REVENUE MANAGEMENT PERFORMANCE DRIVERS: AN EMPIRICAL ANALYSIS IN THE HOTEL INDUSTRY

A Dissertation
Presented to
The Academic Faculty

By

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In Partial Fulfillment
of the Requirements for the Degree
Ph.D in the
School of Georgia Tech College of Management

Georgia Institute of Technology
August 2007

RM PERFORMANCE DRIVERS

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ACKNOWLEDGEMENTS

I could not have completed this dissertation without the help of many people. First, I wish to thank my committee members. Mark Ferguson has unquestionably improved my research skills. He also has infinite patience for which I thank him from the bottom of my heart. Jeff Stratman helped me create a structured argument from chaotic thoughts, and his thorough understanding of empirical methodology greatly improved my comprehension of this subject. Soumen Ghosh helped to frame arguments from a macro level. Koert van Ittersum offered a fresh perspective on my work and reinforced methodological rigor. Laurie Garrow injected industry perspective and modeling expertise into my research. I want to thank all of them for their individual contributions.

I also wish to thank the Operations Management faculty who spent countless hours teaching seminars and critiquing proposals in order to improve my research and method knowledge base. I thank them for their time, energy, and wisdom.

I thank my friends who supported me by offering empathy, laughter, free dinners, and so much more. I am especially grateful to Travis who gave me a place to live.

I thank my family for their unwavering support. Mike and Theresa bought me drinks on Friday nights. Jeff asked thought provoking questions. Kelly cheered me through the whole process. My parents gave me both the educational foundation needed to undertake this challenge and emotional support. And finally, Joe helped me start this adventure and never stopped believing in me.

I thank everyone who helped me along my journey. I hope that I will make you proud in the years to come.

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SUMMARY

Revenue Management (RM) is an important tool for matching supply and demand by segmenting customers into different segments based on their willingness-to-pay and allocating scarce capacity to the different segments in a way that maximizes firm revenues. The benefits of RM are well accepted in the hospitality industry, and the technical aspects of RM form a rich analytical research stream. However, the research is missing a holistic examination of important elements of effective RM. The literature shows that market segmentation, pricing, forecasting, capacity allocation, IT use, organizational focus, aligned incentives, organizational structure, and education and training contribute to effective RM. We group these elements into two concepts: RM technical capability and RM social support capability and propose that these nine elements positively impact RM performance.

We develop scales to measure our constructs and collect responses in the hotel industry. Our survey yields interesting results. In line with expectations, we find evidence that forecasting and organizational focus positively impact RM performance. On the other hand, the results show evidence that improved organizational structure negatively impacts RM performance. We provide a few explanations for this non-intuitive result and proposals for future research.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Companies use Revenue Management (RM) to successfully balance supply and demand and increase profits. To name a few, American Airlines credits RM with increasing revenue by $1.4 billion over three years (Smith et al. 1992) and National Rental Car saw a $56 million revenue increase due to RM (Geraghty and Johnson 1997). In general, most firms attribute a 3 – 7 % increase in profit after implementing RM (Cross 1997: pg 4).

Success stories such as these are not typical of all users; not all users of RM achieve the same magnitude of gains (Lieberman 2003). What drives these performance differences? Judging by the focus of the academic literature, the performance differences could result from the fundamental capacity allocation algorithms – over 75 papers have been published on this topic in the last twenty years. However, based on interviews with leading RM software providers and users, some users, including many in the hotel industry, have been reluctant to implement new algorithmic improvements in their RM systems. In fact, the basic capacity allocation algorithm used in the RM systems of the major hotel chains was developed in the late 1980's (the EMSR-b heuristic by Belobaba 1989). This happens despite the fact that a rich stream of research on improved algorithms has appeared since this time. A possible reason for this reluctance to adopt new algorithms, often proposed by this group of users, is that potential improvements from better algorithmic performance are small compared to other opportunities.

It has been proposed that these other improvement opportunities include “soft” skills and other technical skills beyond algorithmic improvements. We identify and define these possible RM success drivers, then test how they impact firm performance. More generally, we answer the following two research questions:

1. What are the primary skills necessary for effective use of RM?
2. How do these skills impact RM performance?

Answering these questions broadens the traditional RM framework, thus providing researchers with new investigation topics. Additionally, it provides managers with empirical evidence supporting the importance of investing in certain skills.

1.2 Overview of Model

To better understand the antecedents of RM success, we conducted an exploratory, empirical study to determine what drives the differences in RM performance. Specifically, we examined both technical capabilities and social support capabilities as they relate to RM, as supported by existing literature. We defined RM technical capability as the technical processes and routines that facilitate RM. Market segmentation, pricing, forecasting, capacity allocation, and IT constitute the elements of RM technical capability. We defined RM social support capability as a system of shared values and norms that define appropriate attitudes and behaviors for employees regarding RM practices. Organizational focus, aligned incentives, organizational structure, and education and training compose RM social support capability. Using literature from operations management, marketing, organizational behavior and others, we support the inclusion of the nine previously listed elements as significant influencers of RM success.

We propose these elements positively influence RM performance and present appropriate hypotheses representing this proposal. Figure 1 illustrates our overall model.

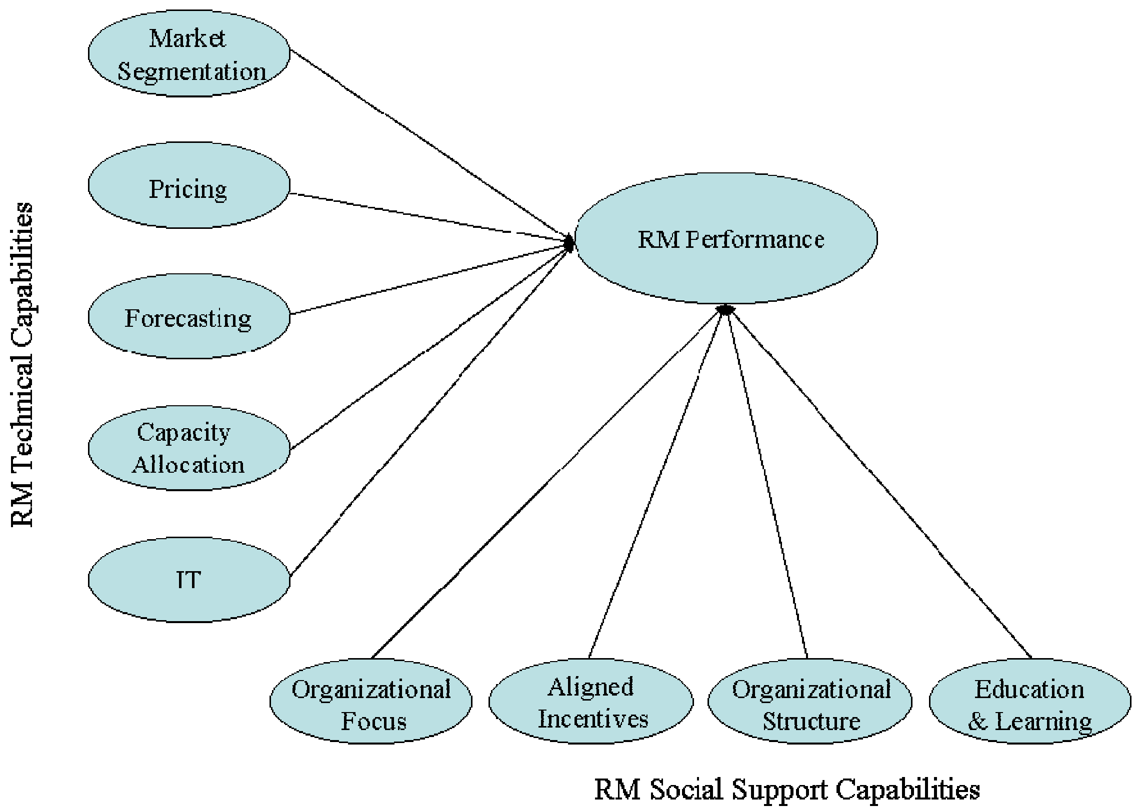

Figure 1 - Drivers of RM Success

1.3 Research Approach

Expert interviews, past literature support, and a large scale survey in the hotel industry inform our research conclusions. We started our research by interviewing RM practitioners and reviewing the existing RM literature. This ensured interest in both the industry and academic communities. We developed theory through the use of existing RM literature and literature in related fields, such as marketing and organizational behavior, in order to create a holistic view of the process. The literature search, complemented by industry interviews, ensured a thorough and relevant set of hypotheses.

Based on this knowledge, we generated items to measure each of the nine constructs hypothesized to drive RM success. We followed best practice guidelines for scale development (Churchill 1979, O'Leary-Kelly, Vokurka 1998), using the items generated in the last step. These guidelines included expert item sorting and a pilot test.

After the scales were developed, we collected responses to our survey. We collected data from US hotels within three different hotel firms which all currently use RM. Based on data from these hotels, we evaluated how our proposed drivers impact RM success.

1.4 Contributions

This research examines the factors which differentiate performance levels within RM. This research contributes to theory by incorporating concepts across disciplines for a complete picture of necessary elements for RM success. This research contributes to practice by empirically testing how the different RM skills impact RM, and the limits of different RM skills.

More specifically, this research is the first, to the author's knowledge, to rigorously test RM skills across firms using empirical data. Previous work has normatively tested individual elements within an RM environment, or anecdotally prescribed best practices. This work is the first to systematically gather data across a large sample size in order to test the drivers of RM and their ultimate impact on RM effectiveness. This provides a foundation for future empirical work in the field.

From a managerial perspective, this research provides evidence for essential building blocks in RM implementation and operations. This evidence applies to the hotel industry, and has potential to apply to other industries.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Our research builds on five major streams of literature: RM research within operations management/ operations research, RM research applied to the hotel industry, marketing (pricing and market segmentation), organizational behavior (organizational structure, executive commitment, and training), and process/ implementation studies within the operations management field. We provide a review of the literature and illustrate how we both build on this literature and further extend it.

2.2 Operations Management Literature

The RM research within the operations management field focuses on normative modeling. The field has made great progress in modeling three different areas: forecasting, pricing, and capacity allocation. We present an overview of these research streams.

Forecasting methods used in RM follow the same trends as the general forecasting literature. This large stream of research, specific to RM, includes arrival pattern approximations, unconstraining and forecasting. Most of the research uses some variation of Poisson arrival process (see McGill and van Ryzin 1999: pg 237 for a review). The unconstraining literature provides statistical methods to approximate total demand for goods or services that have sold out, thus providing more accurate historical data on which to base future forecasts (see McGill and van Ryzin 1999: pg 237; Crystal et al. 2007, Ratliff 2006). RM borrows from the inventory related forecasting stream and uses methods such as smoothing, moving average, Box-Jenkins, etc. (Talluri and van Ryzin 2004, Chapter 9). Arrival rates, unconstraining methods and aggregate forecasting methods all contribute to the quality of a forecast and differing use of these tools among practitioners will lead to differences in forecasting quality. This literature emphasizes the importance of forecasting and the elements of a quality forecast. We extend this literature by testing how forecasting impacts performance.

The operations management field has made significant improvements in capacity allocation algorithms, improving from single-leg (Littlewood 1972, Belobaba 1989, Curry 1990, Wollmer 1992, Brumelle and McGill 1993, Robinson 1995, van Ryzin and McGill 2000) to network control (Dror et al. 1988, Curry 1990, Talluri and van Ryzin 1999, Cooper 2002). Modelers in this area continue to produce more complex and complete models. Some airlines incorporate aspects of these advanced models into practice (Vinod 2006). This literature stream indicates that capacity allocation plays an important role within RM systems. However, most hotel RM systems today use EMSR-b (Belobaba 1989), a method developed by Belobaba in the 1980's, instead of a more advanced method (Steve Swope, personal communication, February 2006). It has been proposed by some RM experts that many hotels have not adopted updated allocation algorithms because potential return on other investments is larger than potential return on upgrading algorithms. This stream guides us to examine how capacity allocation impacts RM performance.

Pricing in revenue management is also a large and growing research stream. Bitran and Caldentey (2003) summarize analytical modeling research in this area. The core model assumes price is a function of inventory (or capacity) and time until the product perishes (Bitran and Caldentey 2003). From these basic assumptions, researchers have discovered how to optimally price products given constraints on pricing functions for a single product with deterministic demand (Bitran and Caldentey 2003). For a single product with stochastic demand, there is no closed form solution, but Gallego and van

Ryzin (1994) find that the deterministic price heuristic is optimal for a large inventory of items to be sold in a sufficiently long selling period. Chatwin (2000) and Feng and Xiao (2000) assume a finite set of price changes allowable over time and show that the optimal price is non-increasing in the inventory and decreasing in the time remaining. For multiple products, and/or stochastic demand, the problem cannot be solved in a closed form solution and researchers have found approximations for the whole problem (Gallego and van Ryzin 1994), or closed form solutions once simplifying assumptions have been made. Cooper et al. (2006) and Jin (2006) show how ignoring competition harms a firm when setting prices. This normative stream of research suggests how to optimally change prices over time based on demand curves and time to perishability, given certain constraints. However, it does not suggest how to set prices to an actual number. The marketing literature takes a strategic view of how to set prices, using a more qualitative perspective.

2.3 Marketing Literature

RM crosses two functional disciplines: operations management (OM) and marketing. We have already addressed some important research in OM. Two marketing topics particularly impact RM: pricing and market segmentation. We do not presume to cover the entire literature in these two areas, but instead provide a general overview, especially as these topics apply to RM.

The marketing function within firms typically controls pricing decisions and bases these decisions on the firm's strategy. A firm may want to set prices to survive, or to maximize profit, revenue, sales growth, or market skimming (Kotler 1998). Depending on the firm strategy, upper and lower price bounds may be set to accomplish these strategies. Within these bounds, a firm must consider three C's in order to set an actual price: cost, competitors' prices, and customers' assessment of the product (Kotler 1988). Since marginal cost for another customer is negligible for yield management, we ignore cost and focus more on competitors' prices and customers' assessment of the product within this research. Smart pricing decisions incorporate demand volume, price elasticity, competitors' price, pricing strategy, value of the good or service, and regulatory constraints (Kotler 1988, Dutta et al. 2003, Monroe 2003). Many firms do not possess the knowledge and processes to consistently translate these factors into optimal or near-optimal pricing decisions (Cressman 1997, Smith 1995, Ross 1984) and therefore pricing can be a key competitive advantage (Monroe 2003, Dutta et al. 2003). From both operations and marketing, we know pricing is an important component of RM and hence we include it as a driver of RM success. We use the marketing literature to define the measurement items of pricing within our research.

Marketing researchers have also investigated market segmentation and concluded that six characteristics determine the desirability of a segmentation: identifiability, substantiality, reachability, stability, responsiveness, and actionability (Frank et al. 1972, Loudon and Della Bitta 1984, Baker 1988, Kotler 1988). Identifiability is defined as the extent to which distinct groups of customers can be recognized in the marketplace by using specific segmentation bases. Substantiality measures whether the targeted segments represent a large enough portion of the market to ensure the profitability of targeted marketing programs. Accessibility measures the degree to which the targeted segments can be reached through promotional or distributional efforts. Responsiveness measures the extent to which segments respond uniquely to targeted marketing efforts.

Stability measures the lack of change in either behavior or composition for a given targeted segment. Finally, actionability measures the extent to which a firm can specifically target a specific market segment based on the firm's skills, strategy, and structure (Wedel and Kamakura 1998). Our market segmentation measurement items originate from these characteristics.

2.4 Organizational Behavior Literature

The organizational behavior literature provides the basis for many of our RM performance drivers. We present brief reviews of the literature streams that support our theory.

Throughout the management literature, researchers assert that organizational structure affects organizational performance (Van de Ven 1976, Hall 1977, Dalton et al. 1980, Galbraith and Lawler 1998). Many support the contingency view, which says that organizational structure must fit with firm strategy, the external competitive environment, and other factors (Lawrence and Lorsch 1967, Galbraith 1977, Ruekert et al. 1985, Nadler and Tushman 1997, Russo and Harrison 2005). Scholars consistently agree that there is no one ideal organizational structure for all organizations (Galbraith 1977, Mintzberg 1980, Van de Ven and Drazin 1985, Galunic and Eisenhardt 1994, Gresov and Drazin 1997). Contingency theory explains that different size firms in different industries have specific needs and a given firm with a specific set of contingent factors should follow a prescribed best organizational structure. (Drazin and Van de Ven 1985). Contrasting contingency theory, equifinality theory proposes that a given level of organizational performance may be reached through many different organizational structures, even if firms have similar competitive pressures and internal processes.

Equifinality suggests that there is no one magic structure and even a good proposed structure has shortcomings that an alternate structure may counter-balance. This theory suggests flexibility in designing high performing organizations (Gresov and Drazin 1997). Even though researchers do not agree which organizational structure is best, they do agree that organizational structure impacts performance. Based on this and work from the hotel literature, we include organizational structure in our research and measure how it impacts performance.

Organizational behavior research also has a strong history of studying how evaluation and compensation impact performance. However, this research stream also contains conflicting views. One stream advocates that incentives linked to performance will improve performance, whereas the other stream maintains that financial incentives reduce intrinsic motivation and thus overall performance. The first stream includes both theoretical and empirical research. Within this stream, researchers include expectancy theory, which states that incentives increase motivation to perform, reinforcement theory which states that money reinforces positive behavior, and goal-setting theory, which advocates money as a method for employees to accept goals (Jenkins et al. 1998). See Jenkins et al. (1998) and Gerhart and Rynes (2003) for literature reviews.

An alternative view stems from Deci and Ryan's (1985) cognitive evaluation theory (CET). CET maintains that monetary incentives tied to performance will diminish intrinsic motivation in individuals and thus reduce performance in the long run. Work from Kohn (1988, 1993) and Herzberg (1968) further support this theory. While the exact relationship between financial incentives and performance is unknown, a meta-analysis of research provides evidence that providing financial incentives for positive performance improves performance (Jenkins et al. 1998). This evidence encourages the use of financial incentives as a RM performance driver, which we test in this research.

2.5 Antecedents to Success Literature

In a more general grouping, research concerning attributes which impact success of a new program, process or change, consistently includes elements such as executive commitment and education and training. This literature spans across disciplines and our review is by no means exhaustive, but representative of a consistent theme. A meta-analysis of executive commitment shows positive influence of management commitment on program success (Rodger et al. 1993). Similar evidence for a positive relationship between executive commitment and the success of a given program or process is found in the research on total quality management (Ahire et al. 1996, Jun et al. 2006), enterprise resource planning (King and Thompson 1996, Stratman and Roth 2002). We see similar evidence for a positive relationship between education and learning and the success of a given process or program. IT implementations have been shown to be more successful with training and education (King and Thompson 1996, Stratman and Roth 2002). Additionally, total quality management programs find the same results (Ahire et al. 1996, Jun et al. 2006). This literature reinforces the necessity of both executive commitment and education and training on new programs. We apply this to RM.

2.6 Hotel Literature

Research specific to hotel RM literature differs greatly from the mainstream RM literature in that there are few analytical models. Instead, the hotel RM literature largely consists of case studies and prescriptive discussions of best practices, with little empirical testing of ideas. Kimes' (1989) seminal article codified RM for the hotel industry. Kimes (1989) described the concept of RM and the industry characteristics which make an industry conducive to RM implementation. Both the work of Jones and Hamilton (1992) and Donaghy et al. (1997) yield valuable information about steps needed for successful RM implementation within the hotel industry. Neither, however, have rigorous methodology supporting their claims. Farrell and Whelan-Ryan (1998) used a semi-structured interview process to gather data from over 50 hotels to support their proposed model of best implementation, including an education and training step and the development of a [RM] culture. We adopt these steps as RM drivers, renaming RM culture as RM social support. Hansen and Eringa (1998) review the existing hotel literature to summarize critical success factors, which we include in our RM drivers. Brotherton and Turner (2001) conduct a case study of a RM implementation, including delineation of success factors. Manzier (2004) describes RM implementations in hotels in general, including areas for implementation improvement. Importantly, he describes the differences between the airline industry and the hotel industry, which explains some significant differences between hotel and airline RM implementation. We lean heavily on this work for the social support skills of RM. We extend this literature by testing the success factors identified in the hotel literature across a large empirical sample.

CHAPTER 3

THEORY DEVELOPMENT AND HYPOTHESES

3.1 Overview

Chapter 2 presents existing RM literature which highlights important components of RM. Additionally, the literature review reveals a scarcity of empirical research. We attempt to provide exploratory research to fill this gap. Section 3.2 theoretically supports the main idea of this research: that RM technical and social support capabilities work together to positively influence RM performance. Section 3.3 defines RM technical capability and the five individual components within it. Five corresponding hypothesis are presented within this section. Section 3.4 defines RM technical capabilities and the four individual components within it. Four corresponding hypothesis are presented within this section.

3.2 Introduction

Many firms have achieved increased profitability due to RM, however, all firms do not achieve the same level of profitability improvements. We argue this difference is due to a combination of technical and social support skills embedded within a company. RM research within the Operations Management (OM) field has concentrated on technical aspects of RM: forecasting, capacity allocation, and pricing. However, these elements alone cannot guarantee superior performance. Other non-technical, or "social support" elements aid performance by reinforcing and encouraging advanced technical skills and improved decision making skills. This claim is supported by socio-technical systems (STS) theory.

STS theory suggests that systems should not dictate how people work, but instead should support and facilitate people in their jobs (Trist and Bamforth 1951, Emery 1959). For a system to work well, all elements should complement each other and align with overall goals.

Alignment of structure and support consistently appears in empirical studies within the OM field. For example, Ahire et al. (1996) draw on the existing Total Quality Management (TQM) literature to develop comprehensive, valid scales for an "integrative QM philosophy" (Ahire et al. 1996: pg 23). Building on the previous literature, their scales include both technical and social support constructs in TQM systems, which work together for the most effective results. Similarly, the ERP literature supports the concept that technical and social support systems must align to achieve the most effective results (King and Thompson 1996, Stratman and Roth 2002). This previous work on program implementation supports the notion that RM should be integrated into an organization to maximize its impact.

We assert RM technical skills and social support skills must complement each other to achieve the best results in RM. Since there are many technical skills included within RM, we group these under the umbrella of RM technical capability. Similarly, we group the many skills of social support under RM social support capability.

A capability is a "firm's capacity to deploy resources" (Amit and Schoemaker, 1993) and is the result of integrating key processes over time through complex interaction in order to provide superior value (Stalk et al. 1992, Amit and Schoemaker 1993). Firms realize capabilities through investing in infrastructure (people, equipment, and processes) for a long-term, global optimal solution to a problem. Capabilities provide advantage through integration of common resources into value-added processes and routines. Firm success depends on how capabilities work with other complementary assets within an organization (Ethiraj, Kale, Krishnan and Singh 2005). Because of this complexity, outside firms cannot easily imitate leading competitors. In the next two sections, we present two important capabilities for RM.

3.3 RM Technical Capability

We define RM technical capability as the technical processes and routines that facilitate RM. Consider a firm implementing RM. First, the firm must segment its customers and charge different prices for each segment (Cross 1997, Talluri and van Ryzin 2004, Phillips 2005). As part of charging differing prices, the firm must forecast demand for each segment and allocate capacity to various segments to know who and when to charge different prices (Cross 1997, Talluri and van Ryzin 2004, Phillips 2005). Because of the significant information needed for analysis in RM, these tasks must be done within the context of an Information Technology (IT) system. This set of steps required for RM forms the basis for RM technical capability. We classify five skills as elements of RM technical capability: market segmentation, pricing, forecasting, capacity allocation, and IT. Next, we define each of these RM drivers and support their inclusion within RM technical capability.

We define market segmentation as "the process of classifying customers into groups based on observed – or inferred – characteristics, behaviors, and preferences" (Talluri and van Ryzin 2004: pg 579). Market segmentation is a necessary, but not sufficient condition for RM to occur. Since RM is based on the practice of charging different prices to different customer segments, an inability to break customers into different segments translates into an inability to practice RM. Therefore, market segmentation ability is an important skill within RM and we include it as part of RM technical capability.

After grouping customers into segments, a firm must set prices for each segment. We define pricing as the process of setting rates to try to extract the optimal revenue from the firm's customers (Dutta et al. 2003, Vorhies and Morgan 2005). RM yields higher revenue to firms because of the ability to charge some customers higher prices than others. However, setting prices wisely has never been an easy task. A manager must consider the value of the good to the customers, the competitors' prices, the customer price elasticities, and many other factors (Monroe 2003). Many of these variables are either unknown to the firm or constantly changing, thereby increasing the difficulty of setting prices. Regardless of the complexity of pricing, it is a critical element of RM (Jones and Hamilton 1992, Bitran and Caldentey 2003, Talluri and van Ryzin 2004, Preslan and Newmark 2004, Phillips 2005) and therefore we include it as one of the constructs of RM technical capability.

Product prices directly impact product demand, which must be estimated in order to determine the optimal capacity to reserve for each customer segment. The process of predicting future demand for a firm's product defines forecasting. Weatherford et al. (2001: pg 54) call forecasting "the key driver of any RM system". Forecasts provide a RM decision maker with approximate demand for each market segment, thereby greatly influencing the amount of capacity to allocate to the highest value segments. Better forecasts incorporate quantitative analysis of past data, (McGill and van Ryzin 1999, Albright, Winston, Zappe 2003) current trends, and various system “upsets” or special events which impact demand (Albright et al. 2003, Schwartz and Cohen 2004).

We use the definition of capacity allocation from Talluri and van Ryzin (2004: pg 3): “the decision of whether to accept or reject an offer to buy; how to allocate capacity to different segments or channels; when to withhold a product from the market and sell at later points in time”. Each time a new customer arrives, RM users must decide if they should sell capacity to the current customer today, or hold that capacity for a later arriving, higher paying customer, who may or may not materialize. Firms allocate capacity using allocation algorithms, incorporating the probability of future demand arriving. In other words, in a world of finite supply, a firm wants to sell that supply at the highest profit. This concept is a key part of RM and so we include it within RM technical capability.

Practitioners make RM decisions based on huge amounts of data stored, cleaned, and analyzed within an IT system and therefore we include IT as a part of RM technical capability. We define IT as the hardware, software, and people necessary to configure and maintain information systems in support of the business (adapted from Stratman and Roth 2002). Firms must use IT resources well to successfully use RM. Firms are able to segment markets, understand consumers’ price elasticity, and allocate capacity more effectively, due in a large part to the data and programs within an IT system (Talluri and van Ryzin 2004: pg 5). While users must apply their own expertise and adjust system recommendations judiciously, IT facilitates the decision process which relies on detailed analysis of sizable data in RM applications.

While it may seem obvious that IT improves RM performance, the impact of IT on performance has been questioned in the past. The term "productivity paradox" has been used often to describe investments in Information Technology unaccompanied by expected increases in productivity (Brynjolfsson and Hitt 1996, Brynjolfsson and Hitt 1998, Carr 2003). However, some researchers have generally shown that IT capability, when used to enhance and complement firm core competencies, can be a competitive advantage for a firm (Brynjolfsson and Hitt 1996, Bhardarwaj 2000, Dedrick et al. 2003, Bhatt and Grover 2005, Ravichandran and Lertwongsatien 2005). The prevailing literature defines IT capability not only as the physical IT assets, but instead as the physical IT assets, the know-how to maintain and update those assets, and the knowledge to apply those assets to assist in the firm's operations (Bhardarwaj 2000, Ravichandran and Lertwongsatien 2005). Using this broader definition of IT capability, both Bharadwaj (2000) and Ravichandran and Lertwongsatien (2005) found that IT capability can provide competitive advantages to firms. Whereas the physical assets of IT can be easily imitated, the knowledge to apply IT assets to a specific business are much more difficult to imitate. This research guides us to think of IT as an enabling component of overall firm performance. We incorporate IT as a factor in a successful revenue management system. We are now ready to propose five hypotheses regarding RM technical capability.

HYPOTHESIS 1. *Increased market segmentation ability positively influences RM performance.*

HYPOTHESIS 2. *Increased pricing ability positively influences RM performance.*

HYPOTHESIS 3. *Increased forecasting ability positively influences RM performance.*

HYPOTHESIS 4. *Increased capacity allocation ability positively influences RM performance.*

HYPOTHESIS 5. *Increased IT ability positively influences RM performance.*

The technical aspects of RM are important, but are not the only influencing factors of RM performance. Based on field interviews and the literature, the social support aspect of RM also impacts performance. We next define the elements contained in social support capability and propose that they positively influence RM performance.

3.4 RM Social Support Capability

Most OM modeling research simplifies situations by assuming that employees responsible for a process or system act consistently and rationally and are not a driving factor in whether or not a system succeeds (Boudreau et al. 2003). This generalization includes RM modeling research. However, employees involved in a system have been shown to be a major factor in whether or not a system or initiative works within the OM field (Bendoly et al. 2006). This holds true within RM; those that implement RM contend that RM employees determine RM success or failure (Yeoman and Watson 1997, Farrell and Whelan-Ryan 1998, Hansen and Eringa 1998, Ingold et al. 2000, Talluri and van Ryzin 2004: pg 16). We fill a gap in RM research by incorporating processes and policies which impact employee behavior through the overall concept of RM social support capability.

Past research within the organizational behavior and strategy fields has supported the argument that firm culture affects firm performance (Kotter and Heskett 1992, Carmeli and Tishler 2004, Russo and Harrison 2005). Within these fields, there are hundreds of definitions of culture (Gordon and Ditomaso 1992). One commonly used definition is that of O'Reilly and Chapman (1996): "a system of shared values (that define what is important) and norms that define appropriate attitudes and behaviors for organizational members (how to feel and behave)". Culture sets "guidelines and rules for how to behave…" (Schein 1991: pg 15) and therefore enables a firm to standardize execution of routines (Sorensen 2002). This standardization helps to reduce the stochastic nature of people. The definition of organizational culture encompasses too broad of an area for our research. Therefore, we use the general meaning from this broad definition, but alter it specifically to RM.

RM social support capability is defined as a system of shared values and norms that define appropriate attitudes and behaviors for employees regarding RM practices (adapted from O'Reilly and Chapman 1996). Literature and field interviews defined of RM social support capability, with specific examples outlined in the upcoming subsections. We classify organizational focus, aligned incentives, proper organizational structure, and education and learning under RM social support capability. The next paragraphs explain each element in greater detail.

We define organizational focus as a cross-functional effort to improve RM from all levels, including executive management. Executive commitment is a subset of our organizational focus construct. Specific to RM, many RM experts explicitly list executive commitment as critical to success (Kimes 1989, Donaghy et al. 1995, Yeoman and Watson 1997, Hansen and Eringa 1998). This has been proposed and supported in various research streams: total quality management implementation (Ahire et al. 1996, Sila and Ebrahimpour 2005, Schroeder et al. 2005) and IT system implementation (King and Thompson 2001, Stratman and Roth 2002). Consistent with other initiatives, RM requires support from the top of an organization to encourage greater effort by employees. Additionally, the RM literature shows that cross-functional support from all levels of the organization contributes to improved performance (Jones and Hamilton 1992, Donaghy et al. 1997, Hansen and Eringa 1998). Through this case based evidence, we propose that organizational focus helps to define appropriate attitude and behavior and is therefore part of social support. Furthermore, increased organizational focus will influence improved RM performance.

Although many RM experts single out "organizational focus," we propose that "aligned incentives" throughout the firm are also necessary for success. The extent to which a firm gives motivation to individuals to choose the best action for the firm defines aligned incentives. Principal – agent theory (Varian 1992) posits that when a principal (manager or owner) gives authority to an agent (worker) to act in ways to benefit the principal, the agent will maximize his own utility, regardless of whether or not that action maximizes the principal's utility. In short, a principal must create rewards that align the agent's goals with the principal's. Case studies and field interviews contend that aligned incentives contribute to RM success (Venkat 2005, Demirag 2006). From this evidence, we contend aligned incentives help to define appropriate RM behavior and therefore contribute to RM performance.

Organizational structure is the third element of RM social support capability. Organizational structure is defined as the "allocation of tasks and responsibilities to individuals and groups within the organization, and the design of systems to ensure effective communication and integration of effort" (Daft and Lengel 1986). Throughout the management literature, researchers assert that organizational structure affects organizational performance (Van de Ven 1976, Hall 1977, Dalton et al. 1980, Galbraith and Lawler 1998). The hotel-based literature also supports the importance of organizational structure in RM (Kimes 1989, Hansen and Eringa 1998). This literature suggests that persons responsible for RM decisions should have a respected voice within the organization and enough authority to create change.

Although it is agreed that organizational structure affects organizational performance, scholars struggle to reach a consensus of what organizational structure will most benefit performance. In fact, scholars consistently agree that there is no one ideal organizational structure for all organizations (Galbraith 1977, Mintzberg 1980, Van de Ven and Drazin 1985, Galunic and Eisenhardt 1994, Gresov and Drazin 1997). More specifically, the contingency view prevails, which says that organizational structure must fit with firm strategy, the external competitive environment, and other factors (Galbraith 1977, Ruekert et al. 1985, Nadler and Tushman 1997, Russo and Harrison 2005). Contingency theory explains that different size firms in different industries have specific needs and a given firm with a specific set of contingent factors should follow a prescribed best organizational structure (Drazin and Van de Ven 1985). Contrasting contingency theory, equifinality theory proposes that a given level of organizational performance may be reached through many different organizational structures, even if firms have similar competitive pressures and internal processes. Equifinality suggests that there is no one magic structure and even a good proposed structure has shortcomings that an alternate structure may counter-balance. This theory suggests flexibility in designing high performing organization (Gresov and Drazin 1997). This reinforces our statement that it is difficult to agree to one best organizational structure. In alignment with others, we believe organizational structure influences RM performance as part of RM social support capability.

Education and learning is the final element of RM social support capability. We define education and learning as the process of educating employees about what RM is and how to use available tools, and well as how to increase knowledge and understanding over time. Education and learning is included as an influencing factor of RM performance because anecdotal and case-based evidence indicates it is a core requirement for successful RM systems (Hansen and Eringa 1998, Skugge 2004). Education and learning are essential for many other operation management programs, such as TQM and ERP (Ahire et al. 1996, King and Thompson 1996, Stratman and Roth 2002). Additionally, it has been cited as a necessity to enable IT. The problem within revenue management has rarely been whether or not to use an IT system. Instead, a problem within revenue management has been the over-emphasis on the IT system and the algorithms within it, to the neglect of the broader revenue management problem (Skugge 2005). Case studies (Jones and Hamilton 1992, Donaghy et al. 1997, Yeoman and Watson 1997, Farrell and Whelan-Ryan 1998, Brotherton and Turner 2001) and anecdotes (Skugge 2005) illustrate problems facing firms that install IT systems without the supporting knowledge structure. Based on evidence from RM and other applications, we contend that education and learning is within the social support capability and positively influences RM.

In summary, social support impacts RM performance through organizational focus, aligned incentives, organizational structure, and education and training. We propose four hypotheses regarding RM social support capabilities.

HYPOTHESIS 6. *Increased organizational focus positively influences RM performance.*

HYPOTHESIS 7. *Increased aligned incentives positively influences RM performance.*

HYPOTHESIS 8. *Improved organizational structure positively influences RM performance.*

HYPOTHESIS 9. *Increased education and training positively influences RM performance.*

CHAPTER 4

METHODOLOGY

4.1 Overview

In this chapter, we explain our survey methodology. A detailed explanation of our methodology establishes a foundation for the credibility of our arguments and conclusions. This methodology explanation includes our choice of industry, response rate, construct validation process, and future research opportunities.

4.2 Theory Tested Within Hotel Industry

We chose to test our theories using data from the hotel industry because of 1) the decentralized structure within the industry, 2) the number of years hotels have been using RM, 3) the sample size possibilities, and 4) the availability of a standardized and objective performance metric. An individual hotel location is our unit of analysis. The choice to focus on one industry increases the strength of internal validity (Ahire et al. 1996).

4.2.1 Decentralized Structure

The majority of RM research focuses on the airline industry, but airlines and hotels applied RM in distinctly different fashions. Airlines created a centralized RM system; hotels, a decentralized system (Vinod 2004). Airlines have a centralized system because an airline owns both the airline brand and the supply of seats. Therefore, a central department within an airline can determine how much supply (how many seats) is available and how to allocate that supply to potential customers. On the other hand, hotel chains typically do not own the supply of rooms. Hotel chains only own room supply if they own or manage a given hotel. Hotel chains do not own the room supply of franchised hotels, which is a large percentage of hotels. Thus, hotel headquarters have limited control over processes and procedures used in RM.

As industries outside of travel-related industries adopt RM systems, many will use decentralized decision-making. For example, many software firms allow individual salespeople to negotiate prices (Preslan and Newmark 2004). Additionally, retail stores, hospitals and restaurants allow local control of RM decisions. As these industries enter the RM arena, they share similarities to the hotel industry and thus can learn from the hotels by understanding the drivers of effective RM.

We argue decentralization brings with it an added dimension of complication in practice. The skills and knowledge to apply optimal decisions differs greatly between a centralized and decentralized system (Manzier 2004). In the centralized airline world, a small group of experts create, implement and control a highly automated RM system (Manzier 2004). In contrast to the airlines, hotels have a group of experts create and implement RM policy and infrastructure, but a large group of dispersed employees control operational RM decisions (Manzier 2004). Because of this decentralized system, hotels face more challenges in training people and garnering cooperation across departments – balancing the technical and social support sides of RM (Brotherton and Turner 2001). This structure provides an ideal environment for us to test our theory that both technical and social support capabilities contribute to RM success.

4.2.2 Experience

Decentralized structure alone will not allow us to test our theory. We need an industry with sufficient experience to have developed best practices and experienced some successes. The hotel industry has used RM for more than 15 years. Because of early RM adoption, hotel employees have gained valuable experience, which makes the hotel industry ideal for testing the drivers of RM performance.

4.2.3 Sample Size

Another advantage of performing our study on the hotel industry is that because of its decentralized structure, we can measure RM performance on a hotel-by-hotel basis. The ability to use an individual hotel as a unit of analysis provides us a large sample size and contrasts greatly to the airline industry where only a small number of airlines compete in each market.

4.2.4 Performance Measures

Not only do hotels measure RM performance on a hotel specific basis, but hotels measure RM performance using a standardized, objective performance measurement. Even though perceptual performance measurements could be used (and we do measure these as well), an objective performance measurement eliminates respondent bias. More specifically, we use a hotel's ranking within its competitive set to determine its RM performance. We explain this further.

Hotels measure their RM performance through RevPAR (Revenue Per Available Room). Hotels also define a competitive set (comp set) of hotels to their own – these are similar service level hotels within the same geographic area. An independent third party firm named Smith Travel Research (STR) aggregates this information and reports performance measurements, compared to the hotel's competitive set, back to the hotels. STR calculates a RevPAR index = $RevPAR_i$ / $RevPAR_{\text{(comp set)}}$ (100), where i = the hotel in question. A firm with a RevPAR index over (under) 100 generated more (less) than their fare share of revenue. The RevPAR metric controls for hotel service levels and outside economic factors, so we do not further control for these effects. STR ordinally ranks all hotels within their competitive set so that the hotel with the highest RevPAR index is ranked first, the second highest is ranked second, and so forth. Because the number of hotels within a competitive set varies, we normalized rankings so performance ranges between 0 and 1.

Let n = number of hotels in the competitive set and r = the hotel ranking within the competitive set. Our objective performance metric = $1 - (r\text{-}1)(1/n)$. Table 1 presents an example of calculated normalized RevPAR metrics for hotels in a competitive set with 5 hotels.

Table 1 - Example Normalized RevPAR Calculation, *n*=5

r	**Normalized RevPAR metric**
1	1.0
2	0.80
3	0.60
4	0.40
5	0.20

In addition to collecting the above described objective performance measure, we collected perceptual performance data. We include the scales for perceptual performance measurement in section 4.4.3.

4.3 Data Description

We collected data from U.S. hotels within 3 different parent hotel companies which use RM. Three different service levels of hotel are included in the survey: luxury, upper mid-scale and mid-scale. Data was collected via a web-based survey. An executive within the parent hotel company contacted potential respondents via email. The email explained the survey purpose and importance and requested the on-site revenue manager participate through a web link to the online survey. Participation was voluntary. The executives sent 2132 email requests. 216 surveys were returned, for a response rate of 10.1%. See Table 2 for a specific distribution of our sample population. Out of the 216 returned surveys, 166 were complete, including objective performance data.

Table 2 - Survey Distribution

	Owned Hotels	**Managed Hotels**	**Franchised Hotels**	**Total**
Parent Company X	26	42	39	107
Parent Company Y	20	32	53	105
Parent Company Z	4	0	0	4
Total	50	74	92	216

4.4 Test for Non-response Bias

We test for non-response bias to minimize systematic error. We provide evidence for non-response bias by comparing the demographics of respondents to the survey population.

First, we compare the respondents versus the population by hotel service level, as demonstrated in Table 3. We see that in each of the three parent companies, the service level with the largest number of hotels had the highest percentage of responses. Using a χ^2 test, the response rate distribution is different from the population distribution ($p<0.01$).

In addition to service level, we examined response rate by management structure. Parent company executives have more influence at owned and managed hotels than they do at franchised hotels. Because of this, RM (and other programs) tend to be implemented more quickly and thoroughly at owned and managed hotels than at franchised hotels. Incidentally, employees at owned and managed hotels tend to respond to headquarters employees more readily than those at franchised hotels. This could be a key reason for the lower response rate at franchised hotels, as headquarters employees sent out the request for participation. Table 4 details the response rates for owned, managed, and franchised hotels versus the population of each parent company. Parent company X shows very low franchised response rates and higher managed response rates than those found in the population. Parent company Y shows consistent response rates with those of the population, and parent company Z has only one structure, and so sample and population demographics are the same. Similarly to the service level distribution statistics, using a χ^2 test, the management structure statistics show a difference in response rate distribution versus population distribution ($p<0.01$).

Our test shows response bias by hotel service level (luxury, upscale, midscale) and by management structure (Owned, managed, franchised). We had a higher percentage of higher service level hotels, and a higher percentage of owned and managed hotels respond than the existing population percentage. Even though our responses are not the same as the population, we received responses from those who care the most about RM. Because higher service level hotels charge higher prices and have a larger range of prices, allocating capacity optimally is more important for higher service level hotels than in lower service level hotels. In short, RM impacts profits more in higher service level hotels than in lower service level hotels. Additionally, hotel headquarters has more influence over owned and managed hotels than franchised hotels. Accordingly, owned and managed hotels typically adopt RM more quickly and thoroughly than franchised hotels. We believe we have an adequate sample to test RM performance drivers, even if it does not correspond exactly to the population characteristics.

Table 3 - Comparison of Respondent Demographics by Hotel Service Level

	n	**Sample percentage**	**Population percentage**
Parent Company X			
Luxury brand hotel	6	5%	1%
Upscale brand hotel	99	93%	60%
Midscale brand hotel	2	2%	39%
Parent Company Y			
Luxury brand hotel	12	11%	4%
Upscale brand hotel	20	19%	13%
Midscale brand hotel	73	70%	83%
Parent Company Z			
Upscale brand hotel	4	100%	100%

Table 4 - Comparison of Respondent Demographics by Management Structure

	n	**Sample percentage**	**Population percentage**
Parent Company X			
Owned	26	24%	11%
Managed	42	39%	12%
Franchised	39	37%	77%
Parent Company Y			
Owned	20	19%	26%
Managed	32	31%	18%
Franchised	53	50%	56%
Parent Company Z			
Owned	4	100%	100%

4.5 Scale Development

A rigorous construct validation process provides assurance that a researcher accurately and consistently measures the intangible concept of a construct that she intends to measure (Churchill 1979, O'Leary- Kelly and Vokurka 1998, Maholtra and Grover 1998) to test her conceptual hypotheses. The construct measurement is never error-free, but a rigorous process aims to reduce measurement error to an acceptable level (Churchill 1979, O'Leary- Kelly and Vokurka 1998, Maholtra and Grover 1998).

Established scales did not exist due to the scarcity of empirical research in this area. Therefore, we developed scales according to accepted best practices (Churchill 1979, Moore and Benbasat 1991, Ahire et al. 1996, O'Leary-Kelly and Vokurka 1998, Maholtra and Grover 1998) to test our hypotheses.

Construct validation is a multi-step process. We borrow from O'Leary-Kelly and Vokurka (1998), who expanded on earlier work from Churchill (1979). According to O'Leary-Kelly and Vokurka (1998), there are three steps to construct validation: content validity, construct validity, and nomological validity. Figure 2 illustrates the three steps.

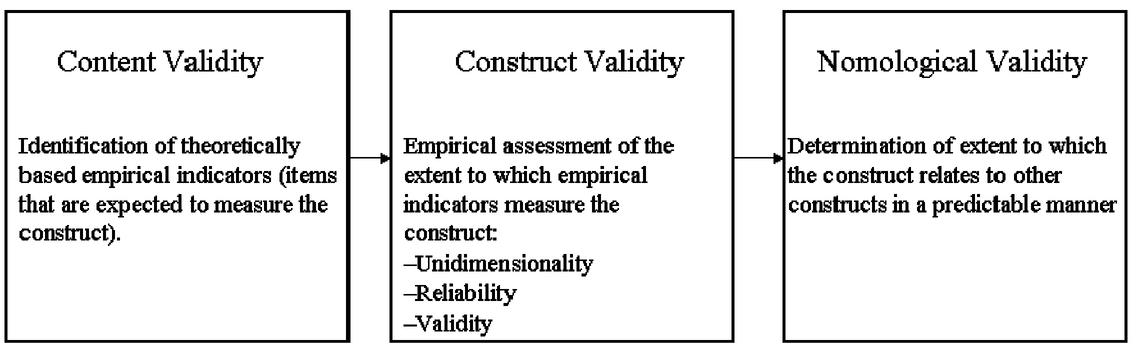

Figure 2 - Construct Validation Process, from O'Leary-Kelly and Vokurka (1998)

Collecting items which theoretically and logically measure the latent construct is the first step of construct validation, called content validity (Nunnally 1978, Churchill 1979, O'Leary-Kelly and Vokurka 1998, Maholtra and Grover 1998). The second step of the construct validation process is assuring construct validity. This step measures "the degree to which the empirical indicators measure the construct" (O'Leary-Kelly and Vokurka 1998: pg 389). The assessment of unidimensionality, reliability and validity are included within the construct validity step. The third attribute of construct validity is the degree to which changes in variable measurements are due to actual variable changes as opposed to outside influences. Scholars call this phenomenon validity and it includes both convergent and discriminant validity (O'Leary-Kelly and Vokurka 1998, Maholtra and Grover 1998). The final step, nomological validity, represents how constructs relate to other constructs and is the hypothesis testing step. The content validity step will be discussed in sections 4.5.1 and 4.5.2. Construct validity will be discussed in section 4.5.3 4.5.7. We present nomological validity (hypothesis testing) in chapter 5.

To develop scales according to best practices, we adhered to the following steps. First, we collected possible measurement items by borrowing scale items from other research efforts where applicable, and creating new items where necessary. After gathering scale items, we further refined these items through expert judging. After receiving our surveys back, we tested the scales for validity and reliability. Because empirical research in this field is in its early stages, the validity and reliability tests highlighted the need for more scale development work. We re-evaluated our construct definitions and redefined our constructs based on empirical findings. Next, we detail these steps.

4.5.1 Operationalization of RM Technical Capability

Content validity confirms that the measurement items of a construct adequately cover the definition of a construct (Churchill 1979, Ahire and Devaraj 2001). Content validity cannot be measured with a single number, but instead we ensure content validity through a thorough literature search and expert judges. We conducted a thorough literature search in order to gather our initial measurement items, and then had expert judges confirm our choices through three rounds of q-sorting.

While gathering initial measurement items, we borrowed established scales and refined them to fit the RM context wherever possible. Where there were no established items, we created new ones. We list each technical construct definition and the initial items included for each construct before scale testing. Key measurement items have been marked with an asterisk (*). Items not marked with an asterisk provide extra detail and clarification to the measure, but are not key items.

4.5.1.1 Market Segmentation

Consistent with other RM researchers, we defined market segmentation as "the process of classifying customers into group based on observed – or inferred – characteristics, behaviors, and preferences" (Talluri and van Ryzin 2004: pg 579). These items were created based on literature in market segmentation and hotel industry expert opinion.

MS1. We group customers into strategic clusters.
MS2. We categorize customers based on similar buying characteristics. *
MS3. We have distinguishable groups of customers who can be separated through identifiable characteristics.
MS4. We promote our hotel differently to different groups of customers.
MS5. We regularly review if we have appropriate, well-defined market segments.

4.5.1.2 Pricing

In line with the marketing literature, we define pricing as the process of deciding rates to try to extract the optimal revenue from the firm's customers (Dutta et al. 2003, Vorhies and Morgan 2005). We adapted the general pricing measurement items found in Smith (1995), Ross (1984), Monroe and Cox (2001), Vorhies and Morgan (2005) and Dutta, et al. (2003) to this research. We list the resulting relevant items below.

P1. Long term customer satisfaction is balanced with short term revenue when setting room rates

P2. My firm has an effective policy for setting room rates. *
P3. We set room rates according to the value customers place on a room. *
P4. Competitors' reactions are considered when deciding room rates
P5. Customers' price elasticity information is considered when setting room rates
P6. Once I change rates, I can easily update these changes to all sources (websites, 3rd party distributors, etc.)
P7. My firm has a consistent policy for setting room rates.

4.5.1.3 Forecasting

Forecasting is the task of predicting future demand. We propose the following as proxy measures of forecasting. There has been minimal survey research in this area of RM, and therefore we could not find existing items to measure forecasting. Therefore, based on the definition and conversations with practitioners, we created the items listed below.

F1. Compared to our competitors, our forcasts are very accurate. *
F2. The revenue manager manually adjusts forecasts often.
F3. We ignore RM system forecasts and instead use forecasts from other sources to drive business decisions
F4. We use accurate and timely data for forecasting customer demand.
F5. Our hotel tracks denials and regrets accurately.
F6. We use the RM system forecasts to drive business decisions.

4.5.1.4 Capacity Allocation

Capacity Allocation – "the decision of whether to accept or reject an offer to buy; how to allocate capacity to different segments or channels; when to withhold a product from the market and sell at later points in time" (Talluri and van Ryzin 2004). There has been minimal survey research in this area of RM, and therefore we could not find existing items to measure capacity allocation. Therefore, based on the definition and conversations with practitioners, we created the items listed below.

CA1. The RM system allocates rooms well to our market segments. *
CA2. We have tools to make profitable, analytic based booking decisions for groups.

CA3. We overbook customers judiciously and understand that walking customers occasionally is part of smart RM.
CA4. Our hotel consistently sells out on a given night of the week.
CA5. When analyzing the value of a given customer, we include customers' auxiliary spend (food and beverage, spa, etc.) in addition to room rate.
CA6. On any given evening, we have a few rooms available for high value customers.

4.5.1.5 Information Technology (IT)

IT – the hardware, software, and people and processes necessary to configure and maintain information systems in support of the business (adapted from Stratman and Roth 2002). We adapted constructs found in King and Thompson (1996) and Stratman and Roth (2002) to this research since both measure the quality level of IT in order to support a specific process or program similarly to our research agenda. We list the resulting relevant constructs below.

IT1. The IT support for the RM system meets our needs.
IT2. Our reservations and RM systems are integrated.
IT3. We create work-arounds for our computer system in order to complete routine RM tasks.
IT4. The RM IT system meets business needs. *
IT5. Our reservations and RM systems are integrated in real time.

4.5.2 Operationalization – RM Social Support Capability

In order to establish content validity for RM social support capability we started the social support scale development by gathering scale items appropriate to the five original proposed skills within RM social support capability: executive commitment, aligned incentives, organizational structure, education and learning. These were the initial scales proposed. Factor analysis revealed inconsistent grouping of survey items. Later in the research process, we revised the constructs to reflect the results of our factor analysis. Here we present the initial five skills and corresponding scale measurement items.

4.5.2.1 Learning Organization

Learning organization – an organization skilled at creating, acquiring, and transferring knowledge, and at modifying its behavior to reflect new knowledge and insights (Garvin 1993). Accordingly, we find the basis for items in Garvin (1993) and additionally in Jones and Hamilton (1992) and Stratman and Roth (2002).

- L1. A revenue manager gives feedback to others explaining how their actions affected RM performance.
- L2. Benchmarking is used to identify cutting edge RM techniques.
- L3. Internal groups meet regularly to share new methods of using the RM system. *
- L4. RM improvement suggestions are regularly collected from multiple employee levels.
- L5. RM experimentation is encouraged even if the proposed improvement is unsuccessful.
- L6. We keep track of RM developments related to our industry.

4.5.2.2 Education and Training

Education and Training **-** The process of preparing employees to use RM by educating employees what RM is and training them to use available tools to implement RM. Stratman and Roth (2002) define education and training as an important element of ERP education and provide a rigorous scale. We borrow items from their scale. Additionally, the hotel literature (Farrell and Whelan-Ryan 1998, Skugge 2003) provides education needs specific to RM, and so we create items based on their work.

- T1. All personnel who contribute to RM (possibly front desk clerks, sales people, etc) understand their role in the RM process.
- T2. Training materials target the entire business task, not just the RM screens and reports.
- T3. A useful formal training program has been developed to meet the requirements of RM system users.
- T4. Employees are tracked to ensure that they have received the appropriate RM training.
- T5. RM training and education meets business needs. *

4.5.2.3 Organizational Structure

Appropriate Organizational Structure **-** "allocation of tasks and responsibilities to individuals and groups within the organization, and the design of systems to ensure effective communication and integration of effort" (Daft and Lengel 1986). Industry experts opined that appropriate organizational structure is essential for successful RM. Therefore, we created items based on their opinions

OS1. The organizational hierarchy within the hotel helps RM. *
OS2. The revenue manager reports to someone who values RM.
OS3. In the hotel hierarchy, the revenue manager (or director of RM) is on the same, or higher level as the sales director.
OS4. RM would work better with a different organizational structure.

4.5.2.4 Aligned Incentives

Aligned Incentives **–** The extent to which a firm gives motivation to individuals to choose the best action for the firm. Preslan and Newmark (2004) and interviewees led us to our measurement scale for aligned incentives.

AI1. Rewards and goals for the sales team conflict with the rewards and goals of the revenue manager.
AI2. Revenue Manger's performance or bonus is directly tied to Smith Travel Research (STR) RevPAR numbers (or other RM metric).
AI3. General manager has his/her bonus partially tied to Smith Travel Research (STR) RevPAR numbers (or other RM metric).
AI4. My hotel's goals are similar to the parent company's goals.
AI5. Hotels employees in different functional areas work towards the same hotel profitability goals.
AI6. Rewards and goals for the sales team align with the rewards and goals of the revenue manager.

4.5.2.5 Executive Commitment

Executive Commitment – "top management's willingness to champion RM within the organization and allocate the resources required for successful [RM]." (adapted from

Stratman and Roth 2002) We chose select items from Stratman and Roth's (2002) work for our measurement because of the similarity of information wanted from both studies.

EC1. Managers assign resources to RM as needed.
EC2. Employees who are assigned to RM are distracted by other commitments.
EC3. The quality of RM has been compromised by short-term cost considerations.
EC4. The need for long-term RM support resources is recognized by management.
EC5. Executive management is enthusiastic about the possibilities of RM. *

4.5.3 Operationalization of RM Performance (Perceptual)

We used perceptual performance measurement items from Stratman and Roth (2002).

Perf1. I believe our firm has achieved a healthy return on our RM investments.
Perf2. My firm's RM actions are extremely effective in increasing both revenue and profitability.
Perf3. We have specific and well-defined metric(s) to measure RM performance.

4.5.4 Q-sort

Following the procedure of Moore and Benbasat (1991), we refined the items presented in the previous section through a q-sort procedure. We first created an initial listing of all items in random order. We asked three professors to put each of the items into one of our 10 constructs (aligned incentives, executive commitment, education and training, learning, organizational structure, market segmentation, pricing, forecasting, capacity allocation and IT use) based on the definition provided for each construct. In addition, we asked the professors to note any unclear questions or missing questions based on our definitions. Once we received feedback from all three professors, we either rewrote questions based on suggestions or stated confusion, or dropped questions which did not consistently fit into a given category. We followed this process for 2 more rounds of q-sorting, using a group of 4 practitioners, and then another group of 3 practitioners.

Q-sorting and the resulting measurement statistics do not guarantee reliable measurement scales. Instead, they are diagnostic tools to indicate generally reliable measurement scales. We used these tools before pilot testing to provide confidence in the scales.

4.5.5 Pre-test scale testing

Using the results from the last round of q-sorting, we measured pretest scale reliability using Perreault and Leigh's measure (Perreault and Leigh 1989) and item placement ratios (Moore and Benbasat 1991). Perreault and Leigh's statistic indicates degree of item measurement convergence. This statistic measures how well judges agree in sorting items into their constructs over and above the agreement expected by chance and improves upon the conservative Kappa measure (Perreault and Leigh 1989). Zero and one bound possible values for this statistic, with a value of zero indicating the level of agreement due to chance and a value of one indicating perfect agreement between judges.

Table 5 shows the Perrault and Leigh values for each pair of judges. A value of 0.65 or greater indicates good inter-rater reliability (Moore and Benbasat, 1991). All of our judge pairs received measurements exceeding 0.65, with an average value of 0.76. This indicates good scale reliability.

Table 5 - Perreault and Leigh Values from Q-sorting

Judge Pair	**Perreault and Leigh value**
1-2	0.80
2-3	0.75
3-1	0.74
Average	**0.76**

As an additional test for our measurement items, we examined item placement ratios as used in Moore and Benbasat (1991). We list item placement ratios in Table 6.

We listed each culture and capability factor as a row and column header, with the row header indicating where an item was meant to be placed and the column header indicating where the judges actually placed items. For example, there are 4 items to measure aligned incentives and 3 judges, and therefore 3 x 4 = 12 possible aligned incentives items. The judges placed 10 of the 12 items into the aligned incentives category and 2 of the 12 into the executive commitment category for 83% correct placement of items. An item placement ratio of 70% or greater is acceptable (Moore and Benbasat 1991). Six of the ten constructs meet the criteria. Because the capacity allocation ratio (67%) is so close to cutoff, we accept this measurement. Organizational structure, pricing, and learning did not meet the criteria, so we added items (OS4, P7, L6) in order to increase the validity of these constructs.

Table 6 - Item Placement Ratios after Q-sorting

		Actual Classification												
		Aligned incentives	Capacity Allocation	Executive Commitment	Forecasting	Information Technology	Learning	Market Segmentation	Organizational Structure	Pricing	Education and Training	NA	Total	Item Placement Ratio
Intended Scales (No. of items in scale)	Aligned incentives (4)	10		2									12	83%
	Capacity Allocation (5)		10			2		2		1			15	67%
	Executive Commitment			10					2				12	83%
	Forecasting (5)				12	2	1						15	80%
	Information Technology (5)			1		13			1				15	87%
	Learning (5)			2		1	6		3		2	1	15	40%
	Market Segmentation							15					15	100%
	Organizational Structure (3)	2		1			1		5				9	56%
	Pricing (7)	1	1		1	2	1	1		13		1	21	62%
	Education and Training (3)								2		7		9	78%
	Total Item Placements: 138		Total Hits: 101		Overall Hit Ratio: 73%									

4.5.6 Pilot Test

Following the best practices recommended by Churchill (1979) and Maholtra and Grover (1998) and implemented by Moore and Benbasat (1991) and Ahire et al. (1996), we collected pilot data to further purify measures. We sent out a request for participation to 120 hotels; we received 40 responses. We analyzed the responses for reliability, but did not have a large enough sample size to test for unidimensionality and discriminant validity.

The pilot test indicates reliable scales for six of the ten scales (alpha > 0.70, Nunnally 1978). For two of the scales which did not make the 0.70 cutoff (aligned incentives and pricing), the reliabilities were close to 0.70 and it was assumed that with a larger sample size, reliability would exceed 0.70. In order to aid scale strength for forecasting, aligned incentives and capacity allocation, we added three items (AI6, CA6, and F6) which were positively worded in case they would be answered more consistently than their negatively worded counterparts (AI1, CA3, and F1). Table 7 lists the reliabilities for each construct scale at the pilot test stage. Next, we sent out requests for a full-scale survey and analyzed the results for validity and reliability.

Table 7 - Scale Reliabilities after Pilot Test

Construct	***n***	**Number of measurement items**	**α**
Market Segmentation	40	5	0.85
Pricing	40	7	0.65
Forecasting	40	5	0.41
Capacity Allocation	40	5	0.23
IT	40	5	0.71
Executive Commitment	40	5	0.71
Aligned Incentives	40	5	0.62
Organizational Structure	40	4	0.72
Education and Training	40	5	0.76
Learning	40	6	0.81

4.5.7 Construct validity

As described earlier, construct validity includes unidimensionality, reliability and convergent and discriminant validity. This section describes how we measured each of these dimensions of our measurement scales.

Unidimensionality refers to "a single trait or construct underlying a set of measures" (Gerbing and Anderson 1988: pg 186) and is essential for valid scales (Gerbing and Anderson 1988, O'Leary-Kelly and Vokurka 1998, Ahire et al. 1996, Ahire and Deveraj 2001). O'Leary-Kelly and Vokurka (1998) recognize Confirmatory Factor Analysis (CFA) as the preferred method to test for unidimensionality. We created two measurement models: one for technical RM capability and one for social support capability. We created two models because our sample size was not large enough to test the entire model simultaneously. The literature (Bollen 1989, Hatcher 1994) considers a model to have good fit if indices are greater than or equal to 0.90. Using CFA, the RM technical capability model yielded fit indices of GFI = .90, NNFI = 0.87, and CFI= 0.90, indicating that the market segmentation, pricing, forecasting, capacity allocation, and IT scales all exhibit unidimensionality. We list measurement item factor loadings for these constructs in Table 8.

Table 8 - Standardized CFA Path Loadings for RM Technical Constructs

Item	Market Segmentation	Pricing	Forecasting	Capacity Allocation	IT
MS2	0.64				
MS3	0.66				
MS5	0.61				
P2		0.29			
P3		0.41			
P4		0.39			
P6		0.64			
P7		0.45			
FOR1			0.23		
FOR2			0.27		
FOR3			0.57		
FOR4			0.58		
FOR6			0.42		
CA1				1.0	
IT1					0.77
IT2					0.45
IT3					0.57
IT4					0.22

The RM social support capability model for CFA yielded unfavorable fit indices, with items of given constructs more closely relating to other constructs. Although CFA is the generally the preferred method to test for unidimensionality in confirmatory research, some researchers argue that exploratory factor analysis (EFA) is more appropriate for exploratory research (O'Leary-Kelly and Vokurka 1998). Because this was exploratory research and our initial CFA for the RM social support constructs yielded unfavorable fit indices, we performed an EFA to determine which items relate to a single construct for items within social support RM capability. We applied the maximum likelihood estimation procedure with varimax rotation for EFA analysis.

EFA analysis must be interpreted not only by numerical results, but also by content validity – whether or not it makes sense that certain items should load on a common factor. Upon examination of the factor analysis results (shown in Table 9), in conjunction with the factor definitions, we classified RM social support measurement items into four constructs. We combined the education and training construct and learning construct into the "Education and Learning" construct. Additionally, we expanded the executive commitment construct to a broader scope now titled "Organizational Focus" which includes both executive commitment items plus other items which target cross-communications and other items indicating how much the organization focuses on RM. We adjusted the definitions of the constructs to what is presented in Chapter 3 in order to account for the expanded scope of each construct. Organizational Structure and Aligned Incentives kept their names, but gained items. Viewing the construct definitions, these changes remain acceptable from a content validity viewpoint. Figures 3 and 4 illustrate how the factors changed due to a combination of factor analysis and reliability analysis.

Table 9 - EFA Factor Loadings for RM Social Support Constructs

Item	Organizational Focus	Aligned Incentives	Organizational Structure	Education and Learning
AI1	0.30			

AI5	0.29			
EC3	0.33			
EC4	0.37			
EC5	0.47			
L3	0.45			
L4	0.74			
T5	0.30			
AI2		0.84		
AI3		0.88		
L2		0.44		
OS1			0.44	
OS2			0.69	
OS3			0.36	
OS4			0.52	
EC1			0.31	
L1				0.41
L5				0.29
T1				0.74
T2				0.69
T3				0.45

Reliability is the second component of construct validity. Reliability is the degree to which items within a given construct vary together and shows the consistency of that given construct. Nunnally (1978) concludes that scales should have an alpha level of 0.70 or higher to be considered reliable. However, Hair et al. (1998: pg 118) state that exploratory, early research scales with $\alpha > 0.60$ are satisfactory. Researchers can drop measurement items (assuming content validity remains) in order to increase reliability levels. Higher levels of α correspond to less random measurement error (Churchill 1979). Market segmentation, organizational focus, education & training, aligned incentives, and perceptual performance met the 0.70 criteria. Forecasting, IT and organizational structure met the 0.60 cutoff, so we also used these scales. We use the pricing scale with $\alpha = 0.55$, even though reliability is slightly below the 0.60 cutoff point. The original measurement items for capacity allocation exhibited a low alpha, so we used a single item measurement instead of a scale. Composite reliability is another method used to test reliability (Hatcher 1994). However, composite reliability can only be used with CFA. Since we used EFA, we only test for reliability using Chronbach's alpha. We dropped 14 items across the instrument to increase reliability. Figures 3 and 4 and Appendix B each indicate dropped measurement items. Table 10 shows reliability levels of our scales.

Table 10 - Scale Reliability Alphas

Construct Scale	**No. of measurement items**	***n***	**α**
Market Segmentation	3	214	0.73
Pricing	5	217	0.55
Forecasting	4	176	0.63
Capacity allocation	1	217	NA
IT	4	214	0.68
Organizational Focus	8	216	0.81
Education and Training	5	214	0.73
Aligned Incentives	3	216	0.77
Organizational Structure	4	214	0.65

Convergent validity assures researchers that if different methods of measuring a construct will result in the same conclusion. For example, if we conducted a survey by both mail and telephone and saw similar results, we have evidence of convergent validity. Similarly, we conducted q-sorts and electronic surveys and saw similar results and clustering of responses. This shows evidence of convergent reliability.

Discriminant validity means that the measurement items for one construct do not measure another construct (O'Leary-Kelly and Vokurka 1998, Ahire and Deveraj 2001). We use a chi-square difference test between each construct within a CFA model, as suggested in Hatcher (1994). The chi-square difference statistic for each of the constructs was significant at the 0.01 level, giving evidence that there is discriminant validity within our model (Hatcher 1994, Anderson and Gerbing 1991).

Common method variance can be detected using Harman's single factor test (Podsakoff et al. 2003). The single factor test requires that a researcher conducts an EFA with all items in a study. If the EFA shows a single factor, or the first factor explains a majority of variance, there is indication of common method variance. We could not include all items into one EFA because of the number of variables and our sample size. Instead, we conducted two separate EFA analyses: one with all technical items, and a one with all social support items. Both analyses revealed multiple underlying factors and no factors which accounted for a majority of variance. Therefore, we have confidence that common method variance is not substantial.

4.6 Future Suggestions

In accordance with the early stage of empirical research within the RM field, we conducted exploratory analysis using regression analysis. This paper will focus on exploratory analysis and insights and leave confirmatory work for future research.

The survey instrument was developed with a strong empathy for the respondent and as such survey length was kept to a minimum. Since there were originally 10 independent variables, plus questions for the dependent variable and demographic questions, each construct scale was limited to 4-7 items in an attempt to keep the questionnaire shorter than 60 questions. These shortened scales greatly hurt our validity and reliability. In addition, the individual items attempted to ask about different attributes of the construct with little overlap. Again, this hurt our validity and reliability.

The next researcher looking to strengthen the scales should aim for 8-10 items on each scale and aim for more overlapping questions.

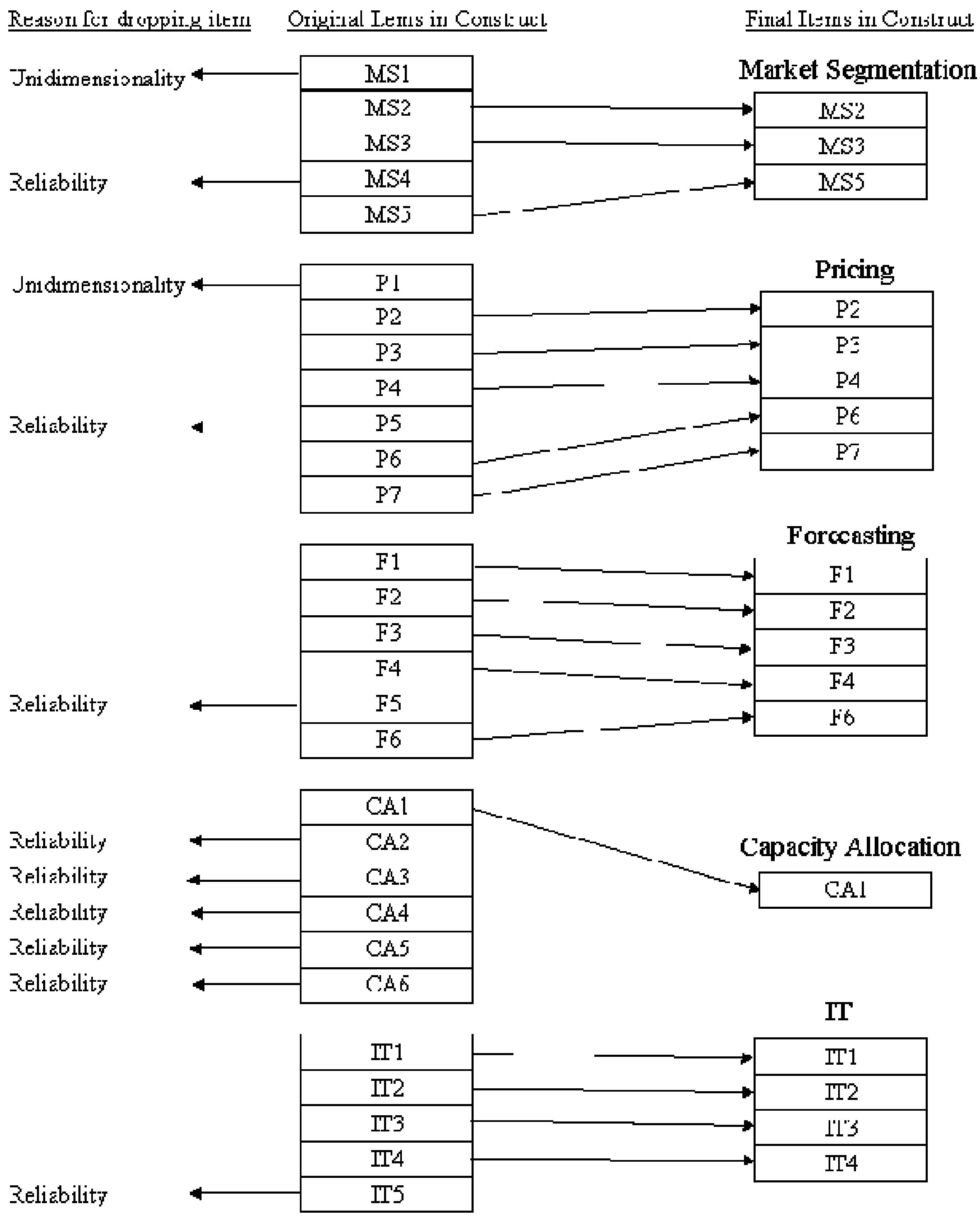

Figure 3 - Changes to RM Technical Capability Measurement Scales

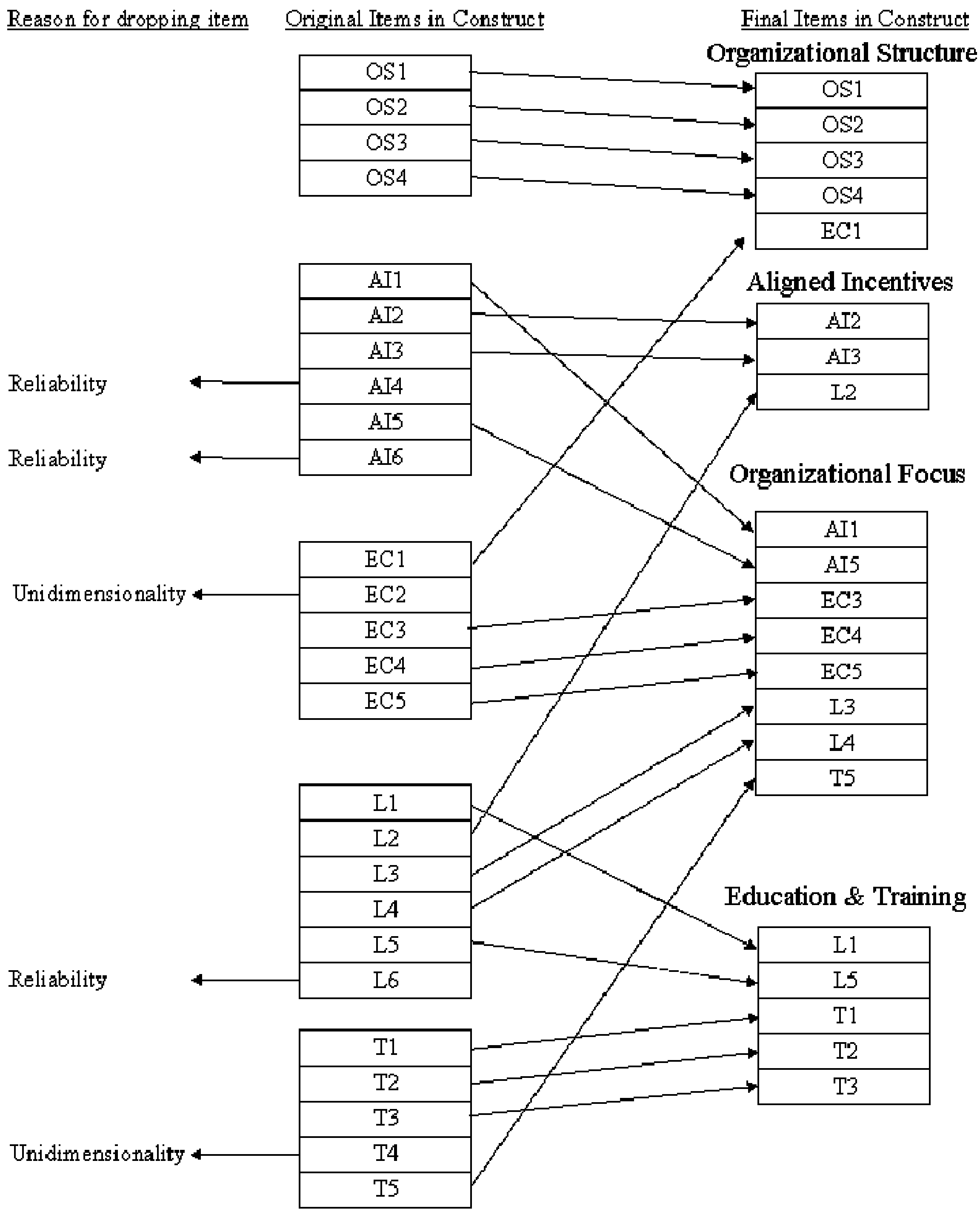

Figure 4 - Changes to RM Social Support Capability Measurement Scales

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Overview

This chapter presents three sets of results: ANOVA results comparing RM drivers between firms, multinomial logit model results using objective performance as a dependent variable, and linear regression model results using perceptual performance as a dependent variable. We describe each analysis and present results. Next, we discuss the significant results and compare and contrast findings across the analyses.

5.2 ANOVA Results

Before we analyzed our data, we examined the data for influential points. These points hinder analyses because they have a disproportionate influence on results which results in misleading conclusions. Consistent with Hair et al. (1998), we deleted points with studentized residuals greater than 3. This resulted in the removal of five data points. This reduced data set is used within all of the analyses presented in this chapter.

Using ANOVA, we assess the skill level of proposed drivers and RM performance between hotel firms X and Y. We test RM performance using both the objective RevPAR measure (described in section 4.2.4) and a perceptual performance measure. Firm Z could not be included in the analysis due to its low sample size (n=4). Firm X outperforms Firm Y in pricing ($p<0.01$), forecasting ($p<0.01$), capacity allocation ($p<0.05$), IT ($p<0.01$), aligned incentives ($p<0.01$), organizational structure ($p<0.05$), training and education ($p<0.01$), and both objective ($p<0.01$) and perceptual performance ($p<0.01$). There is no statistical difference between Firm X and Firm Y in market segmentation and organizational focus. Firm Y does not outperform Firm X on any dimensions. Table 11 lists the ANOVA test results. The objective and subjective performance results provide support that firm X has both higher RM skill levels and better performance than firm Y. Interviews further support this general conclusion, however, why does Firm X outperform Firm Y? We cannot conclude causation because we did not have a controlled experiment, but we can provide some evidence based on correlation with performance through regression analysis. In order to test how these drivers relate to RM performance, we used a multinomial logit model for our objective performance measure and a linear regression model for our perceptual performance measures. In addition, this analysis indicates that brand is an important control variable. Because of this, we will include brand as a control variable in our regression analysis.

Table 11 - ANOVA Test Results

Revenue Management Driver	**Firm X**		**Firm Y**		**F Statistic**
	n	***Mean (SD)***	***n***	***Mean (SD)***	
Market Segmentation	104	5.53 (.80)	103	5.30(.94)	3.56
Pricing	104	5.52 (.70)	103	5.14 (.77)	14.2*
Forecasting	104	5.40 (.69)	103	5.02 (.84)	12.4*
Capacity Allocation	104	5.62 (1.36)	103	5.19 (1.21)	5.6**
IT	104	5.86 (.75)	103	5.25 (1.03)	23.5*
Organizational Focus	104	5.51 (.83)	103	5.41 (.81)	.698
Aligned Incentives	104	6.29 (.99)	103	5.69 (1.27)	13.8*
Organizational Structure	104	4.99 (1.02)	103	4.68 (.93)	4.6**
Training and Education	104	5.67 (.73)	103	5.07 (.96)	25.1*
Objective Performance	93	0.75 (.23)	73	0.62 (.26)	11.2*
Perceptual Performance	102	6.23 (.77)	101	5.61 (1.00)	23.8*

*p<0.01, **p<0.05

5.3 Objective Performance Regression Results

We analyzed our hotel sample using regression to find relationships between RM drivers and performance, based on our objective RevPAR measure (explained in section

4.2.4). A multinomial logit regression model (MNLM) captured the relationship between RM drivers and our objective performance measurement, while a linear regression model captured the relationship between RM drivers and our perceptual performance measurement.

A linear regression model would be the most straightforward model to test the relationship between our proposed RM drivers and objective RM performance. However, a linear regression model is inappropriate for our objective performance data for two reasons. First, a linear regression model does not allow us to set bounds on the dependent variable. However, our objective performance metric is bounded by (0,1] and because we defined "1" as the best performance a hotel can achieve, an answer greater than 1 would not make sense. Therefore, a linear regression model can return nonsense answers. Second, the linear regression model requires the dependent variable to be a continuous variable. Our objective performance metric is not a continuous variable; a given hotel can only achieve one of a handful of discrete values. Because we violate these assumptions inherent to a linear regression model, we look to other models.

Even though we did not use the linear regression model, we did test for multicollinearity. The variation inflation factor (VIF) was less than 3 for every independent variable. Variables with VIF less than 10 are not considered a collinearity problem (Belsley, Kuh, Welsch 1980). Another indication of collinearity can be found by looking at condition indices and estimated proportion of variance from each principal component (Belsley et al. 1980). Principal components with high condition indices and strong contributions (> 0.5) to the variance of more than one variable can signal multi-collinearity. There was no evidence of multicollinearity based on this diagnostic.

An ordered logit or ordered probit analysis may seem to be an appropriate model to use with the objective performance metric. These models seem appropriate because they allow a bounded dependent variable and require a dependent variable with ordered value. Our dependent variable meets these criteria. However, an ordered logit or probit model assumes parallel slopes for the probabilities of each possible outcome (Long 1997: pg 140- 141). A Score test showed that our data violates this assumption (p<0.01), indicating that variables do not have parallel slopes on the probabilities of each outcome. Long (1997: pg 148) suggests a multinomial logit model (MNLM) when data violates the parallel regression assumption. Thus, we evaluated our data using the MNLM.

The MNLM models the probability of a discrete outcome given specific predictors, or independent variables. We define terms as follows: J = number of possible outcomes, m = a specific outcome, x_i = the vector of explanatory variables, β = slope coefficient for each predictor. The MNLM models probability using $\Pr(y_i = m \mid x_i) = \dfrac{\exp(x_i \beta_m)}{\sum_{j=1}^{J} \exp(x_i \beta_j)}$ where $\beta_1 = 0$.

However, interpretation from this formula is difficult and confusing. More understandable interpretation comes from formula manipulation leading to calculation of the odds of one outcome occurring over another outcome occurring. Because the MNLM requires a control outcome, we first compare outcomes 2,3, …, J to 1. Next, we compare outcomes 3, 4,…, J to 2, and so on until we have compared all pairs of outcomes. The MNLM is based on the assumption that the left hand side is a function of the linear combination $x\beta_m$. The vector β_m characterizes the effect of the independent variables on outcome m. (Long 1997: pg 152).

We can not use the normalized RevPAR ranking without modification in the MNLM. Instead, we must convert the rankings into discrete categories. We classified normalized RevPAR rankings into one of five discrete categories. The normalized RevPAR ranking values range from (0,1] with 1 being possible only if a hotel is ranked first in its competitive set. Other discrete values of a normalized ranking were much less likely since there was a range of number of hotels in a competitive set. Therefore, we created other groups with ranges of values. We divided the range into quintiles: (0-0.19), (0.20-0.39), (0.40-0.59), (0.60-0.79), and (0.80-0.99). Because the (0 – 0.19) group was very small (n=4), statistical tests would not be effective. Therefore, we tested if we could combine the (0-0.19) group and the (0.20-0.39) group. Long (1997: pg 162-163) suggests a Wald test to determine whether or not to combine groups. A Wald test shows that there is no difference in model parameters between the groups (p=0.18), and therefore we combined the groups. We list the categories and sample sizes in Table 12. It may seem odd that group A is the only category with a single value. This is a special case, because these hotels have proven to be the best in their competitive set and should be set apart. Additionally, every hotel has the opportunity to achieve a normalized RevPAR ranking of “1”. Only hotels in a competitive set with 5, 10, or 15 hotels have the opportunity to achieve a normalized ranking of “0.80”. Hotels with other numbers of hotels in their competitive set can be close to 0.80, but they can’t achieve that exact number due to the normalized calculation. Therefore, the value of 1.0 is the only one appropriate to have a single category for a single value.

The MNLM simultaneously estimates comparisons between each of the groups, and predicts outcome based on independent variables. Before comparing effects between pairs of groups, we first had to establish the effect of a given independent variable is different from 0. We used a Wald test (Long 1997: pg 161), which has a chi-square distribution, to establish the significant independent variables.

Table 12 - Distribution of Hotel Performance into Categories

Hotel Group	Normalized RevPAR ranking	*n*
A	1.0	41
B	0.80-0.99	32
C	0.60-0.79	33
D	0.40-0.59	35
E	0.00-0.39	25

The Wald test shows evidence that organizational focus (p=0.04), forecasting (p=0.04) and organizational structure (p=0.02) and brand (p<0.01) are significant independent variables. We defined organizational focus earlier as a cross-functional effort to improve RM from all levels, including executive management. Where the organizational focus construct evaluates efforts to encourage and improve RM, the organizational structure construct looks at hierarchical structure and allocation of responsibility. Brand is a binomial variable, distinguishing between parent company X and parent company Y. Our ANOVA results previously had shown a significant difference in both skills and performance between hotels of the two parent companies. We control for brand to account for this difference. We have no evidence that market segmentation, pricing, capacity allocation, IT, training, and aligned incentives affect hotel performance at the $p < 0.05$ level. In other words, we have no evidence supporting hypotheses 1, 2, 4, 5, 7, and 9. We do have evidence supporting hypotheses 3, 6, and 8. These hypotheses examine the impact of organizational focus, forecasting, and organizational structure on RM performance. We will further investigate the details of these supported hypotheses.

In order to understand the three significant predictors, we evaluated pair-wise combinations of the 5 performance based categories (10 comparisons): A vs. B, C, D, and E; B vs. C, D, and E; C vs. D and E; D vs. E. We list the model results for these comparisons in Tables 13, 14, and 15. All independent variables, except for brand, use their average score (based on Likert questions with a range of 1-7) as the level for that independent variable. We used a dummy variable for brand to indicate if the hotel is from parent company X (Brand =1) or parent company Y (Brand =0).

Table 13 - MNLM Results with Group A as Control

Pair-wise comparison	**Logit Model 1 *n* =166 Group E / Group A**	**Logit Model 2 *n* =166 Group D / Group A**	**Logit Model 3 *n* =166 Group C / Group A**	**Logit Model 4 *n* =166 Group B / Group A**
Intercept	-5.15	3.37	-1.41	2.88
Brand	-1.30*	0.26	-0.23	0.16
Market Segmentation	0.53	0.30	0.44	0.87
Pricing	0.67	-0.10	-0.16	-0.09
Forecasting	-0.85	-1.36*	-0.91**	-0.9**
Capacity Allocation	-0.07	-0.13	0.38	-0.03
IT	0.11	0.23	0.25	0.10
Organizational focus	-1.56*	0.03	-0.67	-0.40
Aligned Incentives	0.37	-0.23	0.04	-0.21
Organizational structure	0.87**	0.76**	0.89*	0.32
Education & Training	0.80	-0.09	0.03	-0.21

*p<0.01, **p<0.05

Table 14 - MNLM Results with Group B as Control

Pair-wise comparison	Logit Model 5 *n* =166 Group E / Group B	Logit Model 6 *n* =166 Group D / Group B	Logit Model 7 *n* =166 Group C / Group B
Intercept	-8.03	0.48	-4.29
Brand	-1.47*	-0.43	-0.39
Market Segmentation	-0.33	-0.57	-0.43
Pricing	0.75	-0.02	-0.07
Forecasting	0.05	-0.47	-0.007
Capacity Allocation	-0.04	-0.09	0.41
IT	0.01	0.13	0.15
Organizational focus	-1.16**	0.42	-0.27
Aligned Incentives	0.58	-0.02	0.24
Organizational structure	0.55	0.44	0.57
Education & Training	1.01	0.11	0.24

*$p<0.01$, **$p<0.05$

Table 15 - MNLM Results with Groups C and D as Control

Pair-wise comparison	Logit Model 8 *n* =166 Group E / Group C	Logit Model 9 *n* =166 Group D / Group C	Logit Model 10 *n* =166 Group E / Group D
Intercept	-3.74	4.77	-8.82
Brand	-1.07*	-0.04	-1.04*
Market Segmentation	0.09	-0.14	0.24
Pricing	0.83	0.06	0.77
Forecasting	0.06	-0.46	0.52
Capacity Allocation	-0.45	-0.51	0.05
IT	-0.14	-0.01	-0.12
Organizational focus	-0.89	0.7	-1.59*
Aligned Incentives	0.33	-0.27	0.61
Organizational structure	-0.01	-0.12	0.11
Education & Training	0.77	-0.12	0.9

*$p<0.01$, **$p<0.05$

Logit models can have non-intuitive interpretations upon first examination. To demonstrate how to interpret the results in Table 15 - Table 17, we present an interpretation for Logit Model 1. The probability of a hotel being in performance group E (versus performance group A) increases as a function of Brand, Organizational Structure score, and Organizational Focus score. Other proposed drivers do not significantly change the probability of a firm performing better or worse. More specifically, hotels with Brand Y name, lower organizational focus, and higher organizational structure scores are more likely to be in the group E performance rating than the group A performance rating.

Examining results from the ten logit models simultaneously, we discuss the significant variables. First, we investigated pairwise contrasts within organizational focus. We found three significant comparisons within this group: A vs. E, B vs. E, and D vs. E. The results show higher levels of organizational focus differentiate groups A, B, and D from group E. Specifically, holding all other independent variables equal at their average values, a one unit increase in organizational focus will make a firm 375% more likely to be in group A over E, or 218% more likely to be in group B over E, or 390% more likely to be in group D over E. See Appendix D for odds calculations. The data did not show any difference in organizational focus between group C and E. In other words, a one unit increase (from average organizational focus score) in RM organizational focus score significantly increases the chances of being in group A, B, or D (higher performing hotels) over being in group E (lower performing hotels).

Next, we examined pairwise contrasts within organizational structure. Our MNLM results indicate that controlling for all other variables at their average score, a one unit increase in organizational structure score from its average score reduces a hotel's chances of being in the A or B group compared with being in the C, D, or E group.

Specifically, controlling for all other variables, given an increase of one in a hotel's organizational structure score (from the average), a hotel is 76% more likely to be in group C vs. B ($p=0.08$), and 73% more likely to be in group E vs. B ($p<0.05$). Similarly, controlling for all other variables, given an increase of one in a hotel's organizational structure score, a hotel is 143% more likely to be in group C vs. A ($p<0.01$), 113% more likely to be in group D vs. A ($p=0.02$) and 138% more likely to be in group E vs. A ($p=0.02$). Hence, the data generally indicate that a decrease in organizational structure score correlates with an increase in the probability of being a higher ranked hotel (A, B) compared to being a lower ranked hotel (C, D, E). These results are counter-intuitive, so we suggest some possible explanations in the discussion section.

Finally, we examine the results from forecasting. We do not see any significant differences amongst the B, C, D, and E hotels. We do, however, see significant differences between the A hotels and the B, C, D, and E hotels. Holding all other variables constant at their average score, for a one unit increase from average in forecasting ability, hotels are 145% more likely to be an A hotel than a B hotel ($p=0.05$), 148% more likely to be an A hotel than a C hotel ($p=0.04$), 289% more likely to be an A hotel than a D hotel ($p<0.01$), and 133% more likely to be an A hotel than a E hotel ($p=0.08$).

5.4 Discussion

Examining all of the results together, we see evidence for specific constructs differentiating hotel performance groups. Figure 4 illustrates this point. Generally, lower organizational focus scores separated E hotels from A, B, C, and D hotels. Higher forecasting scores separated A hotels from the B, C, D, and E hotels. Lower organizational structure scores separated the A and B hotels from the C, D, and E hotels.

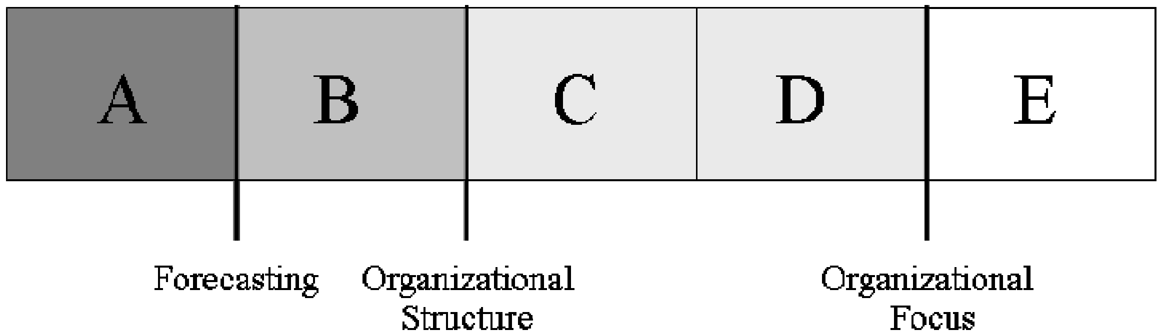

Figure 5 - Differentiation of Hotel Group by Constructs

5.4.1 Organizational Focus Discussion

Results indicated an increase in organizational focus decreases a hotel's chance of being in group E, but does not change a hotel's chance of being in any other group. In other words, a hotel may need to increase organizational focus to rise out of the E group, but there is no evidence that further increases will help that hotel rise to greater performance levels. We measure organizational focus with items including enthusiasm from management, an understanding across various levels and roles of how to improve revenues, and support for long-term decision-making. One could interpret this result to say management should invest resources to improve the awareness of the discipline of RM in order to form a foundation for improved RM, but focus on organizational focus alone will not help a hotel achieve the highest levels of performance; a hotel must improve in other areas to achieve further performance gains.

5.4.2 Organizational Structure Discussion

Next, we see a counterintuitive result: higher organizational structure scores negatively impact RM performance. A decrease in the organizational structure score separates the A and B hotels from the lower ranked C, D, and E hotels. This surprising result requires a more in-depth investigation to fully understand the result. However, we offer a few possible explanations.

Changes in a hotel's organizational structure are often be seen as changes in form rather than substance. Lorange and Nelson (1987) suggest that organizational restructuring and planning can be one of many causes of organizational decline and an easy distraction to focus internally rather than externally on the customer. Robert Cross (personal communication, February 22, 2007) similarly believes that organizational structure change can be a distraction in order to avoid the real work of RM improvement. If a structural change comes at the expense of developing other important skills within RM, it may harm performance. This could be tested by conducting in-depth interviews with respondents to better understand their organization's structure, including how that structure impacts daily operations and decisions.

Conversely, changes in organizational structure could be the result of performance measures, instead of organizational structure causing performance. Russo and Harrison (2005) investigate a similar phenomenon concerning the relationship between organizational structure and environmental performance in electronics facilities. Russo and Harrison (2005) posit that facilities which have environmental managers reporting directly to plant managers and facilities in which environmental managers have a strong degree of influence in decision making will have lower environmental emissions than other plants. The researchers did not find support for their initial hypotheses, but after further investigation found support for a surprising conclusion: high emissions in the past caused positive changes within organizational structure. Russo and Harrison supported this conclusion through longitudinal data and investigation. We do not have access to longitudinal data and can not further test this supposition. However, there are many parallels between their conclusion and a possible explanation to our results. It could be proposed that past poor RevPAR performance has spurred organizational structure change. This organizational change could have a lag effect. After some time, this new structure could positively impact RM performance. Future studies should measure the length of time that a hotel has performed under a new organizational structure to see if this is a significant factor in RM performance.

Our results show that the best performers (A and B) have a lower organizational structure score, meaning there is room for improved organizational structure. Possibly, as hotels improve their RM abilities and become more independent, they may need to change their structure to adapt to a more independent and fluid structure. As hotels (and the employees within them) start to understand RM and how to use it better, they may want more independence to try new ideas and to have more ownership of the process. Additionally, one of our questions measured the degree to which RM would work better with a different structure. Possibly the best performing hotels know that there is always room for improvement and always think there is a better way to do things, including the structure of the organization. Possibly, the best performing hotels have a more critical view of needed changes. Thus, hotels may need to progress and change structure in order to improve performance.

Scholars consistently agree that there is no one ideal organizational structure for all organizations (Lawrence and Lorsch 1967, Galbraith 1977, Mintzberg 1980, Van de Ven and Drazin 1985, Galunic and Eisenhardt 1994, Gresov and Drazin 1997). Contingency theory explains that different size firms in different industries have specific needs and a given firm with a specific set of contingent factors should follow a prescribed best organizational structure. (Lawrence and Lorsch 1967, Galbraith 1977, Drazin and Van de Ven 1985). Expanding contingency theory, equifinality theory proposes that a given level of organizational performance may be reached through many different organizational structures, even if firms have similar competitive pressures and internal processes. Equifinality suggests flexibility in designing high performing organization (Gresov and Drazin 1997) and further proposes there is no one magic structure and even a good proposed structure has shortcomings. For example, a hotel may be designed sub-optimally for revenue management, but optimally for customer service. Equifinality could explain the confusing results in our analysis – there is no one best structure.

Another possible explanation for this unexpected result could be due to inherent utilization conflict within higher performing hotels. Higher performing hotels tend to have higher occupancy rates than lower performing hotels. This higher occupancy rate translates to room allocation conflict between directors of RM and sales. Because of high occupancy, the director of RM may want to save more rooms for higher paying customers, while simultaneously the director of sales wants to sell the rooms to a group, which typically pays a discounted rate. This leads to arguments about how the rooms should be allocated. This is different than a lower performing hotel with lower occupancy. If occupancy is lower, there are not as many arguments about how to allocate rooms – employees are instead enthusiastic about selling the rooms to a willing buyer. Even if the director of RM and director of sales are on equivalent hierarchical levels, the organizational structure may not seem optimal to the director of RM when conflict arises. The elevated level of arguments and tensions may have led respondents to indicate that the organizational structure needs improvement. This theory could be tested in the future by comparing organizational structure scores, RevPAR performance, and occupancy levels.

5.4.3 Forecasting Discussion

The top hotels (A hotels) differentiate themselves from all other hotels through increased forecasting abilities. Intuitively, accurate forecasting should play a fundamental role in RM. Forecasts directly impact the optimal capacity to allocate for high value customers. This capacity allocation (and subsequent sales at high prices) lies at the heart of RM and increases revenue. The data show that the best hotels within a competitive set show significantly higher forecasting ability than the lower ranked hotels. The competitive landscape bounds hotel prices and therefore hotels cannot differentiate themselves on price. Instead, they must differentiate themselves based on the amount of rooms sold to higher paying customers. This is achieved by reserving the right number of rooms, which is accomplished through accurate forecasting.

5.5 Perceptual Performance Regression Results

In addition to performing analysis using objective performance data, we also analyzed perceptual performance data. Although objective performance data is preferable to perceptual performance data because of its unbiased nature (Dess and Robinson 1984), it is useful to collect perceptual data in case the objective data has a low response rate and in order to compare and contrast the results. We regressed the RM performance drivers against the dependent variable of perceptual performance.

The linear regression model with perceptual performance as a dependent variable has an R^2 equal to 46.4%. Forecasting, aligned incentives and organizational structure all prove to be positive and significant predictors of performance. Table 16 lists the model coefficients. These results show that both technical and social support capabilities are important for improved performance. We do not see evidence that all of the suggested drivers significantly impact performance.

Table 16 - Linear Regression Results with Perceptual Performance as Dependent Variable

	Linear Regression Coefficient
Intercept	0.470
Brand (control variable)	0.244*
Market Segmentation	0.125
Pricing	0.079
Forecasting	0.251**
Capacity Allocation	0.028
IT	0.079
Organizational Focus	0.102
Aligned Incentives	0.099*
Organizational Structure	0.138*
Training	0.095
R^2	46.4%

*p<0.01, **p<0.05, n= 203

We see both similarities and differences between the results from the perceptual performance model and the objective performance model. Similarly, forecasting is a significant and positive predictor for both models. Also similarly, both technical and social support variables contribute to improved RM performance. By contrast, organizational focus is a positive and significant predictor for the objective performance model, but is not significant in the perceptual performance model. Aligned incentives is not significant in the objective model, but is positive and significant in the perceptual model. Finally, organizational structure is significant in both models, but negative in the objective performance model and positive in the perceptual performance model. And, managers take actions based on what they perceive to be the truth. However, their perceptions may be misguiding them in many cases to the wrong corrective action.

5.6 Comparison of Cross Industry Results to Hotel Results

In addition to the hotel survey, we conducted a small cross-industry study. See Appendix A for details and results. Comparing correlations between the hotel survey and the cross industry survey, we find interesting results. The hotel regression analysis shows that forecasting, organizational focus, and organizational structure significantly correlate with RM performance. The cross industry survey supported evidence that market segmentation, pricing, capacity allocation, organizational focus, and education and learning correlate with RM performance. The cross industry survey did not include survey items about organizational structure, so we cannot compare results regarding that construct.

Regarding technical skills, the cross industry finds market segmentation, pricing, and capacity allocation skills to be significant whereas the hotel industry results found forecasting to be a significant skill. The only consistent finding within the technical skills results was that neither survey found IT skills to significantly correlate with RM performance.

The cross-industry study has a very small sample size and thus conclusions are tentative. However, it serves as a starting point for future research. Additionally, it lends added support to the theory that both technical and social support positively influence RM performance.

CHAPTER 6

CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

6.1 Conclusions

We have developed a framework which postulates relationships between the elements of RM technical capability, RM social support capability, and RM performance. This framework incorporates the technical skills of market segmentation, pricing, forecasting, capacity allocation, and IT use. Additionally, it incorporates the social support infrastructure of organizational focus, organizational structure, aligned incentives, and training and education. This framework allows both researchers and practitioners to view RM problems with a broader lens than traditionally used, allowing a more complete picture of the RM problem.

In addition to a theoretical framework, we developed scales to measure and test this framework. Researchers have conducted limited empirical research in this area, so scales did not exist previously. This initial scale development effort provides a foundation for further research.

We tested our framework within the hotel industry, using both objective and perceptual performance measures. Common to both tests was consistent evidence that both RM technical and social support skills contribute to RM performance.

The hotel analysis with the objective performance measurement showed evidence that improved forecasting and organizational focus positively correlates with improved performance. This same analysis indicated that higher organizational structure scores negatively correlate with improved performance. We have suggested some explanations for this non-intuitive result and future research opportunities in this arena.

The hotel analysis with perceptual performance measurement showed evidence that improved forecasting, organizational focus, and aligned incentives positively correlate with improved performance. These results tell researchers how managers perceive the RM skill level and RM performance of their hotel. Additionally, it provides support for the theory that both technical and social support capabilities impact RM performance.

In summary, we have proposed a more holistic lens with which to view a RM system, which includes both technical and social support aspects. We developed scales to measure our proposed constructs and tested our theory within the hotel industry. Our data consistently support the idea that both technical and social support skills contribute to performance. We have also shown how organizational focus, organizational structure, and forecasting contribute to and differentiate various performance levels of hotels.

This paper is the first (to the authors' knowledge) to empirically test RM performance drivers across a large sample size. This work contributes to the academic literature by empirically testing if the RM elements suggested by the academic literature impact RM performance. Furthermore, this work combines both technical and social support skills. Previous work tended to look at one or the other in isolation. This work suggests that both are important aspects of RM success. The existing rich analytical research stream has provided many insights. We argue that it needs a parallel, and supporting empirical stream to test and validate the existing theories.

This research contributes to the practitioner literature by quantifying how individual aspects of a RM system impact RM performance. This information will aid managers in allocating resources to improve their RM performance.

6.2 Limitations and Future Research

This research examines skill levels and how they impact performance. We focus on one industry to avoid industry specific effects which would unnecessarily complicate the study. We chose the hotel industry because of its experience, large sample size, decentralized structure, and standardized, objective performance measure. However, as with any single industry research, conclusions drawn from this study cannot necessarily be applied to other industries. In light of this limitation, investigation of RM performance drivers in other industries provides a future research opportunity.

We included three hotel parent companies in this research. A future study could work to include a broader sample of hotel chains. Additionally, we focused on the U.S. market in order to control for national culture differences. Future work should investigate RM performance drivers in countries outside of the U.S.

This research relies on perceptual items to measure drivers of RM. Objective proxy measures for these drivers would reduce some respondent bias. Therefore, work should be done to find objective, consistent measures for the 9 proposed performance drivers. Additionally, our perceptual measures were an initial effort to operationalize the scales, and hence had low reliability, as is typical in exploratory research. Higher reliability may lead to finding more significant effects within our constructs. Further scale development and hypothesis testing could lead to discovering more significant factors of RM success.

Our objective performance measure could be improved. Currently, we use the RevPAR ranking within a competitive set to measure performance. However, these competitive sets are not perfect matches for a given hotel. Hotels must have at least five hotels within the competitive set. If the hotel is located in an area with few hotels, the hotel may include hotels with higher (lower) service levels within their competitive set. A lower (higher) service level hotel must charge lower (higher) rates than a higher (lower) service hotel, and therefore can not expect to yield the same RevPAR. Some hotels are attempting to rectify this problem through a value analysis. Instead of aiming for a RevPAR index of 100, the hotels evaluate an appropriate RevPAR index goal. Then, the hotel is judged on meeting that goal instead of meeting the standard goal of 100. Comparing a hotel's actual RevPAR index to its goal RevPAR index may be a more accurate depiction of performance than our current objective performance measure. There are two problems with this proposed performance measure: 1) Not all hotels have a goal RevPAR index 2) Hotels set their own goal RevPAR index, so there is opportunity for bias.

Finally, our data yielded counter-intuitive results regarding the role of organizational structure in RM. We advocate a further examination of why decreased scores are associated with higher performance. This could be accomplished through further field discussions, both at the hotel level and headquarters level. Additionally, data could be collected on hotel utilization to compare how utilization rates and organizational structure scores correlate in order to test if increased utilization impacts organizational structure dissatisfaction.

APPENDIX A

CROSS INDUSTRY STUDY RESULTS

We have established that RM increases profits in many firms, and we have proposed RM success requires a combination of technical and social support skills. We tested how skills relate to performance within the hotel industry, and have presented evidence supporting our argument that both technical and social support skills together influence RM performance in the hotel industry. However, these results do not necessarily translate to other industries.

Traditionally, RM has been accepted in hospitality industries (lodging, rental cars, airlines) because of the perishability of the product. As firms outside of the hospitality industries adopt RM, they should have evidence of where to deploy resources for the best return on investment. In order to generalize results to an audience outside of the hospitality industry, we need cross industry research to guide recommendations.

The theory proposed earlier, consisting of both RM technical skills and RM social support skills, is a broad theory for RM in all industries. We tested it specifically within the hotel industry. We use the same theory as a basis for a cross industry examination of the drivers of successful RM and test the same hypotheses. In addition to the hotel industry survey, we administered another survey to a sample of firms in different industries.

HYPOTHESIS 1. *Increased market segmentation ability positively influences RM performance.*

HYPOTHESIS 2. *Increased pricing ability positively influences RM performance.*

HYPOTHESIS 3. *Increased forecasting ability positively influences RM performance.*

HYPOTHESIS 4. *Increased capacity allocation ability positively influences RM performance.*

HYPOTHESIS 5. *Increased IT ability positively influences RM performance.*

HYPOTHESIS 6. *Increased organizational focus positively influences RM performance.*

HYPOTHESIS 7. *Increased aligned incentives positively influences RM performance.*

HYPOTHESIS 8. *Improved organizational structure positively influences RM performance.*

HYPOTHESIS 9. *Increased education and training positively influences RM performance.*

The survey used for this research focus was adapted from the larger hotel survey. The hotel items were reworded so they would be applicable to a broader audience. Next, items were compared to respective construct definitions to determine if each were needed for face validity. Redundant and overlapping questions were removed in order to minimize the length of the survey. Industry experts then reviewed the questions for face validity. The survey included questions pertaining to eight different RM drivers, plus three questions relating to RM performance. See appendix C for survey questions.

Key informants responded to our survey. Key informants can best answer surveys because they are least likely to be biased. Our key informants were directors or VPs of RM in their respective companies. We asked attendees at two separate RM conferences to complete paper surveys. Separately, we asked professional contacts to complete surveys online. We recognize the inherent bias in asking known contacts and those specifically attending a RM conference. However, RM conferences can be the best forum to find a large quantity of willing survey participants in a narrow focus survey. We characterize responses by industry in Table 17.

Table 17 - Cross Industry Survey Response by Industry

Industry	**Number of responses**
Hospitality	10
Airlines	3
Rail	2
Cargo	1
Retail	2
Consumer Packaged Goods	1
Other	16
Total	**35**

Performance data for this survey is perceptual. We operationalize performance as an average of three measures relating to the extent of return on investment of RM, effectiveness of RM in increasing revenue and profitability, and ability to measure RM performance. Respondents answered these three questions using a Likert scale ranging from 1 to 7.

Scale reliability measures the proportion of a scale's variance due to the true score of the underlying construct and is measured by Cronbach's alpha. The brevity of each scale makes high reliability difficult. Therefore, for all scales with $\alpha < 0.68$, we adopted a single item to measure the construct in order to test our hypotheses. We list the resulting reliabilities in Table 18.

Table 18 - Scale Reliability Alphas

Construct Scale	Items	*n*	α
Market Segmentation	3	35	0.68
Pricing	4	35	0.70
Forecasting	1	N/A	N/A
Capacity allocation	1	N/A	N/A
IT	2	35	0.84
Organizational Focus	1	N/A	N/A
Education and Training	4	35	0.68
Aligned Incentives	1	N/A	N/A
Perceptual Performance	3	35	0.89

Results

We test RM drivers using the scales developed in the previous section. Using these scales, we analyze our sample using correlations, shown in Table 19. Regression analysis was not feasible due to the small sample size of our survey.

Table 19 - Cross Industry Construct Correlations

	MS	Price	For	CA	IT	OF	AI	E&L	Perf
MS	1.0								
Price	.34**	1.0							
For	.49*	.34**	1.0						
CA	.59*	.24	.28	1.0					
IT	.14	.07	.20	.50*	1.0				
OF	.51*	.62*	.40**	.52*	.04	1.0			
AI	-.10	-.19	-.01	.18	.09	-.01	1.0		
E&L	.59*	.58*	.25	.45**	.05	.63*	-.23	1.0	
Perf	.36**	.60*	.24	.51*	-.01	.70*	-.31	.65*	1.0

* $p<0.01$; ** $p<0.05$

Where MS= Market Segmentation; Price= Pricing; For = Forecasting; IT = IT use; OF= Organizational Focus; AI = Aligned Incentives; E& L = Education and Learning; Perf = Performance.

We see that three of the five technical skills significantly and positively correlate to performance: market segmentation, price, and capacity allocation all significantly and positively correlate to performance. Meanwhile, two of the three cultural skills correlate with performance: executive commitment and education and learning significantly and positively correlate with performance.

The survey indicates that market segmentation positively correlates with performance ($p<0.05$). Many of the firms in our survey are one of the first firms in their industry to use RM. This market segmentation ability is very important when first applying RM. It may not be as important in industries with more established RM practices since many firms essentially copy how other firms segment markets. For example, once American Airlines created the business and leisure segments and established a 21-day advanced purchase rule for leisure prices, other airlines quickly copied. However, firms starting to use RM in retail and business services may be quietly creating segments and fences. This separation of customer class may greatly add to RM profitability.

Pricing ability significantly and positively correlates with RM performance ($p<0.01$) in our survey. While developing our hypothesis, we showed support from both the academic and popular press literature for this hypothesis.

Capacity allocation significantly and positively correlates with RM performance ($p<0.01$) in our survey. This complements the academic literature which focuses on improving capacity allocation algorithms. Forecasting and IT skills did not significantly correlate with RM performance.

Two of the three cultural skills correlate with performance: organizational focus ($p<0.01$) and education and learning ($p<0.01$) significantly and positively correlate with performance. Organizational focus creates urgency for employees to care about RM. Additionally, one can think of organizational focus as the foundation required for other skills to occur, including both technical and social support. Education and learning allows employees to understand and improve how decisions impact RM performance.

Aligned incentives was the only social support skill tested to not significantly correlate with RM performance. According to one RM veteran, RM initiatives succeed in spite of the incentives, not because of the incentives. This same veteran has seen so few companies with aligned incentives, that she found it understandable that we did not see a correlation.

Limitations

Our results must be considered with limitations in mind. Limitations can be grouped into two categories: 1) the sample itself 2) construct measurement.

The sample itself has many biases, including the nature of the sample, sample size, and the breadth of industries included in the sample. We reached the respondents through conferences and professional contacts, which can be considered a convenience sample. Convenience samples may be considered biased. Additionally, the respondents come from a wide range of industries, each of which can confound results. These may add to the noise in responses unknowingly. Next, we have a small sample size (n=35), which will limit the applicability of results. Nonetheless, it is a cross sample of firms indicating which skills correlate with performance, which is a contribution to the field of RM.

Construct measurement provides some limitations to our study. Because of the cross industry nature of the study, items were worded generically and may not be applicable to all industries. Because of the generic wording, some items may not have measured exactly what was meant to be measured. In addition to generic wording, our construct reliability was low in four scales and so constructs were measured with a single item. Single item measurement prevents us from accounting for error and is not recommended.

Conclusions

A wide range of skills contribute to RM success. We show that organizational focus is a cornerstone of RM success. Additionally, other technical and social support elements may contribute to RM success, but which ones contribute most may depend upon the industry and competitive pressures.

Our research does not show that aligned incentives correlates with increased RM success, but we do not think that means aligned incentives are unimportant. On the contrary, principal agent theory strongly supports aligned incentives. From anecdotal evidence, we believe firms succeed in spite of unaligned incentives. We believe firms should work to align their incentives to further encourage employees to focus and excel in this area.

This research is the first (to the author's knowledge) to systematically and empirically test RM performance drivers across diverse industries. In order to systematically test RM drivers, we develop a framework for RM, including separating and defining nine separate drivers within RM. This research examines cross industries a step beyond case studies in order to understand how skills contribute to RM success. This work provides evidence that both technical and social support skills contribute to increased RM performance. More work should be done on which skills need to be further developed in particular industries, but all industries using RM should be aware of the range of skills contributing to RM success.

APPENDIX B

HOTEL SURVEY MEASUREMENT ITEMS

The following scales were used to measure our constructs of interest.

Market segmentation	
MS2	We group customers into strategic clusters.
MS3	We categorize customers based on similar buying characteristics.
MS5	We have distinguishable groups of customers who can be separated through identifiable characteristics.
Dropped	We promote our hotel differently to different groups of customers.
Dropped	We regularly review if we have appropriate, well-defined market segments.

Pricing	
P2	Competitors' reactions are considered when deciding room rates.
P3	Long term customer satisfaction is balanced with short term revenue when setting room rates.
P4	We set room rates according to the value our customers place on a room.
P6	My firm has an effective policy for setting room rates.
P7	Customers' price elasticity is considered when setting room rates.
Dropped	Once I change rates, I can easily update these changes to all sources (websites, 3rd party distributors, etc.).
Dropped	My firm has a consistent policy for setting room rates.

Forecasting	
FOR1	We ignore RM system forecasts and instead use forecasts from other sources to drive business decisions. (Reverse coded)
FOR2	Compared to our competitors, our forecasts are very accurate.
FOR3	We use accurate and timely data for forecasting customer demand.
FOR4	Our hotel tracks denials and regrets accurately.
FOR6	We use the RM system forecasts to drive business decisions.
Dropped	The revenue manager must manually adjust forecasts often. (Reverse coded)

Capacity Allocation	
CA1	RM system allocates rooms well to our market segments.
Dropped	We have tools to make profitable, analytic based booking decisions for groups.
Dropped	We overbook customers judiciously and understand that walking customers occasionally is part of smart RM.
Dropped	Our hotel consistently sells out on a given night of the week. (Reverse coded)
Dropped	When analyzing the value of a given customer, we include customers'

	auxiliary spend (food and beverage, spa, etc.) in addition to room rate.
Dropped	On any given evening, we have a few rooms available for high value customers.

Information Technology	
IT1	The RM IT system meets business needs.
IT2	Our reservations and RM systems are integrated.
IT3	The IT support for the RM system meets our needs.
IT4	Our reservations and RM systems are integrated in real time.
Dropped	We create work-arounds for our computer system in order to complete routine RM tasks. (Reverse coded)

Organizational Focus	
Dropped	The quality of RM has been compromised by short-term cost considerations. (Reverse coded)
EC3	Executive management is enthusiastic about the possibilities of RM.
EC4	The need for long-term RM support resources is recognized by management.
EC5	Managers assign resources to RM as needed.
L3	RM experimentation is encouraged even if the proposed improvement is unsuccessful.
L4	RM improvement suggestions are regularly collected from multiple employee levels.
T5	All personnel who contribute to RM (possibly front desk clerks, sales people, etc) understand their role in the RM process.
AI1	Hotel employees in different functional areas work towards the same hotel profitability goals.
AI5	My hotel's goals are similar to the parent company's goals.

Aligned Incentives	
L2	A revenue manager gives feedback to others explaining how their actions affected RM performance.
AI2	The general manager's bonus or evaluation is partially tied to Smith Travel Research (STR) RevPAR numbers (or other RM metric).
AI3	The revenue manger's performance or bonus is directly tied to Smith Travel Research (STR) RevPAR numbers (or other RM metric).
Dropped	Rewards and goals for the sales team conflict with the rewards and goals of the revenue manager. (Reverse coded)
Dropped	Rewards and goals for the sales team align with the rewards and goals of the revenue manager.

Organizational Structure	
OS1	The organizational hierarchy within the hotel helps RM.
OS2	The revenue manager reports to someone who values RM.
OS3	In the hotel hierarchy, the revenue manager is on the same, or higher level as

	the sales director.
OS4	RM would work better with a different organizational structure (Reverse coded)
EC1	Employees who are assigned to RM are distracted by other commitments. (Reverse coded)

Education and Learning	
T1	Training materials target the entire business task, not just the RM screens and reports.
T2	RM training and education meets business needs.
T3	A useful formal training program has been developed to meet the requirements of RM system users.
L1	Benchmarking is used to identify cutting edge RM techniques.
L5	Internal groups meet regularly to share new methods of using the RM system.
Dropped	We keep track of RM developments related to our industry.
Dropped	Employees are tracked to ensure that they have received the appropriate RM training.

APPENDIX C

CROSS INDUSTRY SURVEY MEASUREMENT ITEMS

Market Segmentation	
MS1	We categorize customers based on similar buying characteristics.
MS2	We regularly review the quality of our market segmentation.
MS3	We promote our product or service differently to different groups of customers.

Pricing	
P1	Customers' price elasticity information is considered when setting prices.
P2	We understand the value our customers place on our product or service and set rates accordingly.
P3	My firm has an effective policy for setting prices.
P4	Competitors' reactions are considered when deciding prices.

Forecasting	
Dropped	We override the inventory control recommendations of the RM system almost always. (Reverse coded)
F2	Our monthly forecasts are accurate.
Dropped	We track unmet demand accurately.

Capacity Allocation	
CA1	The RM system allocates products/ services well to our market segments.
Dropped	We consider the different profit margins of each customer/ product segment when deciding how much volume to set aside for each segment.

Information Technology	
IT1	The IT support for RM systems meets our needs.
IT2	The RM IT system meets business needs.

Organizational Focus	
Dropped	Employees who support RM are constantly distracted by other commitments. (Reverse coded)
EC2	Senior management in my reporting structure understand and value RM.
Dropped	The quality of RM has been compromised by short-term cost considerations. (Reverse coded)

Aligned Incentives	
AI1	Rewards and goals for salespeople conflict with the rewards and goals of the RM personnel. (Reverse coded)

Dropped	Our Revenue Manager's performance or bonus is directly tied to a RM performance metric.

Education and Learning	
T1	All personnel who contribute to RM understand their role in the RM process.
T2	RM training materials target the entire business task, not just the RM tasks and screens(if applicable).
L1	RM experimentation is encouraged even if the proposed change is unsuccessful.
L2	Internal groups meet regularly to share ideas of how to better apply RM practices.

Performance	
Perf1	I believe our firm has achieved a healthy return on our RM investment.
Perf2	My firm's RM actions are extremely effective in increasing both revenue and profitability.
Perf3	We have specific and well-defined metrics(s) to measure RM performance.

APPENDIX D

EXPLANATION OF MULITNOMIAL LOGIT MODEL (MNLM)

This section serves as a basic explanation of the MNLM. Further details on the model and interpretation of the model can be found in Long (1997), Pampel (2000) and Eliason (2007).

The MNLM serves as an extension to a binary logit model. A binary logit model uses a natural log transformation to calculate the probability of one of two outcomes occurring. The MNLM extends this model by allowing more than two discrete outcomes as possibilities.

The base equation for the MNLM is $\Pr(y_i = m \mid x_i) = \dfrac{\exp(x_i \beta_m)}{\sum_{j=1}^{J} \exp(x_i \beta_j)}$ where $\beta_1 = 0$ (Long 1997; 153). We define terms as follows: J= number of possible outcomes, m = a specific outcome, x_i = the vector of explanatory variables (assumed to be categorical, not continuous for definition of odds ratio), β = slope coefficient for each predictor. We solved for model coefficients using maximum likelihood estimation.

In order to interpret results, first we must determine which independent variables are statistically significant across the set of J-1 coefficients. This is done using a Wald chi-square test (Long 1997, Eliason 2007). We list results from this test in Table 20. Results show that independent variables organizational focus, forecasting, and organizational structure are all significant at the p<0.05 significance level. Because these variables are significant across the model, we can investigate how these variables act in pair-wise comparisons.

Table 20 - Testing for Variable Effect

	Degrees of Freedom	χ^2	**Prob >** χ^2
Intercept	4	9.74	0.04
Brand	4	16.42	0.0025
Organizational Focus	4	9.84	0.04
Forecasting	4	9.71	0.04
IT	4	0.61	0.96
Education and Training	4	5.88	0.20
Pricing	4	3.16	0.53
Capacity Allocation	4	4.40	0.35
Market Segmentation	4	5.18	0.27
Organizational Structure	4	11.18	0.02
Aligned Incentives	4	4.72	0.31

One interpretation of the MNLM is that of an odds model. The idea is to calculate the odds of being in hotel group A (highest performing) versus hotel group E (lowest performing) given a specific score for each of the independent variables. Once this is done for group A and E, then it is done for every other pair-wise combination of the 5 levels of performance. This odds model is written as $\Omega_{m|n}(x_i) = \frac{\Pr(y_i = m \mid x_i)}{\Pr(y_i = n \mid x_i)} = \frac{\exp(x_i \beta_m)}{\exp(x_i \beta_n)}$.

Re-evaluating Table 13, how do we interpret the results? Looking at logit model 1, we see the coefficients for a MNLM comparing Group E to Group A. Only the three variables found to be statistically significant across the set of J-1 coefficients (organizational focus, organizational structure, and forecasting) can be interpreted. Examining organizational focus, we see it is significant at the *p*=0.01 level. These results show the effects of predictor variables on the log-odds of being in group E versus being in group A. Controlling for all other independent variables (brand, forecasting, IT, Education and Training, Pricing, Capacity Allocation, Market Segmentation, Organizational structure, Aligned Incentives), on average, an increase of 1 in organizational focus score results in an probability increase of being in group E over group A by $e^{(-1.56)} = 0.21$ times. Conversely, this can be inverted to be interpreted to say that an increase of 1 in organizational focus score results in a probability increase of being in group A over group E by $1/0.21 = 4.75$ times. This almost 5-fold probability increase corresponds to a 375% increase in the odds of this hotel being an "A" performing hotel versus being an "E" performing hotel if organizational focus score increase by one.

In other words, a higher organizational focus score greatly increases the probability of being in group A (highest performing hotels) over group E (lowest performing hotels). The other variables and pair-wise comparison models are interpreted in the same fashion.

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