DECISION SCIENCES
A JOURNAL OF THE DECISION SCIENCES INSTITUTE

Decision Sciences
Volume 48 Number 3
June 2017

Classifying Revenue Management: A Taxonomy to Assess Business Practice*

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ABSTRACT

As revenue management (RM) techniques evolve there is a need to take stock of how organizations practice RM and the interactions among techniques. This would help practitioners and researchers better understand how RM practice is influenced by the business setting, including those not traditionally associated with advanced RM techniques. Also, it would facilitate investigations of which practices lead to better outcomes in different contexts. Research to date has focused on individual techniques within individual business settings, with limited attention to the range of environments in which RM practice occurs. This suggests a need for a common framework to classify and assess differences in practice. In this article, we present a taxonomy which comprises (i) seven indicators of practice and (ii) a decision tree to measure RM across diverse businesses. We test the classification system in a survey of 232 businesses. Results show the taxonomy provides a comprehensive view of RM practice, with meaningful discrimination across settings. Findings also offer insight into how practices vary across different settings. Our taxonomy contributes to future research by facilitating systematic comparisons of RM practices, the settings in which it is adopted, and its impact on performance. [Submitted: October 22, 2015. Revised: April 11, 2016. Accepted: April 12, 2016.]

Subject Areas: Field Studies, Revenue Management, Survey Research, and and Taxonomy.

INTRODUCTION

Revenue management (RM) provides a variety of concepts and tools for use in improving a business's revenue generation. Researchers and practitioners have advanced the range of techniques to analyze demand (Cleophas, Frank, & Kliewer, 2009; Yelland, Kim, & Stratulate, 2010), capitalize on customer willingness to pay (Hanks, Cross, & Noland, 2002), and investigate performance (Jones, 2000). Historically associated with the airline, hotel, and car rental industries, there is increasing interest in its application to other business settings (Kroll, 1999;

*The authors gratefully acknowledge Lily Chen, participants at the INFORMS 2012 annual conference, and participants at the University of Auckland and Victoria University of Wellington's seminar series for their helpful comments. We are also grateful for valuable comments from the associate editor and three anonymous reviewers. Financial support was received from the University of Auckland Doctoral Scholarship.

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Elmaghraby & Keskinocak, 2003; Kimes, 2004; Cross, Higbie, & Cross, 2010), which has driven an increase in the range of RM techniques such as package offers, alternative pricing methods, and tools to improve process efficiency.

The continued spread of RM, however, has also led to a complex and diverse field of research, which has been criticized for being fragmented and repetitive (Okumus, 2004). In particular, the current focus in the literature is on individual techniques, leaving a gap in understanding the full range of ways in which businesses make revenue-focused decisions. To date, researchers have highlighted points of difference for individual concepts and techniques, rather than considering the package of business practices (Arthur Andersen, 1997; Norman & Mayer, 1997). There have also been few cross-sectional studies, which systematically examine differences in RM practice among businesses (Shields, 2006b). Lists of preconditions have been developed in the literature to identify settings where RM is appropriate (Kimes, 1989; Weatherford & Bodily, 1992). For example, it is argued that RM is not appropriate if a business does not have perishable goods, cannot segment markets, does not sell products in advance, has stable demand, and can produce additional products for sale cheaply (Oberwetter, 2001). Yet, it is unclear how these preconditions influence the way RM is practiced.

We argue there is a need for a taxonomy that comprehensively captures (i) the key RM activities conducted, differences in their practice, and how they interact; and (ii) differences in RM practice across different contexts. Such a taxonomy would extend our understanding of RM practice in several ways. First, capturing all key RM practices will allow researchers and practitioners to diagnose areas of strength and weakness in current RM practice, to better understand how practices should fit together to improve performance. Second, comparing RM across settings facilitates empirical examinations into how contextual factors, for example, size, industry, and preconditions, affect the way RM is practiced. This would help identify possible barriers limiting more sophisticated RM practice. Third, combining different levels of RM sophistication into a single taxonomy creates a continuum from very simple to very complex RM practice. A continuum would contribute to practice by offering a tool that guides "next-step" improvements for all types of organizations, rather than focusing on businesses that already practice more sophisticated types of RM. Our taxonomy contributes a common measurement approach, which will assist research by facilitating empirical comparisons, helping structure the literature across studies and different levels of RM practice, and revealing gaps for future research.

This article describes a taxonomy of RM, consisting of seven indicators and a decision tree. A multimethod approach is used to explore differences in practice, develop our classification system, and empirically validate the resulting taxonomy. This involves cross-sectional interviews at seven organizations combined with academic and practitioner RM literature to develop a taxonomy and survey instrument of RM practice. The results of a survey of 232 businesses are used to gauge differences in practice and validate the survey instrument. Results show considerable diversity at the overall RM level as well as individual indicator level. In particular, the high frequency of low level RM signals a need for more research into rudimentary and intermediate practices.

The article is structured as follows. The next section provides an overview of RM and critiques attempts to date at developing a comprehensive taxonomy of practice. Next, the methods used in the study are described followed by a presentation of the findings and discussion of key results. We conclude with limitations and avenues for future research.

OVERVIEW OF RM

Diversity in RM Research

RM is a business practice that employs a systematic approach to optimize revenues by setting prices and managing product availability based on patterns of demand and customer willingness to pay (Talluri & van Ryzin, 2004). Despite this overarching theme, researchers note disagreement about the meaning of the term "RM" (Weatherford & Bodily, 1992; I. Ng, 2008). These differences in definitions can be attributed to the evolution of RM research from its origins in the airline industry to the current diversity in industry settings and sophistication of practices. Weatherford and Bodily (1992), for example, restrict the meaning of RM to techniques used in determining the amount of inventory made available at any point in time. Other researchers adopt a broader definition of RM that includes overbooking, forecasting, duration management, and product customization (Cross, 1997b; Kimes, Barrash, & Alexander, 1999; Talluri & van Ryzin, 2004; Shields, 2006a; I. Ng, 2008).

However, there is some consensus in the literature that there are four subsystems within RM, which we term "modules," that make up the essential components of RM practice. The combination of the four is argued to represent a complete description of RM (Talluri & van Ryzin, 2004; Shields, 2006b; F. Ng, Harrison, & Akroyd, 2013). While businesses are expected to have all four present, individual practices will vary in intensity and sophistication within each module.

The first module ("demand management") concerns the pricing and adjustment of supply to react to changes in demand. This is the dominant strand of RM research (Okumus, 2004) and comprises research related to pricing-based and quantity-based methods (Talluri & van Ryzin, 2004; Kocabiyikoglu, Popescu, & Stefanescu, 2014). Pricing-based research includes auctions methods, lowest price guarantees, successive-generation pricing, and the formation and manipulation of pricing rules (Baker & Murthy, 2002, 2005; Kasap, Sivrikaya, & Delen, 2013; Şen, 2013; R. Yin, Li, & Tang, 2015). Quantity-based research includes overbooking, length of stay controls, channel management, designing flexible products, and strategic interaction with key account management (Weatherford, 1995; Baker & Collier, 1999; Choi & Kimes, 2002; Gallego & Phillips, 2004; Ivanov & Zhechev, 2011; Wang & Brennan, 2014; Heo, 2016).

The second module ("resource management") refers to the configuration of internal activities to facilitate demand management techniques. This module provides the process infrastructure needed to respond to and take advantage of shifts in demand (Talluri & van Ryzin, 2004). While playing a relatively small role in earlier RM research, extensions to new industries have elevated its importance as a separate area of research (Kimes & Chase, 1998; McGuire & Kimes, 2006; Shields, 2006a). Product configuration studies describe the different ways that firms can differentiate products to support customer segmentation and price differentiation (Wedel & Kamakura, 1998; Zhang & Bell, 2012; Hadjinicola, Charalambous, & Muller, 2013). Duration controls aim to manage the length of time to service a customer (Kimes & Chase, 1998; Kimes et al., 1999; Kimes, 2004; Barut & Sridharan, 2005), using methods such as process mapping (Kimes et al., 1999; Kimes, 2004) and optimizing seat configurations (Kimes & Thompson, 2004; Barut & Sridharan, 2005).

The third module ("data analysis and modeling") refers to the analysis of demand and customer willingness to pay. This typically involves demand modeling and optimization for the most profitable mix of prices and products to sell (Chen & Kachani, 2007; Bobb & Veral, 2008; El Gayar et al., 2011). Studies of underlying assumptions of demand include myopic/strategic behavior and opportunity costs (Bitran & Caldentey, 2003; Elmaghraby & Keskinocak, 2003; Deng, Wang, Leong, & Sun, 2008), customization for different business models such as up- or down-selling (Belobaba & Weatherford, 1996; Baker, Murthy, & Jayaraman, 2002), group reservations (Brumelle & Walczac, 2003; Choi, 2006), the role of analyst involvement (Mukhopadhyay, Samaddar, & Colville, 2007), and the integration of economic forecasts with neural networks (Hogenboom et al., 2015).

The fourth module ("data collection") refers to the collection of data to understand patterns of demand. This includes the collection of internal data about transactions and historical trends (Phillips, 2005; Ivanov & Zhechev, 2011) and external data about customer habits and trends and competitor tactics (Talluri & van Ryzin, 2004). Sophisticated RM systems use automated data collection, linking it with existing reservation systems (Geraghty & Johnson, 1997; Boyd & Bilegan, 2003; Ivanov & Zhechev, 2011), while smaller businesses access customer data from e-mails and telephone calls (Shields, 2006b).

Classification of RM

The above highlights the diversity in the definition of RM and the range of different practices examined in the literature. Researchers have attempted to classify RM across different types of businesses, some focusing on specific parts of RM, for example, price-fences to develop a classification, while others have attempted a more holistic approach. Table 1 shows that existing classification systems have spanned all four modules, but with varying coverage of each. None have incorporated all four in their classification systems.

Some studies have developed categorical scales to classify practice, identifying alternative techniques with no inherent ranking. For example, Kimes and Chase (1998) use a two-by-two matrix that classifies businesses by differential pricing (whether prices are variable or fixed) and duration (predictable or unpredictable). Similar studies have classified rate fences (Zhang & Bell, 2012), practices used in small businesses (Shields & Shelleman, 2009), capacity allocation problems (Weatherford & Bodily, 1992), and demand functions in decision modeling (Huang, Leng, & Parlar, 2013). Accordingly, these classifications are limited as they focus on only one or two modules and have limited ability to rank differences in practice.

Table 1: Classifications of RM.

Study	Scale	Basis	Demand Management	Resource Management	Data Analysis and Modeling	Data Collection
Kimes and Chase (1998)	C	Theory	X	X		
Zhang and Bell (2012)	C	Theory		X		
Weatherford and Bodily (1992)	C	Theory	X		X	
Shields and Shelleman (2009)	C	Survey	X		X	X
Huang et al. (2013)	C	Theory			X	
Norman and Mayer (1997)	O	Case			X	X
Hanks et al. (2002)	O	Theory	X			
Franses (2011)	O	Theory			X	
Shields (2006a)	O	Survey		X		
Arthur Andersen (1997)	O	Case	X		X	
Shields (2006b)	O	Survey	X		X	X

RM = revenue management, C = categorical, O = ordinal; Basis: Theory = theoretically developed, Case = case studies, Survey = survey-based.

Other studies use ordinal rankings but only for individual RM activities. Hanks et al. (2002) identify three levels of hotel pricing practices that combine multiple room prices and discount categories, with each level incorporating additional demand characteristics. Similar classifications have described differences in the resources invested in RM (Norman & Mayer, 1997), quality of forecasting (Franses, 2011), and use of duration control procedures (Shields, 2006a). While the use of ordinal classifications is an improvement over categorical classifications, they are still not exhaustive and focus on only one or two modules.

Two studies were identified that create ordinal rankings to classify RM systems, rather than individual activities. Arthur Andersen (1997) provides a classification of RM practices based on a case study of small- and medium-sized firms in the tourist industry. Businesses were categorized into four groups (low, medium, high, and very high) based on characteristics of yield, understanding of RM, pricing philosophy, and pricing practices. Medium practice, for example, reflects intuitive use of RM without formal systems. For each characteristic, the classification provides ordinal scales to rank different practices. However, this approach does not provide a complete description of RM practices. As shown in Table 1 the classification emphasized demand management with limited attention to resource management and data collection.

Shields (2006b) developed a survey instrument to examine RM practices in small and medium organizations. This covered accessing data (e.g., by e-mail and telephone), recording data (e.g., shopping and profitability data), analyzing and segmenting (e.g., grouping customers by categories), and targeting and pricing (e.g., providing better services to more profitable customers, and marking up prices during busy periods). This approach covers three of the modules but resource management was not included. Additionally, Shields' classification identified examples of techniques rather than providing an underlying scale along which practices vary.

Classification systems offer a tool to describe and measure an object, helping researchers identify differences and similarities across objects of interest and can be divided between typologies and taxonomies (Simpson, 1961; K. Bailey, 1994; Ghauri & Gronhaug, 2005). Typologies are relatively simple classification systems that define objects through broad, conceptual descriptions while taxonomies require (Bailey, 1994) an exhaustive set of characteristics (criteria 1), drawn from an empirical examination of practice (criteria 2). To facilitate comparison, characteristics should be measured on an ordinal scale or better as these scales can be used to rank objects (criteria 3).

No research was identified that satisfied all three criteria. Regarding criteria 1, the classification systems reviewed primarily examined individual techniques, rather than complete systems. As a consequence, although the four modules cover the necessary areas in RM, current descriptions are insufficient to provide a taxonomy of practice. Regarding criteria 2, the majority of classifications found were developed theoretically, rather than from empirical examination. A few studies employed a single-method, for example, survey only. However, a multimethod approach would enhance both generalizability and conceptual validity of constructs (Grafton, Lillis, & Mahama, 2011). Regarding criteria 3, several of the classifications used only categorical scales, limiting our understanding of how practices can be improved. The classifications that do develop ordinal scales provide an incomplete picture of RM as they rely on examples of techniques to define differences in practice, rather than investigating the underlying scale along which practices vary.

In summary, the literature review reveals the lack of a comprehensive taxonomy of RM that spans all four modules of RM practice, covers different industries and levels of RM sophistication, and meets all three of the criteria (Bailey, 1994). In terms of internal and external validity, combining case studies and surveys would help provide a detailed understanding of practices while also providing more generalizable findings.

METHOD

A multimethod approach was used to develop and validate a taxonomy of RM. Figure 1 summarizes the three stages: (i) development of conceptual taxonomy; (ii) confirming the survey instrument; and (iii) validation of indicators and decision tree.

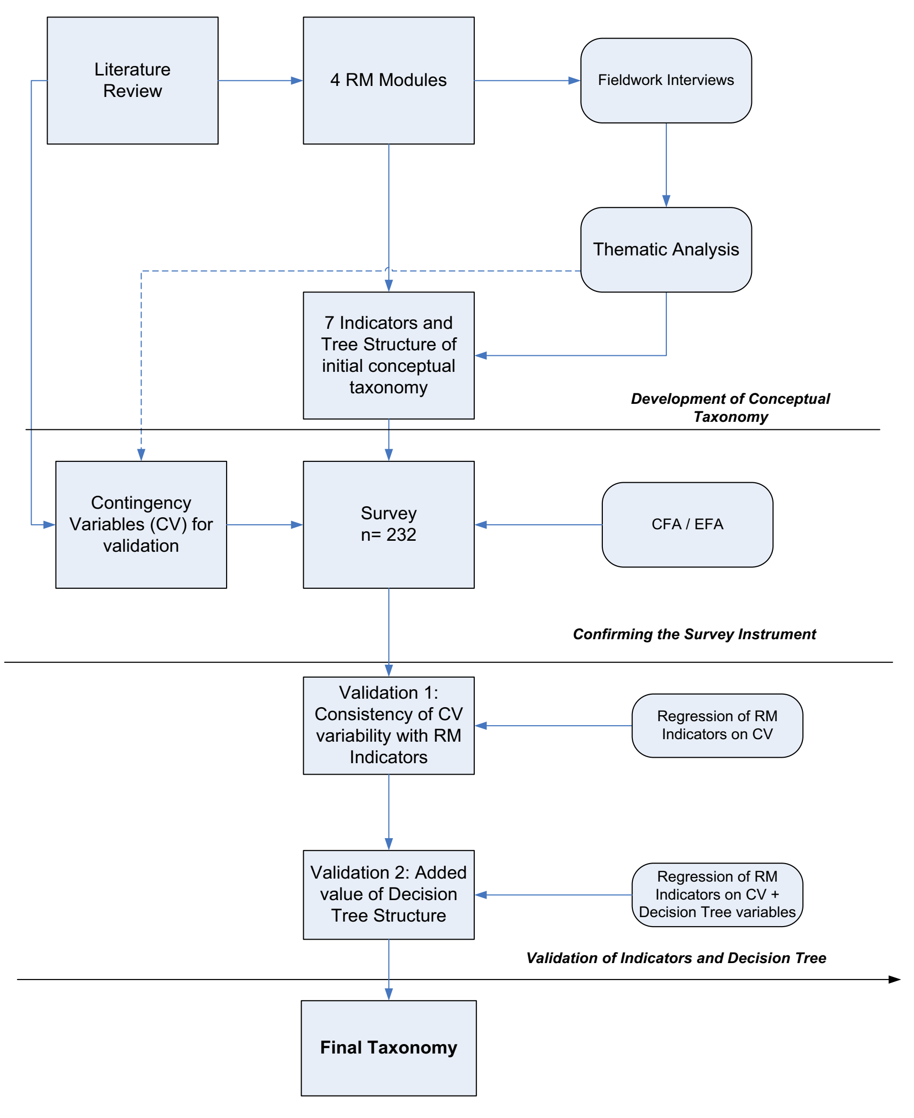
Stage 1: Development of Conceptual Taxonomy

The goal of Stage 1 was to develop a conceptual taxonomy that captured the full scope of RM practice. We started with the four modules identified in the literature. Fieldwork interviews were used to extend the literature by empirically confirming the comprehensiveness of the four modules and refining their conceptual definitions to facilitate measurement and across-business comparison.

Purposive sampling was used to select a list of organizations that would maximize cross-sectional differences in industry, business size, organizational structures, and target markets. Consistent with the literature our sample was confined to service organizations operating in the private sector (see the Appendix for details). Twenty-two interviews were conducted, lasting 1 hour on average. Participants spanned a range of positions and departments based on the different decision-making structures across businesses: owner-operators, marketing, RM, accounting, operations, sales, supply-chain, procurement, area managers, and front-line managers. Where possible, we interviewed several managers in a business to obtain a breadth of opinion and improve validation (H. Rubin & Rubin, 2005; Myers, 2009). A semistructured interview approach (C. Bailey, 2007) was adopted and respondents were encouraged to use their own terminology, which helped reveal common terms as well as the different ways key activities were conducted. Publicly available information was collected to help corroborate interview responses. Thematic analysis was used to integrate fieldwork interviews with the literature's four modules to develop our conceptual taxonomy (Lillis, 1999). Details of the fieldwork are available from the corresponding author.

Analysis began using a within-business focus to ensure that our conceptual taxonomy was able to comprehensively describe each firm's entire RM system. A key outcome was the refinement of the four modules into seven indicators, where each indicator is a uni-dimensional construct that measures a specific area of RM practice. The decomposition was required as our thematic analysis indicated the demand management, resource management, and data analysis and

Figure 1: Research method.



modeling modules each covered more than one area of RM practice. For example, demand management was found to encapsulate a firm's pricing philosophy and inventory restrictions. Hence, we divided the demand management module into two indicators—pricing-basis and inventory allocation—to achieve the uni-dimensional constructs needed for ordinal scales. Resource management was divided into product configuration and duration control, and data analysis and modeling into analytical approach and types of data. Data collection remained as originally defined but was renamed collection method for clarity.

We next conducted across-business analysis to form rankings for these seven indicators. For each indicator, we analyzed examples of practice from the literature and fieldwork to understand differences in the degrees of RM sophistication and intensity of use. The highest levels of practice were defined by recommendations in the literature, practices of the large fieldwork organizations, and interviewee responses on what they viewed as ideal RM practice. The lowest level of practice was defined by the "absence" of best practice and examples of simple RM practice. For example, RM advocates pricing by customer willingness to pay, hence we define the low-end of practice for the pricing-basis indicator as resource-based decision making, which prioritizes costs rather than willingness to pay.

Within-business and across-business analyses produced a set of seven indicators to capture RM, each with a single conceptual scale of practice. These were combined into a decision tree to calculate an overall classification score. The rationale for a decision tree approach instead of a simple sum of scores is based on propositions in the literature about what constitutes "higher" or "lower" levels of RM. For example, Talluri and van Ryzin (2004) state that high levels of RM are characterized by rigorous analytical processes, while Kimes and Chase (1998) argue that a firm's ideal mix of demand management and resource management strategies depends on its industry setting.

Stage 2: Confirming the Survey Instrument

Stage 2 operationalized the Stage 1 conceptual taxonomy into a survey instrument to ensure it appropriately captured the range of RM practices. We used four questions to measure each of the indicators, based on psychometric theory on reliability and factor analysis (Hinkin, 1998; Hair, Black, Babin, Anderson, & Tatham, 2006). Where possible, questions from existing survey instruments were used. Additional questions were developed as needed using fieldwork and the literature. The survey was pilot tested by 10 academics and 10 business staff, including one manager who participated in the fieldwork. Details of the survey instrument are available from the corresponding author.

Three mailing lists were used to reach a range of business sizes and industry types: a research organization, CFOs who were members of a professional accounting body, and university alumni. The research organization provided the majority of responses, although mainly in small businesses. Responses from larger organizations were received from the CFO and alumni groups. For confidentiality reasons, survey distribution was overseen by the mailing list owners. Distributors were asked to target individuals in positions of managerial responsibility or self-employment, using size and industry criteria. One follow-up was sent to the CFO group, with no follow-up permitted by the remaining two distributors. Preliminary factor analysis showed consistent factor structures between these groups. Accordingly, the samples were pooled to improve statistical power (Tabachnick & Fidell, 2007).

Table 2 compares the survey characteristics to the population for New Zealand (NZ) businesses. It shows the sample was representative of NZ businesses, indicating results offer direct generalizability and providing evidence against nonrespondent bias. The only major differences between the sample and population relate to

Table 2: Industry breakdown of survey sample and population of New Zealand firms.

	Survey		
Industry	Frequency	%	Population (2011)%
Accommodation	9	3.9	4.0
Administrative and support services	10	4.3	3.3
Agriculture, forestry, and fishing	16	6.9	15.9
Airline	1	0.4	[a]
Arts and recreation services	11	4.7	2.1
Car rental or other vehicle rental	3	1.3	[a]
Construction	28	12.1	11.0
Education and training	18	7.8	1.7
Electricity, gas, water, and waste services	5	2.2	0.2
Financial and insurance services	8	3.4	6.7
Health care and social assistance	1	0.4	3.8
Information media and telecommunications	6	2.6	1.1
Manufacturing	20	8.6	4.7
Mining	0	0.0	0.1
Professional, scientific, and technical services	35	15.1	11.0
Public administration and safety	1	0.4	0.3
Real estate services and property rental	3	1.3	21.4
Restaurants and cafes	10	4.3	[a]
Retail trade	28	12.1	5.8
Transport, postal, and warehousing	10	4.3	3.2
Wholesale trade	9	3.9	3.8
Total	232	100.0	100

[a]Separate industry category created based on revenue management literature.

(i) real estate services and property rental and (ii) agriculture, forestry, and fishing industries, which are underrepresented in the sample. There were 573 responses, received from the 2981 surveys distributed; a response rate of 19.2%. Responses were checked for nonqualifiers (e.g., not involved in RM decisions), incomplete surveys, flat-lined, or speeder responses (Dillman, 2000; Frazer & Lawley, 2000). This removed 341 responses, leaving a final sample of 232. No meaningful differences were found between early and late respondents. Following recommendations by Newman (2009) and Roth, Switzer, and Switzer (1999), missing value imputation procedures were applied. Five sets of imputations were produced and analyses were run on pooled results. Where pooled procedures were not available, analysis was run on each imputation set and results compared.

Variables from the survey were then mapped to the conceptual taxonomy to test construct validity. Exploratory factor analysis was used to generate alternative models to the theorized seven-indicator structure, and confirmatory factor analysis was used to compare alternative models. Analyses supported the seven-indicator structure and determined the survey questions to be used to measure the indicators.

Stage 3: Validation of Indicators and Decision Tree

Stage 3 comprised two steps to test the validity of the taxonomy (seven indicators and decision tree) developed in Stage 1 and populated with the variables for measurement in Stage 2.

First, a contingency theory approach was used to assess the discriminatory power of the taxonomy. Contingency theory examines how an object of interest is influenced by contextual factors external to the object of study (T. Burns & Stalker, 1961; Galbraith, 1973). The literature and fieldwork identified nine relevant contextual factors expected to influence RM practice: size, life cycle, competitive environment, customer segmentation, time sensitivity, varying demand, organizational structure, strategy, and industry. We tested the taxonomy by regressing the RM score, as calculated by the proposed taxonomy, against these contextual factors. The regression model was specified such that higher levels of contextual variables (e.g., greater rivalry in competitive environment) were expected to be related to higher levels of RM practice.

Second, we tested whether a decision tree structure added more explanatory power compared to a simpler, "sum of scores" approach, that is, where the RM score is the total of the seven individual indicator scores. Regression results using the sum of scores and contextual factors provided a baseline comparison. The decision tree structure was then added to this model to test the incremental explanatory power added by the structure.

As an additional test, we examined the association between our classification of RM practice and respondents' self-ranked measures of performance and decision-making confidence. Support for the taxonomy is obtained if higher levels of RM are associated with higher levels of performance.

FINDINGS

Stage 1: Conceptual Taxonomy of RM—Seven Indicators and a Decision Tree

Seven indicators of RM

Stage 1 analyses identified seven indicators were needed to capture the entire RM system: *pricing-basis*, *inventory allocation*, *product configuration*, *duration control*, *analytical approach*, *types of data*, and *collection method*. Table 3 summarizes the taxonomy and details the indicators, ordinal scale to measure practice from low to high levels of practice, and relationship to the original four modules. For each indicator, we present key features of variation to help describe differences in RM. For example, for the pricing-basis indicator, lower levels of RM practice employ resource-focused pricing, characterized by cost-based pricing, fixed or infrequent price changes, and pricing by regional segments. Higher levels of practice employ customer-needs focused pricing, characterized by pricing based on willingness to pay, daily price changes, and pricing that recognizes differences across individual customers.

Measuring a firm's practice along these seven indicators facilitates a richer description of differences. Within a firm, indicator levels are likely to be correlated as they are driven by context, for example, higher levels of pricing-basis are

Table 3: RM indicators.

Module	Indicator	Description	Key Features of Variation in Practice (from Low to High RM Practice)
Demand management	Pricing-basis	Factors used in setting prices and the objectives of pricing. Practices range from resource-focused pricing to customer-needs focused pricing.	• *Pricing-basis*: cost, competitor, customer • *Frequency of change*: fixed, seasonal, day-part • *Segmentation*: regional, customer groups, individuals
	Inventory allocation	Structures used to match the supply of goods or services to changes in demand. Practices range from *ad hoc* changes to systematic adjustments.	• *Granularity of change*: across-board, seasonal, individual product • *Update frequency*: after-problem response, one-off study, continuous • *Structure*: intuition, observation, policies, decision-rules
Resource management	Product configuration	Range of inputs and processes needed to provide the business's menu of products. Practices range from product configuration by physical differences to those built using non-physical differences.	• *Product aims*: *ad hoc* goals, marketing, customer segmentation • *Source of difference*: inherent differences, add-ons, terms/conditions • *Resource diversity*: unique resources, common resources, identical resources
	Duration control	Stabilising customer usage by reducing variation in the time it takes to service a customer or make customer arrivals more predictable. Practices range from those aimed at reactive improvements, to those aimed at stabilising usage of business capacity.	• *Process objectives*: fix problems, expedite all areas, reduce variation • *Response to variance*: ignore variation, respond to variation, stabilize behavior • *Approach*: manager intuition, formal policies, automation

Continued

Table 3: Continued

Module	Indicator	Description	Key Features of Variation in Practice (from Low to High RM Practice)
Data analysis and modeling	Analytical approach	Analysis done to inform demand management and resource management techniques. Practices range from intuitive analysis to computational approaches.	• *Analytical basis*: experience, frameworks or formulae, software • *Theoretical grounding*: atheoretical, demand drivers, OR/econometrics • *Formalization*: irregular or casual calculations, structured analysis
	Types of data	Range of data available and how it is used to inform analysis. Practices range from internal, aggregated data, to broad-scope, specific data.	• *Scope*: transactions only, product data and strategies, external data • *Aggregation*: periodic summaries (e.g. daily, weekly), transaction-level • *Categorization*: product types, time periods, customer identity
Data collection	Collection method	The way RM data are collected in the organization. Practices range from informal, experience-based data collection to formalized, continuous data collection.	• *Method*: unrecorded observation, manual collection, automated collection • *Sources*: third-party sources, ongoing transactions, purpose-collected • *Frequency*: one-off study, periodic collection, continuous

RM = revenue management.

with higher levels of inventory allocation. However, we consider the indicators to be conceptually independent as high levels in one indicator do not necessarily mean high levels in other indicators. For example, two airlines can actively manage demand (high levels of pricing-basis and inventory-allocation) informed by rigorous analysis (high analytical approach). However, their product configuration may differ significantly. One airline may segment the market using low cost rate fences, such as advanced purchase. The other airline may use higher cost points of difference such as first-class versus economy seats (inherent differences) or optional meals (add-ons).

In addition, the key features of variation were used to generate the survey of RM for Stage 2. For example, survey questions for pricing-basis were developed to cover the importance placed on cost, competitor, and customer; the frequency of change; and recognition of different segments. The score for each indicator was calculated as the mean of the associated questions, scaled from 1 to 4, and used in the decision tree to classify a firm's overall RM practice.

Decision tree

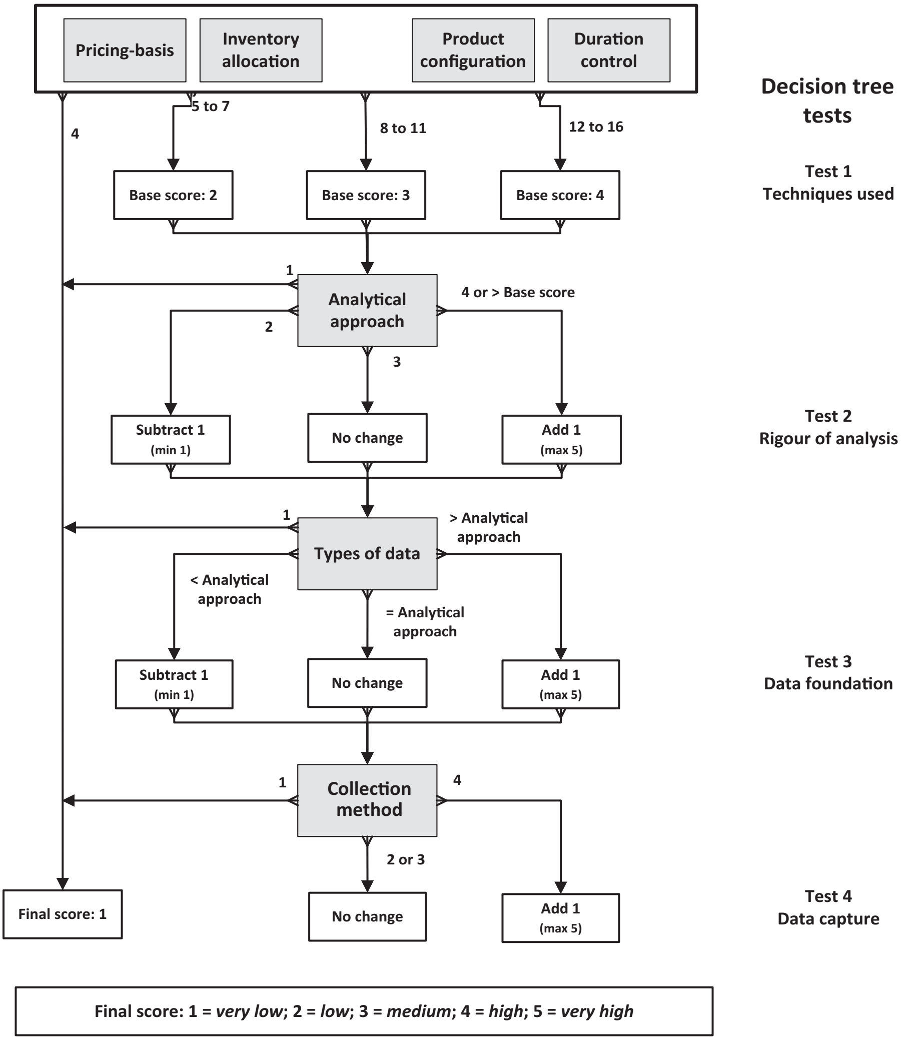
The conceptual taxonomy uses a decision tree to combine the seven indicators. Figure 2 shows how the decision tree combines the scores by applying four tests. These tests are based on the literature dealing with trade-offs between indicators, recommended levels of analysis, and the relative scarcity of sophisticated RM practices. The decision tree produces a classification along a continuum of very low, low, medium, high, and very high RM practice, labeled 1 to 5, respectively. Higher categories reflect an emphasis on analysis and comprehensive data. Lower categories reflect an emphasis on manager experience and intuition.

Test 1 starts with the four indicators located at the top of the tree. This embodies the two main areas of RM strategy use noted by Kimes and Chase (1998): demand management represented by pricing-basis and inventory allocation, and resource management represented by product configuration and duration control. These four indicators are combined in a single test based on arguments that different practices, and hence individual indicators, may be more or less important in different settings (Kimes & Chase, 1998; Shields, 2006a). Combining the scores provides a simple way of recognizing different priorities without weighting any particular technique too strongly. Test 1 produces a base score, which is adjusted by the remaining tests. This can involve a change up or down by one classification (e.g., from low to medium), be unchanged, or end testing for the business (classifying the business as having very low practice). This method follows the literature and was based on recommended minimum levels of analysis in RM and to calibrate the classification on the empirical scarcity of sophisticated RM practice (Cross, 1997a; Talluri & van Ryzin, 2004).

Test 2 examines the rigor of analysis as captured by the score for analytical approach. A business's analytical approach must align with the level of techniques used (Arthur Andersen, 1997; Kroll, 1999); more sophisticated techniques require more rigorous analysis (Talluri & van Ryzin, 2004).

Test 3 examines the range of data available and how it influences analysis. Businesses can conduct better demand analysis with detailed data, collected

Figure 2: Decision tree to classify revenue management.



regularly. This test compares the scores for types of data and analytical approach recognizing data requirements differ depending on the firm's analytical approach (Kimes, 1989; Maguire & Rouse, 2006).

Test 4 examines the regularity and completeness of data collection and checks for extremes in practice. If data are collected irregularly or records are incomplete (i.e., *collection method* = 1), then there is insufficient guidance for RM decisions (Kimes, 2004) and the business is classified as having very low RM. In contrast, continuously updated data collected using fully computerized systems (i.e., *collection method* = 4) suggests very high RM (Arthur Andersen, 1997; Talluri & van Ryzin, 2004).

We illustrate the decision tree and four tests using a fieldwork example (*Retailer*). *Retailer* yielded seven indicator scores describing their RM practice: *pricing-basis* = 2, *inventory allocation* = 3, *product configuration* = 2, *duration control* = 1, *analytical approach* = 2, *types of data* = 3, and *collection method* = 2. Details about *Retailer* and the basis for selecting the scores is available from the corresponding author.

Test 1 sums the scores for the demand management and resource management techniques used in the business; *pricing-basis* (2), *inventory allocation* (3), *product configuration* (2), and *duration control* (1). The total (8) is used to assign a base score of 3 for *Retailer*, which is modified by subsequent tests. The base score was determined as follows, the cut-offs were calibrated using survey findings to obtain an even spread of firms across the four possible base score classifications:

Total 4: Base score = 1 (very low)

Total 5 to 7: Base score = 2 (low)

Total 8 to 11: Base score = 3 (medium)

Total 12 to 16: Base score = 4 (high)

Test 2 examines the rigor of analysis and modifies the base score as follows:

Analytical approach = 1: End testing (classification = very low)

Analytical approach = 2: Subtract 1 from base score (minimum 1)

Analytical approach = 3: No change

Analytical approach = 4 or > base score: Add 1 to base score (maximum 5)

Retailer had a score of 2 for *analytical approach*. Therefore, 1 was subtracted from the base score, giving a score of 2 at the end of Test 2. The purpose of adding or subtracting is to shift a business's classification up or down a level. *Retailer's* demand management and resource management practices were supported by relatively simple levels of analysis, suggesting a low level of practice. In contrast, if the business' *analytical approach* score is higher than the base score, 1 would be added to the base score to reflect a narrow set of techniques used at a high level of sophistication.

Test 3 examines the quality of data which inform analysis as follows:

Types of data = 1: End testing (classification = very low)

Types of data < *Analytical approach*: Subtract 1 (minimum 1)

Types of data = *Analytical approach*: No change

Types of data > *Analytical approach*: Add 1 (maximum 5)

Retailer had a score of 3 for *types of data*; a higher score than for *analytical approach* (2). Therefore, 1 was added giving a score of 3 at the end of Test 3. This offsets the adjustment in Test 2 recognizing that, at *Retailer*, manager's judgment is supported by in-depth data.

Table 4: Goodness-of-fit statistics.

Item	Criteria	Model 1	Model 2	Model 3
χ^2 (df)	Smaller the better	408.82 (252)	441.1 (258)	399.53 (246)
χ^2/df	< 2	1.62	1.71	1.62
AIC	Smaller the better	554.8	575.1	557.5
Tucker-Lewis index	$> .90$	.91	.90	.91
Comparative fit index	$> .90$	.93	.91	.93
Root mean square error of approximation	$< .06$	.052	.055	.052
Standardized root mean square residual	$< .08$	.056	.063	.055

Test 4 uses the score for *collection method* to assess the data collection as follows:

Collection method = 1: End testing (classification = very low)

Collection method = 2 or 3: No change

Collection method = 4: Add 1 (maximum 5)

Retailer had a score of 2 for *collection method.* Accordingly, *Retailer*'s final score remains at 3, classifying it as practicing medium RM.

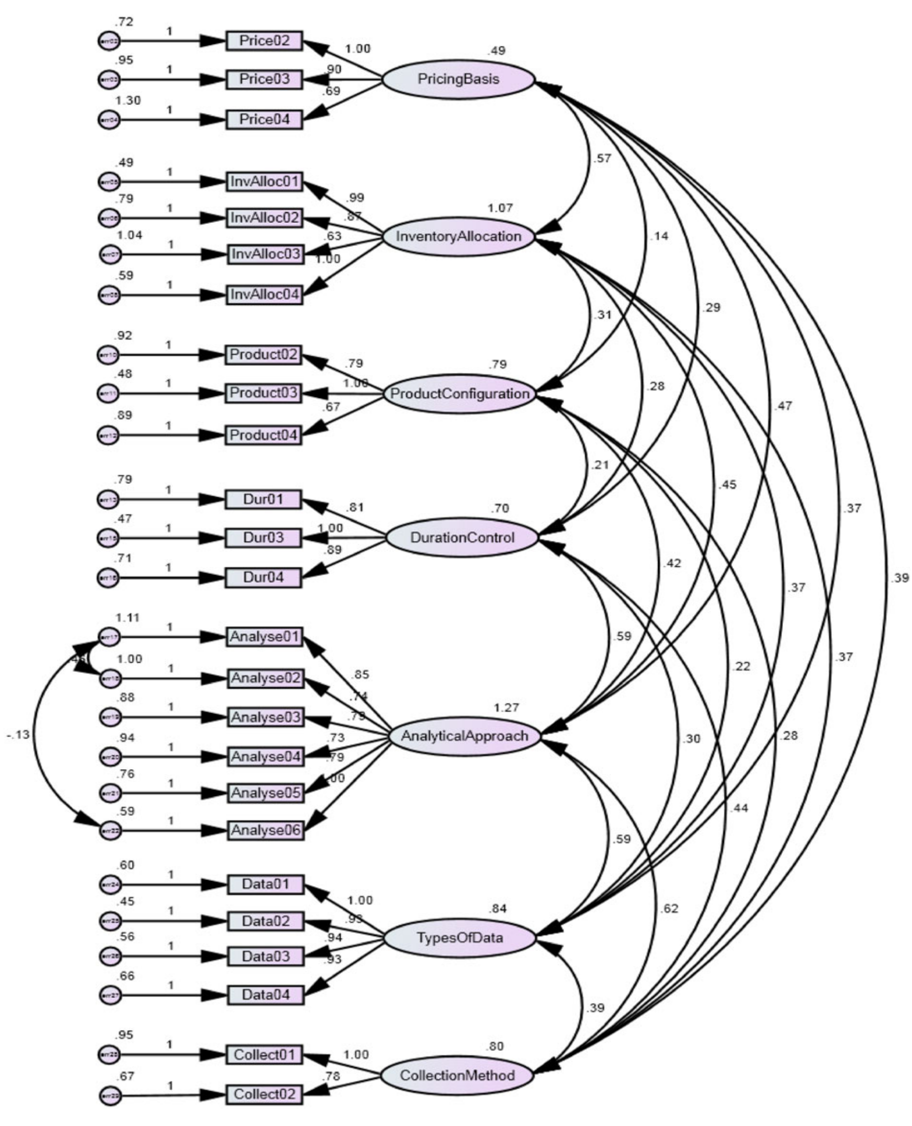
In summary, the conceptual taxonomy and decision tree extend the partial, technique-specific attempts of classification developed in the literature, resulting in a more comprehensive classification system.

Stage 2: Confirming the Survey Instrument

Stage 2 analysis began with exploratory and confirmatory factor analyses to test the seven-indicator structure. First, exploratory factor analysis was used to identify groups of associated variables, thus providing a data-driven approach to identify potential factor structures (Hair et al., 2006). The exploratory factor analyses (untabulated) identified three alternative factor structures: Model 1 used the theorized seven-indicator structure developed in fieldwork; Model 2 used six indicators, combining pricing-basis and inventory allocation into a single indicator with the remaining indicators unchanged; Model 3 used eight indicators, splitting analytical approach into two indicators with the remaining indicators unchanged. Other alternative factor structures were tested, and were rejected as they performed poorly compared to the first three.

Second, confirmatory factor analysis was used to refine the models by removing variables that did not load onto their associated factor and adjusting for measurement error. We assessed the goodness-of-fit between the survey data and alternative factor structures to determine which model best described the data (Hair et al., 2006). Table 4 shows the results for the three factor structures.

Figure 3: Model 1 structure with results.



The base model, Model 1, provided the best fit on the basis of goodness-of-fit statistics and the literature. It had the lowest Akaike information criterion and exceeded all recommended cut-off criteria, indicating a strong degree of fit between the data and theorized structure. Figure 3 shows the results of the final structure of Model 1.

Table 5 reports the final variables in the taxonomy, listing the variable name, question items, reliability statistics (α), and confirmatory factor analysis statistics. The regression weights shown were all statistically significant ($p < .01$),

Table 5: Final set of variables used in taxonomy.

Variable	α	Item	S.RW	U.RW	SE
Price02	0.52	We always change our prices in response to competitor price movements	0.64	1.00	
Price03		Even if costs are unchanged, we regularly revise our prices according to projected demand	0.54	0.90	0.14**
Price04		We price our products or services differently for different customer segments	0.39	0.69	0.14**
InvAlloc01	0.81	When we are busy we reserve products or service capacity for customers willing to pay a higher than average price	0.83	0.99	0.08**
InvAlloc02		We offer a "last minute" discount for products or services which would otherwise be unsold or when we would otherwise be idle	0.71	0.87	0.08**
InvAlloc03		Rules have been set regarding how our prices or available offerings should change according to expected demand	0.54	0.63	0.08**
InvAlloc04		We charge higher prices or change our available offerings during times of high demand	0.80	1.00	
Product02	0.66	We try to limit the number of products or services that are very different from other products or services we sell	0.59	0.79	0.13**
Product03		We often create new product offerings by bundling together existing offerings	0.79	1.00	
Product04		We target specific products or services to certain customer segments	0.54	0.67	0.11**
Dur01	0.72	We monitor the extent to which staff follow established operating processes	0.61	0.81	0.11**
Dur03		Actions are taken to make customer behaviour more predictable	0.77	1.00	
Dur04		A lot of effort is spent to reduce the time it takes to serve a customer without affecting their experience	0.66	0.89	0.11**
Analyse01	0.86	Computer modeling or computer simulation tools	0.67	0.85	0.09**
Analyse02		Mathematical analysis or other formulae	0.64	0.74	0.08**
Analyse03		Scenario modeling ("what if" analysis)	0.69	0.79	0.07**
Analyse04		Historic trends	0.65	0.73	0.07**
Analyse05		Questionnaires or focus groups	0.71	0.79	0.07**
Analyse06		Comparisons or benchmarking	0.83	1.00	
Data01	0.84	The size of our target markets and customer demographics	0.76	1.00	
Data02		Why customers buy our product or service	0.78	0.93	0.08**
Data03		How much customers would pay for our products or services—their price sensitivity	0.75	0.94	0.09**
Data04		Competitors' products or services, pricing, strategies, and strengths	0.72	0.93	0.09**
Collect01	0.60	A lot of our sales data are automatically recorded using a computer with very little manual staff input	0.68	1.00	
Collect02		Our decision making relies on data records rather than manager experience	0.65	0.78	0.12**

S.RW. = standardized regression weights, U.RW. = unstandardized regression weights, SE = standard error of unstandardized regression weights.
**Significant at 1%.

Table 6: Descriptive statistics—RM.

Indicator	Variable	Mean	*SD*	Min–Max
Pricing-basis	Pricing	2.96	0.84	1–5
Inventory allocation	InvAlloc	2.44	1.00	1–5
Product configuration	Product	3.15	0.89	1–5
Duration control	Duration	3.32	0.89	1–5
Analytical approach	Analysis	2.84	1.02	1–5
Types of data	Data	2.56	1.01	1–5
Collection method	Collect	3.21	0.95	1–5
Overall score	TreeScore	2.17	1.30	1–5

RM = revenue management.

providing strong support for the model. Cronbach's alpha provided an assessment of reliability. Alpha levels of .6 (Hair et al., 2006) and .7 (Cortina, 1993; Hinkin, 1998) are the most commonly recommended minimum alpha scores. All indicators were above .6 except pricing-basis, which was only above .5—a level suggested as acceptable for exploratory studies such as this study (Nunnally, 1967).

Stage 3: Validation of Indicators and Decision Tree

The taxonomy structure was applied to the survey data to obtain indicator scores and an overall score of RM practice for each respondent. Indicator scores were calculated as the mean of all related questions included in the model; for example, the pricing-basis score is the mean of Price02, Price03, and Price04. Overall scores were calculated by scaling responses to a four-point scale and then applying the decision tree method to the seven-indicator scores. This provided a score out of five for each business in the survey.

Descriptive statistics for indicator scores and the decision tree score are summarized in Table 6. Results show a variety of RM practices were captured, with firms classified across all levels of RM. The decision tree and indicator scores all showed a high standard deviation (from 0.84 to 1.30) and covered the full range of responses (1–5 for all scales). The spread of scores across the range from 1 to 5 suggests that our taxonomy captured a continuum of practice as some firms were ranked at each level of practice.

A validation model was developed to assess the theoretical consistency and discriminatory power of the taxonomy. The model tested the relationship between the overall score calculated, and contextual factors selected from the literature and fieldwork as follows.

First, size was included as expensive analytical tools and dedicated RM staff are not generally available to smaller businesses. Size is measured using the number of staff, with turnover included as a robustness test. Second, life cycle was included as organizations in growth phases are likely to lack historical data to support RM analysis (Talluri & van Ryzin, 2004). Manager attention may also be focused on developing organizational processes (Gupta & Govindarajan, 1984) and so may deemphasize RM techniques. Mature firms, in contrast, are expected to place a stronger emphasis on maximizing revenue from current operations. Third, competitive environment was included because RM is often driven by growing competition in an industry (Boyd, 2007). Fourth, customer segmentation was included as clearly defined segments allows for pricing based on willingness to pay, facilitating demand management (Kimes, 1989). Differentiated market segments also provide opportunities to create targeted products. Fifth, time sensitivity was included as it relates to the perishability of product offerings—the speed with which the value of a finished good or unit of service capacity diminishes over time. Time sensitivity encourages organizations to use dynamic pricing and inventory allocations to prevent a loss of value (Weatherford & Bodily, 1992). Sixth, varying demand was included to capture variation in demand relative to a firm's ability to supply products. In times of high demand fluctuations, there is incentive to adopt higher levels of demand management and resource management (Boyd, 2007). Seventh, organizational structure was included because centralized decision making and formalized structures require increased analytical rigor and communication to effectively understand demand trends and disseminate decisions. Eighth, strategy was included as it affects the level of hostility and uncertainty in the operating environment (Chenhall, 2007). Strategies characterized by greater risk and change in operations can expose the organization to greater environmental uncertainty. Based on findings regarding the competitive environment, firms pursuing these strategies may practice higher levels of RM. Strategy is measured using narrative descriptions (James & Hatten, 1995) based on Miles and Snow's (1978) prospector, analyzer, defender, and reactor classification. Analyzers are the baseline comparison, with dummy variable for prospectors, defenders, and reactors. Last, industry was included as certain industries have been associated with higher levels of RM. Dummy variables were used for "traditional" RM and goods-based industries, with service organizations as the baseline comparison. Compared with service organizations, traditional industries were expected to have higher RM scores, while goods-based businesses were expected to have lower scores.

Table 7 describes how these contextual factors were operationalized, along with descriptive statistics. The model is specified such that higher levels of contextual factor variables (e.g., greater rivalry in competitive environment) are expected to relate to higher levels of RM practice. New measures were developed for customer segmentation and varying demand. Caution must be exercised in interpreting results for these measures as the Cronbach's alpha (Table 7) were below recommended cut-offs of .5 (Nunnally, 1967). A review of the data confirmed that these scores were driven by multidimensionality in the measures and the smaller number of variables used to measure the construct (Schmitt, 1996; Sijtsma, 2009).

An OLS regression was run to determine the significance of the nine contextual factors in relation to the RM scores ("TreeScore"). The regression model used the scores calculated from the survey results combined using the decision tree as follows:

$$\mathit{Tree\,Score} = f\,(\mathit{Staff}, \mathit{Age}, \mathit{Comp}, \mathit{Sort}, \mathit{Time}, \mathit{Vary}, \mathit{Org}, \mathit{Prospector}, \mathit{Defender}, \mathit{Reactor}, \mathit{Goods}, \mathit{RM}),$$

where TreeScore is the score calculated for each respondent in the survey using the decision tree; Staff is the size proxy measured by the number of staff; Age is the life cycle proxy measured by the age of the company; Comp is the measure of the

Table 7: Contextual factor descriptive statistics.

Size (Staff)			
Group	Count	Group	Count
No additional staff hired	66	50–99	10
1–9	101	100–249	10
10–19	12	250–499	13
20–49	11	500+	9
Size (Turnover)			
Less than \$200k	107	\$5m–\$50m	27
\$200k–\$500k	31	\$50m–\$500m	16
\$500k–\$2m	37	\$500m–\$1b	0
\$2m–\$5m	12	\$1b or more	2
Life Cycle (Age)			
Less than 2 years	25	10–20 years	49
2–5 years	34	20–40 years	38
5–10 years	57	40 + years	29

Competitive Environment (Comp)			
Customer preferences or required features change very quickly in our market	**Mean**	***SD***	**Max–Min**
Competitor products and services change very quickly in our market	3.44	0.91	1–5
There are many promotion wars in our market	**Alpha = .747**		
Price competition is a major feature in our market			
Customer Segmentation (Sort)			
Customers often place orders or bookings well before the date of delivery or consumption	**Mean**	***SD***	**Max–Min**
It is easy to limit the number of customers who can buy at a discount price	3.57	0.81	1–5
We can easily categorize our customers into different groups	**Alpha = .468**		
Time Sensitivity (Time)			
Our finished product or service cannot be stored, or can only be stored at significant cost	**Mean**	***SD***	**Max–Min**
We can either stockpile our product or queue up our customers for service	2.97	1.02	1–5
It is difficult to match our product or service availability with customer demand	**Alpha = .525**		
Varying Demand (Vary)			
It is very expensive to increase our capacity	**Mean**	***SD***	**Max–Min**
Once a certain number of units are sold, it does not cost much more to sell another unit.	3.53	0.71	1–5
We experience wide seasonal variation in customer demand	**Alpha = .396**		
There are periods when we have too much capacity and periods when we have too little capacity			

(Continued)

Table 7: Continued

Organizational Structure (Org)			
In this organisation, very few actions are taken without the approval of a supervisor	**Mean**	***SD***	**Max–Min**
Duties, authority, and accountability of personnel are documented in policies, procedures, or job descriptions	3.28	1.16	1–5
Written procedures and guidelines are available for most work situations	**Alpha = .760**		

Strategy			
Group	Count	Group	Count
Prospector	36	Reactor	30
Analyser	94	Missing	6
Defender	66		

Industry			
Group	Count	Group	Count
Traditional (RM)	13	Goods-based (Goods)	101
Service	118		

RM = revenue management.

level of competition; Sort is the measure of the level of customer segmentation; Time is the measure of the time sensitivity of products or services; Vary is the measure of varying demand; Org is the measure of the organizational structure; Prospector, Defender, and Reactor are the measures of business strategy; Goods is the measure of whether the respondent is in a goods-based industry; and RM is the measure of whether the respondent is in one of the traditional RM industries.

Table 8 shows the regression results. These support the use of the taxonomy for measuring RM as the contextual factors explained a significant level of variation in the TreeScore classifications. Adjusted R^2 was .372 and almost all coefficients had the expected sign, with several significant at the $p < 0.01$ level: size (Staff), competitive environment (Comp), customer segmentation (Sort), and organizational structure (Org). Nonsignificant variables were in the correct direction, with the exception of the age of the firm. This indicated that the TreeScore captured variations in RM practice as predicted in the literature. Given the directional relationships were found when simultaneously examining a diverse set of contextual factors, these findings are unlikely to be driven by a single underlying relationship.

An additional test investigated the explanatory power of the decision tree against a sum of scores approach that added the seven-indicator scores together. This assessed the benefit of using a structured approach over a naïve, unstructured approach. The decision tree structure was tested by examining

Table 8: RM score validation.

Variable	Expected Sign	*B*	*SE*	*t*	Sig.[a]
(Constant)		−1.58	0.58	−2.74	0.01
Staff	+	0.21	0.04	4.93	0.00**
Age	+	−0.10	0.06	−1.79	0.04*
Comp	+	0.26	0.08	3.21	0.00**
Sort	+	0.29	0.09	3.27	0.00**
Time	+	0.01	0.07	0.19	0.43
Vary	+	0.15	0.10	1.43	0.08*
Org	+	0.34	0.06	5.45	0.00**
Prospector	?	0.40	0.20	1.96	0.05*
Defender	?	−0.20	0.17	−1.15	0.25
Reactor	?	0.20	0.23	0.86	0.39
Goods	-	−0.10	0.15	−0.66	0.25
RM	+	0.35	0.31	1.13	0.13

RM = revenue management, Dependent variable: TreeScore; Adjusted R^2 = .372; *F*-test (Sig) = 11.96 (.00).
[a]Significance is reported at the one-tailed level when there is an expected sign. Otherwise, two-tailed significance levels are reported.
**Significant at 1%.
*Significant at 10%.

the incremental change in explanatory power over the sum of scores measure when adding the four decision tree tests. The baseline regression for this test was:

$$SumScore = f\,(Staff, Age, Comp, Sort, Time, Vary, Org, Prospector, Defender, Reactor, Goods, RM)\,,$$

where SumScore is the sum of scores measure created in the preceding section, and the dependent variables are those identified previously. To this baseline regression, the four tests from the decision tree were added in turn to assess the change in explanatory power. Test 1 is the RM techniques used, Test 2 is the rigor of analysis, Test 3 is the data foundation, and Test 4 is data capture. The model adds the incremental effect of each test.

Conceptually, each test is expected to “refine” the sum of scores measure to align with literature expectations. For example, for Test 1, which is the base score as calculated by the decision tree, the regression model is modified as follows:

$$SumScore = f\,(Staff, Age, Comp, Sort, Time, Vary, Org, Prospector, Defender, Reactor, Goods, RM, Test1)\,.$$

Table 9 shows the results of this analysis, reporting the change in adjusted R^2 separately for each test.

Results show a large improvement in the adjusted R^2 for all decision tree tests, indicating that the decision tree structure offers additional explanatory power over the unstructured sum of scores approach. Test 1 (techniques used) adds the greatest improvement in adjusted R^2. This reflects the nature of the test, which provides the base score that is modified in the subsequent tests. We conducted two split-sample analyses (untabulated) to validate these tests, being (i) split-sample

Table 9: Regressions assessing taxonomy structure.

			Decision Tree Tests							
	Sum of Scores Only		Test 1		Test 2		Test 3		Test 4	
Variable	*B*	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
(Constant)	3.28	.03	−1.70	.16	6.42	.00	3.85	.01	5.16	.00
Staff	0.44	.00	0.43	.00	0.23	.02	0.44	.00	0.32	.00
Age	−0.25	.04	−0.18	.06	−0.18	.08	−0.25	.04	−0.16	.11
Comp	1.04	.00	0.47	.00	0.77	.00	1.08	.00	0.97	.00
Sort	0.84	.00	0.43	.01	0.69	.00	0.83	.00	0.67	.00
Time	0.25	.09	0.15	.14	0.34	.03	0.23	.11	0.25	.08
Vary	0.79	.00	0.31	.06	0.76	.00	0.75	.01	0.61	.01
Org	0.82	.00	0.52	.00	0.64	.00	0.74	.00	0.80	.00
Prospector	1.09	.04	0.73	.07	0.70	.15	1.02	.05	1.12	.02
Defender	−0.07	.89	0.31	.37	0.12	.77	−0.14	.75	0.17	.68
Reactor	−0.06	.92	0.23	.60	−0.18	.74	−0.01	.99	0.09	.87
Goods	−0.40	.15	−0.08	.39	−0.12	.37	−0.38	.16	−0.23	.26
RM	0.95	.12	0.24	.35	1.09	.07	0.83	.15	1.01	.09
Test 1			**3.64**	**.00**						
Test 2					**0.29**	**.00**				
Test 3							**0.18**	**.01**		
Test 4									**0.29**	**.00**
Adj. R^2	.409		.668		.521		.432		.504	
F-test (Sig)	13.69 (.00)		35.88 (.00)		19.14 (.00)		13.88 (.00)		18.24 (.00)	

RM = revenue management.

Table 10: Correlations between RM practice and performance measures.

	Performance				Decision-Making Confidence		
Variable	**PSales**	**POverall**	**PCust**	**PPrice**	**ConfProd**	**ConfCust**	**ConfCap**
TreeScore	.178** (.01)	.207** (.00)	.257** (.00)	.256** (.00)	.316** (.00)	.265** (.00)	.282** (.00)

RM = revenue management.
**Significant at 1%.

validation for multiple regression and (ii) holdout validation. We used an 80–20 split for both analyses, these tests confirmed that the decision tree structure added value over a naïve sum of scores approach.

As an additional robustness test, we examined the association between the level of RM practice and measures of performance and decision-making confidence. Performance was measured using four self-ranked measures, ranking perceived performance over the last 12 months compared to similar organizations: sales volume in dollars (PSales), overall financial performance (POverall), perceived increases in the customer base for the firm's products and services (PCust), and perceived increases in the amount current customers pay for the firm's products and services (PPrice). Decision-making confidence was measured using three self-ranked measures: confidence in choosing which products to "push" to maximize revenue (ConfProd), confidence in maximizing the revenue earned from their existing customer base (ConfCust), and confidence in maximizing the revenue earned from existing capacity (ConfCap). Table 10 reports correlations between the performance and decision-making confidence measures and the level of RM practice (TreeScore). Statistically significant, positive correlations were found for all comparisons. Results suggest higher levels of RM were associated with improved perceived performance and increased decision-making confidence. This supports the validity of our taxonomy.

DISCUSSION AND CONCLUSION

This research used fieldwork interviews to investigate the different ways firms practiced RM and the interactions among various techniques, thus providing a conceptual foundation for our taxonomy. A survey was then used to validate our conceptual taxonomy, translating the qualitative taxonomy into a quantitative taxonomy. Exploratory and confirmatory factor analyses were used to evaluate the goodness-of-fit of various measurement models. Findings supported the use of our seven-indicator structure and identified the survey variables to use. This was a crucial step in translating internal validity (from the fieldwork) into external validity (from multiple survey responses). The taxonomy was validated using contextual factor variables from a contingency theory perspective, and self-ranked measures of performance. Regression results showed our RM measure corresponded with almost all contextual factor variables, possessing the correct directional influence with statistically significant results for most variables. Analysis also supported the decision tree structure used in our taxonomy, showing a significant improvement in explanatory power compared to when no structure is imposed. The resulting taxonomy hence provides a suitable approach for measuring differences in individual indicators and the overall level of RM practice.

Survey results also provide initial insights into common areas of strengths and weaknesses in RM practice. The majority of respondents were categorized as very low RM practice. The significant and positive associations between RM practice and performance indicate opportunities to improve a firm's RM practice and performance. Low rankings were mainly driven by early termination in the decision tree, where the firm was classified as having very low RM by scoring a 1 in any of Test 2, 3, or 4. This result was expected, given that small businesses made up a large proportion of the sample and were expected to have lower levels of RM given limited resource availability. Accordingly, these respondents were more likely to indicate a low level of practice for *analytical approach*, *types of data*, and/or *collection method*.

Considering the seven indicators, *Duration controls* had the highest mean and a comparatively low standard deviation. This highlights a strength in practice where control procedures are relatively well understood. In contrast, *inventory allocation* had the lowest mean score and a comparatively high standard deviation. This suggests that *inventory allocation* is generally practiced at a lower level than *duration controls*, but with greater variation in practices. Lower levels of responses were also found for *analytical approach* and *types of data*, consistent with expectations in the literature that relatively few firms practice rigorous analysis when making RM decisions (Cross, 1997a).

Regression results showed coefficients for the industry variables were consistent with the expected direction. Firms in industries traditionally associated with RM reported higher levels of practice than other service organizations. Although service organizations report higher levels of RM than goods-based organizations, differences were not statistically significant. We speculate this is due to significant variation in RM practice between industry leaders and standard practice, signaling opportunities for knowledge transfer within industries. Contrary to expectations, age of the firm was found to have a statistically significant, negative association with RM practice. This suggests possible barriers of RM for mature organizations that do not have a history of RM practice. Time sensitivity is a commonly cited RM precondition but was not found to have a statistically significant effect on practice. Other preconditions—ability to segment customers, and varying demand—appear to have greater importance.

Our findings signal several areas for future research. There are opportunities to develop simpler RM analytical approaches for use by smaller businesses as well as mature businesses in industries not traditionally associated with RM. The measures developed in this study could be used to explore theories about where RM is appropriate. For example, our findings support theoretical predictions that RM is practiced to a greater extent in industries where prices are variable and customer duration is predictable. Further research could investigate whether the lists of preconditions prevalent in the literature are meaningful predictors of RM practice. Additional research is needed to understand the relationship between contextual factors and RM. The results of the survey show that RM practices generally increase in sophistication when the contextual factors are present, with age as an unexpected exception. However, as the contextual factor variables were used solely for validation in this study, future research is needed to explore these relationships further. Research could also investigate the significant associations found between self-ranked performance and decision-making confidence, to examine which parts of RM have the strongest impact on performance.

There are limitations to this study. First, commercial sensitivity around firms' RM practices meant that we could not obtain access to certain business settings. Accordingly, certain practices incorporated in the taxonomy were not directly observed during our fieldwork. For example, large hotel chains commonly use centralized RM practices. This differs from the practices of *BigStay* (who use decentralized decision making) as well as that of *SmallStay* and *MediumStay* (standalone properties). The focus on NZ businesses excludes very large, multinational organizations. While the survey considers variations in size, the sample is dominated by small firms. Validation procedures also relied on contextual factors which have not been thoroughly examined in the literature. Fieldwork was used to inform the relevant contextual factors and questions from existing literature were used when possible. Notably, when drawing insights into the effects of context on RM the results for customer segmentation and varying demand must be treated with caution. These have been retained in the validation analysis due to their importance in the literature and this is the first attempt to measure their effect.

In conclusion, we provide a comprehensive taxonomy to classify RM practice. A multimethod approach was used to develop this taxonomy, involving case studies and a survey. We classify RM practice using seven indicators, being *pricing-basis*, *inventory allocation*, *product configuration*, *duration control*, *analytical approach*, *types of data*, and *collection method*. Qualitative and quantitative scales were developed for each indicator, allowing for description as well as measurement of various aspects of a business's RM practice. A decision tree method was developed using these scores to classify RM practices from very low to very high groups. Such an approach was used to recognize trade-offs between different activities in the business and overcome bias toward specific techniques. Our taxonomy provides a new, comprehensive picture of RM, thus enabling a more accurate assessment of the landscape of practice. We hope that these indicators, decision tree, and survey instrument will provide valuable foundations for future research into the practice, adoption, and impact of RM.

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APPENDIX

CASE STUDY SITES

Airline is a commercial carrier serving international and domestic routes. It is the largest organization investigated here with over 2000 staff employed. *Airline* serves both premium and low cost markets.

BigStay is a budget accommodation chain with more than 50 properties throughout NZ. It is affiliated with an international brand but is free to make its own strategic and day-to-day management decisions.

MediumStay is a 125-room serviced apartment located in Auckland City Central. It serves a mix of hotel guests, long-term leases, and privately owned units. Strategically, *MediumStay* serves a middle-of-the-line price point.

SmallStay is a 15-unit beachside motel in an Auckland suburb. It is owned by an overseas investor who delegates day-to-day management to a team of two managers. *SmallStay* serves a premium market.

BigFood is the NZ arm of an international fast food brand. It has more than 70 restaurants around the country. While a part of an international franchise, *BigFood* management is relatively free to make strategic and day-to-day management decisions within broadly prescribed limits.

SmallFood is a standalone Malaysian restaurant owned by a husband and wife team. It seats a maximum of 36. The owners have held managerial and head-office positions at several international fast food chains. *SmallFood* is the fifth restaurant they have set up and is the only one they currently manage.

Retailer is a standalone entertainment store focused on the second-hand market, supplemented with an in-depth range of new product. It sells a range of music formats, gaming formats, clothing, and books. *Retailer* is run by two owner/operators who oversee 27 staff members.

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