Price to Average Net Price:

$$NETPAVG_{ij} = \frac{P_{ij} \times (1 - \beta_{jr})}{\sum_J P_{ij} \times \frac{(1 - \beta_{jr})}{J}} \tag{20}$$

Equations (11) and (12) capture the characteristics of an individual supplier's capacity as well as its competitor's. These capacity to demand ratios show whether or not the supplier dominates the market. In a BVD environment, the discount rate is associated with the dollar amount purchased from a supplier. However, the supplier's capacity limits the business volume and further restricts the options of discount rates. We have an assumption if a supplier possesses a higher capacity than its peers do, then it is more likely to become the best candidate. In the development of structural equations, we confirm that the capacity to demand ratios are influential to the dependent variable and they have a positive effect. Equations (13)-(17) account for price and discount advantages. As two basic elements of business volume, we believe that the price premium and the discount information account for a great influence on the total purchasing cost. In addition, discount breakpoints play a big part in the decision of purchasing the dollar amount and the associated discount. In Equation (18), we use the maximum breakpoint to the total cost where the supplier serves as a sole supplier to account for the incentive to buy more from that supplier. Equations (19) and (20) represent whether or not a supplier has a net price advantage over an average or the cheapest supplier. We think these two ratios account for the cost competitiveness of the suppliers, which would affect the customer's choice.

2.5 Development of structural equations

2.5.1 Initial conditions

In this section, we utilize predictive global sensitivity analysis to create structural equations. While many different complicated versions of BVDs can appear in reality, for illustration purposes, we have chosen scenarios that cover typical characteristics of customers and suppliers.

Our framework incorporates 10 products with 5 suppliers. For the experimental design, we applied three mean levels of demand: Low, Medium, and High, at 1,000 units, 10,000 units, and 100,000 units respectively. Mean product price levels were set at \$10, \$50, \$100, and \$500. Table 1 displays the mean demand and the mean price levels for each of the 10 products in our design. For supplier initial conditions, we assumed they had either a *tight* or a *loose* capacity. A tight capacity represents when a product demand has to be fulfilled by at least three suppliers. A loose capacity implies that each supplier possesses enough capacity to potentially be the sole source for customer demand (see Table 2.2).

We designed two levels of BVD rates, *low* and *high*, as well as two breakpoints levels for required business volumes, *low* and *high*. With the combination of both characters, we obtain four different categories of BVD. Within each discount scheme, we had two levels of discount rates that were associated with two breakpoints (see Table 2.3). Low mean discount rates were 5% and 10%, and high mean rates were 10% and 20%. We created the breakpoints as percentages of the potential maximum business volume purchased from one supplier. Low and high percentages were 20% and 40%, and 40% and 80% respectively. We calculated the potential maximum business volume by multiplying the product price by the minimum of the demand and the supplier capacity.

Table 2.1 Initial conditions of each product

Product	*Demand*	*Price*
1	1,000	$ 50.00
2	1,000	$ 100.00
3	1,000	$ 500.00
4	10,000	$ 10.00
5	10,000	$ 50.00
6	10,000	$ 100.00
7	10,000	$ 500.00
8	100,000	$ 10.00
9	100,000	$ 50.00
10	100,000	$ 100.00

Table 2.2 Types of supplier capacity

Supplier capacity type	*No. of suppliers used*
Tight	3, 4, or 5
Loose	1, 2, 3, 4, or 5

Table 2.3 Discount categories

Category	*Mean Breakpoint (% of max BV from a supplier)*	*Mean Discount rate*
Low	20%	5%
	40%	10%
High	40%	10%
	80%	20%

2.5.2 Experimental design

To build structural equations, we needed a large experimental dataset. We solved the BVD optimization model with different parameter values multiple times using GAMS. We archived all the values of each independent and dependent variable during each run.

We randomized each input parameter by setting a band drawn from a uniform distribution over the initial values (see Table 2.4). Our goal was to create a dataset that contained a wide variety of BVD setups.

Table 2.4 Randomization of the input parameter values

		Kij		β_{jr}				u_{jr}			
				Low	*Low*	*High*	*High*	*Low*	*Low*	*High*	*High*
Di	*Pij*	Tight	Loose	β_{j1}	β_{j2}	β_{j1}	β_{j2}	u_{j1}	u_{j2}	u_{j1}	u_{j2}
±25%	±5%	(20% *Di*, 40% *Di*)	(20% *Di*, 120% *Di*)	±1%	±2%	±2%	±4%	±10%	$2u_{j1}$	±20%	$2u_{j1}$

Combining two levels of the capacity, two of the discount rates, and two of the breakpoints, we created eight general types of suppliers. Holding the demand and price constant, we only varied the levels of capacity, discount rates, and breakpoints for each run and we ran the optimization model eight times to cover all eight types of suppliers. For each run, we obtained 50 order quantities. Then we introduced a new set of demand and price and randomized the capacity and discount scheme again for another 40 runs of optimization. In total, we ran the model 400 times, and we obtained 20,000 data points. We used half of the dataset to train regressions and build structural equations and reserved the other half for validation purposes.

2.5.3 Structural equations development

We constructed two models to capture the patterns of the customer's behavior. We utilized a logistic regression model to fit the binary dependent variable. When the dependent variable equals one, it meant the customer purchased a positive amount of the item from the supplier. When the dependent variable was zero, it indicated the customer ordered no units of that item from that supplier. We want to be able to predict whether we should buy from a supplier or not. After determining the set of suppliers for a particular product, we apply the linear regression model to predict the percentage of demand that should be purchased from each supplier.

We began our analysis by running one-at-a-time linear regressions on the entire training dataset, including all the zeros and non-zeros of the dependent variable. It was not surprising that the individual effect of each independent variable on the dependent variable was weak. We suspected that the zeros in the dependent variable were creating a substantial noise in the model. Thus, we introduced the logistic regression model.

We defined p as the probability of whether or not the consumer would order from the supplier. We included all the possible independent variables with their polynomial terms and cross combinations in the initial model. We ran a stepwise logistic regression, and 16 independent variables were retained in the model. We performed the Hosmer and Lemeshow test for the goodness-of-fit for the logistic regression (see Table 2.5). A positive p-value of the test indicated that the null hypothesis, the logistic model fits the data well, was not rejected. As can be seen from Table 2.6, the test partitioned the data into equal sized groups and assessed whether or not the observed and expected events were matching each other.

Table 2.5 Hosmer and Lemeshow goodness-of-fit test

Chi-Square	*DF*	*Pr > ChiSq*
8.7202	8	0.3664

Table 2.6 Partition for the Hosmer and Lemeshow Test

		logit = 1		*logit = 0*	
Group	*Total*	*Observed*	*Expected*	*Observed*	*Expected*
1	1000	103	109	897	891
2	1000	237	223	763	777
3	1000	329	329	671	671
4	1000	449	454	551	546
5	1000	564	583	436	417
6	1000	701	702	299	298
7	1000	822	805	178	195
8	1000	900	890	100	110
9	1000	945	950	55	50
10	1000	982	987	18	13

The resulting structural equation is shown below.

$$\log\left(\frac{p}{1-p}\right) = 276.3 + 21.6445 NETPMIN_{ij}{}^{-1} \cdot NETPAVG_{ij}{}^{-2} - 0.0894 KAVGD_{ij} \cdot UMAX_j{}^{-2} + 14.6225 KAVGD_{ij}{}^{-1} \cdot PAVG_{ij} - 5.6178 UMAX_j{}^{2} \cdot BAVG_j{}^{2} - 13.1382 KAVGD_{ij}{}^{-1} \cdot NETPAVG_{ij}{}^{-2} - 4.5935 PAVG_{ij}{}^{-2} \cdot UMAX_j{}^{2} - 6.5795 UMAX_j{}^{-1} \cdot PMIN_{ij}{}^{-1} + 17.2324 UMAX_j \cdot BAVG_j + 15.5151 KAVGD_{ij}{}^{-1} \cdot NETPMIN_{ij}{}^{-1} +$$

$$0.2682KAVGD_{ij}{}^{-2} \cdot BAVG_j{}^{-2} - 28.0057KAVGD_{ij}{}^{-1} \cdot NETPAVG_{ij}{}^{2} + 10.5946KAVGD_{ij}{}^{-1} \cdot NETPMIN_{ij}{}^{2} - 85.9161PAVG_{ij}{}^{-2} \cdot NETPAVG_{ij}{}^{-1} - 460.8PAVG_{ij} \cdot NETPAVG_{ij} + 240.1PAVG_{ij} \cdot NETPAVG_{ij}{}^{2} + 7.8471UMAX_j{}^{-1} \cdot NETPAVG_{ij}{}^{-2} \quad (21)$$

We used Equation (21) to predict the dependent variables. After applying the equation, we obtained *p*, the probability of whether or not the consumer would order from the supplier, of values between 0 and 1. We utilized a decision rule if *p* was equal to or greater than 0.5, we set it to one, meaning the customer should order. Otherwise, we set it to zero, meaning the customer should not order. The total misclassified cases using the logistic model were only 2,212 out of 10,000 (see Table 2.7), which further supported the model fit.

Table 2.7 Performance of the logistic regression

logit = 1			*logit = 0*					*Overall*
		Correct			*Correct*	*Total*	*Total correct*	*correct*
Observed	*Expected*	*%*	*Observed*	*Expected*	*%*	*obs.*	*classifications*	*%*
6302	4985	79.10%	3938	2773	70.42%	10000	7788	77.88%

We experimented on setting cut-off points ranging from 0.10 to 0.95 in the classification decision rule. The model performed the best when the cut-off point was 0.55 (see Table 2.8) for the training data and the correct classification percentage was 77.96%. We examined the correct classifications of 1 (include the supplier) when predicted probability exceeds the threshold level (see Table 2.9) as well as the correct classifications of 0 (exclude the supplier) when predicted probability falls below the threshold level (see Table 2.10). We observed that the classification performed very well with a higher than 85% accuracy when the predicted probability was above 0.60 or below 0.20.

Table 2.8 Correct classifications under different decision rules

Cut-off point	*Total correct classifications*	*Overall correct %*
0.10	6386	63.86%
0.15	6705	67.05%
0.20	6988	69.88%
0.25	7263	72.63%
0.30	7446	74.46%
0.35	7610	76.10%
0.40	7708	77.08%
0.45	7762	77.62%
0.50	7788	77.88%
0.55	7796	77.96%
0.60	7746	77.46%
0.65	7655	76.55%
0.70	7497	74.97%
0.75	7292	72.92%
0.80	7012	70.12%
0.85	6638	66.38%
0.90	6158	61.58%
0.95	5405	54.05%

Table 2.9 Correct classification of 1 (include the supplier) when predicted probability exceeds the threshold level

Outcome threshold	*Observed*	*Expected*	*Correct %*
0.95	1476	1515	97.43%
0.90	2289	2388	95.85%
0.85	2844	3018	94.23%
0.80	3308	3572	92.61%
0.75	3685	4046	91.08%
0.70	4023	4517	89.06%
0.65	4321	4955	87.20%
0.60	4574	5370	85.18%

0.55	4792	5756	83.25%
0.50	4985	6150	81.06%

Table 2.10 Correct classifications of 0 (exclude the supplier) when predicted probability falls below the threshold level

Outcome threshold	*Observed*	*Expected*	*Correct %*
0.05	88	91	96.70%
0.10	383	412	92.96%
0.15	748	823	90.89%
0.20	1114	1272	87.58%
0.25	1504	1777	84.64%
0.30	1827	2240	81.56%
0.35	2137	2696	79.27%
0.40	2875	3574	80.44%
0.45	2606	3482	74.84%
0.50	2803	3850	72.81%

In creating the second structural equation, we extracted only the non-zeros of the dependent variable and ran the one-at-a-time regressions again. We obtained a much better result than what we acquired from the whole dataset. The independent variable KD_{ij} had the highest adjusted R^2 of 0.4667 (see Table 2.11). We have also investigated the number of polynomial terms that should remain in our models. At first, we experimented with keeping 12 polynomial terms of each independent variable with the power indices ranging from negative six to positive six. Then we tried a simpler model containing four polynomial terms, power indices ranging from negative two to positive two. The results showed the difference between the two models was insignificant. Thus, we decided to use the latter model for simplicity as well as the ease of interpretation.

Table 2.11 Adjusted R^2 values for one-at-a-time regression models

	Independent Variable	*With zeros*	*Without zeros*
1	KD_{ij}	0.0328	0.4667
2	$KAVGD_{ij}$	0.0064	0.2316
3	$PAVG_{ij}$	0.1307	0.1031
4	$PMIN_{ij}$	0.1127	0.0901
5	B_j	0.0492	0.0022
6	$BMAX_j$	0.0725	0.0255
7	$BAVG_j$	0.0822	0.0304
8	$UMAX_j$	0.015	0.0038
9	$NETPMIN_{ij}$	0.1857	0.1192
10	$NETPAVG_{ij}$	0.2077	0.1283

Even though some independent variables by themselves had low adjusted R^2 values, we believed the interactions of such variables and other ones may have a significant impact on the dependent variable. We decided to keep all the independent variables and combined them as described in the previous section for a stepwise regression. We built a structural equation of 30 terms, provided below. The adjusted R^2 for the final structural equation was 0.6041.

$$QD_{ij} = 2.27807 - 0.00495 KAVGD_{ij}{}^{-2} \cdot BAVG_j{}^{-2} - 0.05532 KAVGD_{ij}{}^{-2} \cdot NETPMIN_{ij}{}^{-1} - 0.02473 KAVGD_{ij}{}^{-2} \cdot PMIN_{ij} + 0.00037729 KAVGD_{ij}{}^{-2} \cdot UMAX_j{}^{-2} - 0.00035739 KAVGD_{ij} \cdot B_j{}^{-2} - 0.0109 KD_{ij}{}^{-2} \cdot BAVG_j - 0.00531 KD_{ij}{}^{-2} \cdot KAVGD_{ij}{}^{-2} + 0.01475 KD_{ij}{}^{-2} \cdot KAVGD_{ij}{}^{-1} + 0.02768 KD_{ij}{}^{-2} \cdot PAVG_{ij}{}^{2} + 0.04084 KD_{ij}{}^{-1} \cdot KAVGD_{ij}{}^{-2} - 0.08183 KD_{ij}{}^{-1} \cdot KAVGD_{ij}{}^{-1} - 0.24862 KD_{ij}{}^{-1} \cdot NETPMIN_{ij}{}^{-2} - 0.00781 KD_{ij}{}^{-1} \cdot UMAX_j{}^{2} + 0.06856 KD_{ij} \cdot KAVGD_{ij}{}^{-2} - 0.75131 KD_{ij} \cdot KAVGD_{ij} + 0.71376 KD_{ij} \cdot BMAX_j{}^{-2} - 0.82649 KD_{ij} \cdot PAVG_{ij}{}^{2} +$$

$$0.45992KD_{ij}{}^2 \cdot KAVGD_{ij}{}^2 + 0.8778KD_{ij}{}^2 \cdot BMAX_j{}^2 - 0.67924KD_{ij}{}^2 \cdot PMIN_{ij}{}^2 + 1.8033BMAX_j \cdot NETPMIN_{ij}{}^{-2} + 0.62663BMAX_j{}^2 \cdot PMIN_{ij}{}^2 - 2.60874NETPMIN_{ij} \cdot NETPAVG_{ij}{}^2 - 2.66507PAVG_{ij} \cdot NETPAVG_{ij}{}^{-2} + 3.14905PAVG_{ij} \cdot NETPMIN_{ij} - 1.32508PAVG_{ij}{}^2 \cdot BMAX_j{}^2 - 0.82787UMAX_j{}^{-1} \cdot NETPAVG_{ij}{}^{-2} - 1.08506UMAX_j{}^{-1} \cdot NETPAVG_{ij}{}^2 + 1.02292UMAX_j{}^{-1} \cdot NETPMIN_{ij}{}^{-2} + 0.85989UMAX_j{}^{-1} \cdot NETPMIN_{ij}{}^2 \qquad (22)$$

We predicted the QD_{ij} values using Equation (22) and the mean absolute deviation of the predicted values was 0.080. We had 70.36% of predicted values falling with a ±10% deviation from the optimal proportion and 87.70% of them were within a ±20% band. We considered the structural equation having an adequate fit.

2.6 Validation of structural equations

To validate the first structural equation, we examined the whole holdout dataset. Our goal was to check how accurately we could predict whether the customer should buy from a supplier. We utilized the cut-off point of 0.5 in classifying p to either one or zero. The equation performed better on the cases of buying than those of not buying by 10.70%. The overall performance of our equation was good with a close to 80% accuracy in prediction. The model classified 7,835 cases correctly out of 10,000 cases (see Table 2.12). We tried different cut-off points in the decision rule of classification for the holdout data. The cut-off point of 0.5 performed the best (see Table 2.13). We investigated the correct classifications of including the supplier when predicted probability exceeds the threshold level (see Table 2.14) as well as the correct classifications of excluding the supplier when predicted probability falls below the threshold level (see Table 2.15). When the predicted probability was above the threshold of 0.65 or below 0.20, the accuracy of classification was above 85%.

Table 2.12 Validation of the logistic structural equation

logit = 1			*logit = 0*					
Observed	*Expected*	*Correct %*	*Observed*	*Expected*	*Correct %*	*Total obs.*	*Total correct classifications*	*Overall correct %*
5961	4928	82.67%	4039	2907	71.97%	10000	7835	78.35%

Table 2.13 Correct classifications under different decision rules for holdout data

Cut-off point	*Total correct classifications*	*Overall correct %*
0.10	6281	62.81%
0.15	6623	66.23%
0.20	6921	69.21%
0.25	7232	72.32%
0.30	7463	74.63%
0.35	7611	76.11%
0.40	7743	77.43%
0.45	7827	78.27%
0.50	7835	78.35%
0.55	7791	77.91%
0.60	7701	77.01%
0.65	7601	76.01%
0.70	7469	74.69%
0.75	7281	72.81%
0.80	7039	70.39%
0.85	6685	66.85%
0.90	6184	61.84%
0.95	5431	54.31%

Table 2.14 Correct classification of 1 (include the supplier) when predicted probability exceeds the threshold level for holdout data

Outcome threshold	*Observed*	*Expected*	*Correct %*
0.95	1414	1436	98.47%
0.90	2220	2295	96.73%
0.85	2802	2958	94.73%
0.80	3257	3514	92.69%
0.75	3614	3986	90.67%
0.70	3928	4426	88.75%
0.65	4212	4862	86.63%
0.60	4475	5288	84.63%
0.55	4721	5690	82.97%
0.50	4928	6060	81.32%

Table 2.15 Correct classifications of 0 (exclude the supplier) when predicted probability falls below the threshold level

Outcome threshold	*Observed*	*Expected*	*Correct %*
0.05	79	92	85.87%
0.10	356	392	90.82%
0.15	765	868	88.13%
0.20	1161	1362	85.24%
0.25	1578	1885	83.71%
0.30	1896	2290	82.79%
0.35	2180	2710	80.44%
0.40	2449	3116	78.59%
0.45	2703	3540	76.36%
0.50	2907	3940	73.78%

Turning now to the validation of the second structural equation, we separated the holdout dataset by zeros and non-zeros for the dependent variable and applied the equation to the non-zero ones. We calculated the predicted values of the dependent variable. Since the proportions of each product ordered from its chosen suppliers should add up to 100%, we divided each predicted dependent variable by the total proportions of those suppliers to normalize the data. Then we examined the mean absolute value (MAD) of the residuals. On average, the percentages of product demand ordered from one supplier estimated by the structural equation was 0.079 away from those estimated by the BVD optimization model. We also inspected on the proportion of the predicted values being within a tight band around the optimized values. As shown in Table 2.16, 70.61% of the predicted values were within a ± 0.1 band over the optimal percentages, and 88.14% of the predicted fell into a ± 0.2 band. Both results suggested a good fit for the first structural equation.

Table 2.16 Residual analysis for the linear structural equation

Model	*MAD*	*Within ± 0.1 band*	*Within ± 0.2 band*
Linear Regression	0.079	70.61%	88.14%

2.7 Conclusions

Solving a supplier selection problem with BVD needs much more effort than calculating structural equations. We apply predictive global sensitivity analysis to build two structural equations that can help managers choose desirable suppliers in no time.

An important use of an approach such as the one developed in this paper would be to help managers make supplier selection decisions for new entrants in the market. In lieu of needing to repopulate and rerun the entire model, the parameters for the new supplier could be entered into the structural equations for a quick indicator of the extent of the attractiveness of that supplier. The equations can be used as tools during negotiations where the customer can quickly determine the size of discount necessary for that supplier to become competitive.

An extension of this work would be to switch the focal firm of the study by exploring how to design the most effective BVD for a supplier giving the market information.

References

Chaudhry, S. S., Forst, F. G., & Zydiak, J. L. (1993). Vendor selection with price breaks. *European Journal of Operational Research*, *70*(1), 52–66. https://doi.org/10.1016/0377-2217(93)90232-C

Dahel, N. (2003). Vendor selection and order quantity allocation in volume discount environments. *Supply Chain Management: An International Journal*, *8*(4), 335–342. https://doi.org/10.1108/13598540310490099

Goossens, D. R., Maas, A. J. T., Spieksma, F. C. R., & van de Klundert, J. J. (2007). Exact algorithms for procurement problems under a total quantity discount structure. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2006.03.010

Kouvelis, P., Li, R., & Ding, Q. (2013). Managing Storable Commodity Risks: The Role of Inventory and Financial Hedge. *Manufacturing & Service Operations Management*, *15*(3), 507–521. https://doi.org/10.1287/msom.2013.0433

Kouvelis, P., Munson, C. L., & Yang, S. (2013). Robust Structural Equations for Designing and Monitoring Strategic International Facility Networks. *Production and Operations Management*, *22*(3), 535–554. https://doi.org/10.1111/j.1937-5956.2012.01418.x

Lee, C., & Munson, C. L. (2015). A predictive global sensitivity analysis approach to monitoring and modifying operational hedging positions. *International Journal of Integrated Supply Management*, *9*(3), 178–201.

Manerba, D., & Mansini, R. (2014). An effective matheuristic for the capacitated total quantity discount problem. *Computers and Operations Research*. https://doi.org/10.1016/j.cor.2013.07.019

Munson, C. L., & Jackson, J. (2015). Quantity Discounts: An Overview and Practical Guide for Buyers and Sellers. *Foundations and Trends® in Technology, Information and Operations Management*, *8*(1–2), 1–130. https://doi.org/10.1561/0200000041

Stadtler, H. (2007). A general quantity discount and supplier selection mixed integer programming model. *OR Spectrum*, *29*(4), 723–744.

Wagner, H. M. (1995). Global Sensitivity Analysis. *Operations Research*, *43*(6), 948–969. https://doi.org/10.1287/opre.43.6.948

Xia, W., & Wu, Z. (2007). Supplier selection with multiple criteria in volume discount environments. *Omega*, *35*(5), 494–504. https://doi.org/10.1016/J.OMEGA.2005.09.002

Zhang, G., & Ma, L. (2009). Optimal acquisition policy with quantity discounts and uncertain demands. *International Journal of Production Research*, *47*(9), 2409–2425. https://doi.org/10.1080/00207540701678944

Zhang, J., & Chen, J. (2013). Supplier selection and procurement decisions with uncertain demand, fixed selection costs and quantity discounts. *Computers & Operations Research*, *40*(11), 2703–2710. https://doi.org/10.1016/J.COR.2013.05.016