Integrating Data-Driven Decision-Making in the Egyptian Hotel Industry: Revenue Management Perspective

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Abstract

This study presents a new model of intelligent pricing that concentrates on using data-driven decision-making (DdDM) as a new approach to hotel revenue management **(**RM). The study aims to assess the role of DdDM in leveraging hotel RM. The results were divided into three main parts. *First*, the findings indicated that (traditional data) observations, focus groups and structured interviews achieved the highest manager perceptions degrees, respectively. It is noted that (Digital data) electronic surveys, search engine queries and click stream approximately represent high degrees of perception, respectively. Eye-tracking data represents higher degrees of perception than facial electromyography one. *Second*, transactional, historical and marketing data approximately represent high degrees of manager perceptions, respectively. Also, hotel distribution sources revealed of the approximately perception to all sources. It was noted that hotel Res centers, integration with Res system, global distribution system and hotel website represent the highest degrees, respectively. *Third*, there was no significant relation between sources of data and using data-driven decision-making. On the other hand, the types of data, hotel distribution sources and managers' concerns about DdDM have positive and moderate relations with using DdDM. The results showed also, in line with expectations, a significant and positive correlation between using DdDM as an intermediate variable and pricing decisions.

Keywords: Data-Driven, Decision-Making, Revenue Management, Hotel Industry.

Introduction

RM is a new approach which aims to maximize company profit and customer satisfaction through efficient price and capacity management. RM provides both strategic and operational decision-making support with regard to pricing, inventories and customer management, which is especially useful for companies with limited capacity, such as hotels (Talón-Ballestero *et al.,* 2014). A successful revenue manager should have technological, analytical and communication abilities, an understanding of analytical pricing models and a command of social media technologies (Kimes, 2011). An RM model can be considered as an implementation tool to support a customer-oriented pricing strategy, which provides rules and boundaries for this optimization. A well-engineered RM model for optimizing hotel pricing should have enough rules to ensure the competitiveness of the price offered to the customer (Butscher *et al.,* 2009).

The term Data-driven Decision Support System (DdDSS) refers to a system that emphasizes access to, and manipulation of, a time-series of internal company data and sometimes external data. DdDSS should have an easy and rapid access to a large amount of well-organized multidimensional and valid data (Power, 2002). A major advance in technical capabilities for DdDSSs occurred with the introduction of Online Analytical Processing (OLAP). "*OLAP is made up of numerous, speculative "what-if" and/or "why" data model scenarios executed within the context of some specific historical basis and perspective. OLAP systems were characterized by: multidimensional conceptual view; link to a variety of data sources; easy for users to access and understand; multi-user support; intuitive data manipulation; flexible reporting; and analytical capabilities"* (Codd *et al.,* 1993, *P.12*). Depending on the internet, DdDSS with OLAP provide the highest level of functionality because it is linked to a large collection of company historical data, especially important for hospitality organizations (Power, 2002).

There are two features that characterize this study. First, it covers a wide range of RM leverage issues whereas previous papers focused on particular issues. Second, the study surveys a model of intelligent pricing that concentrates on using DdDM as a new approach to hotel RM. So the study aims to: identify different sources, types and distribution methods of data inputs that are used by revenue managers in hotels; assess the relation between the different sources, types and distribution methods of data inputs and efficiency of DdDM; assess the relation between revenue managers' concern and using DdDM; assess the relation between using DdDM and the output of intelligent pricing.

Literature

Using data driven decision-making

Data-driven decision-making (DdDM) takes into account relevant, cultural and institutional factors, such as: data quality; calibration; principal leadership; involvement; collaboration (Kim, 2012). These factors can be identified as follows:

- Data quality requires high quality and precise data. It gives the accompanying data to managers and policy makers.
- Calibration characterized as collective reflectivity or thought is consolidated with how managers characterize indicator use, how showing behavior under these definitions, how they assess, and how they respond to results (Young, 2006).
- Principal leadership is joined with principals' investment and support for the utilization of data framework (Copland, 2003). The principal is considered as a vital player in data utilization (Marsh *et al.*, 2006). Then again, managers should focus on distributed leadership, being stretched over more broadly and distributed beyond individuals (Park and Datnow, 2009).
- Involvement needs to do with employee engagement and enthusiasm to the data era, utilization and application for their work. Elements to advance the data utilization rely upon responsibility approaches and intrinsic motivation (Marsh *et al.*, 2006).
- Collaboration is reliable on employees' data sharing and co-utilizing. Coordinated effort for DdDM is firmly related with hierarchical, cultural and organizational authority (Marsh *et al.*, 2006).

DdDM refers to comprehensive measurable data connected to produce and uses the precise information of procedure and performance in complex associations (Gaither *et al.,* 1995) and composed of quantitative information and result-oriented indicators (Kim, 2012). DdDM implies that policymakers use and analyze data to enhance adequacy and to perceive the estimation of data (Marsh *et al.,* 2006; Park and Datnow, 2009). The term

DdDM has been for the most part used with data-based decision-making, research-based decision-making, and proof-based decision-making interchangeably (Honig and Coburn, 2008). As indicated by Marsh *et al.* (2006), DdDM implies the systematically collection and analysis of various types of data, including input, process, result and fulfillment data, to guide a range of decisions to help improvement and success. Typical indicators include: input indicators, process indicators, and outcome indicators. Accordingly the data-driven decision-making process could be summarized as shown in figure 1.

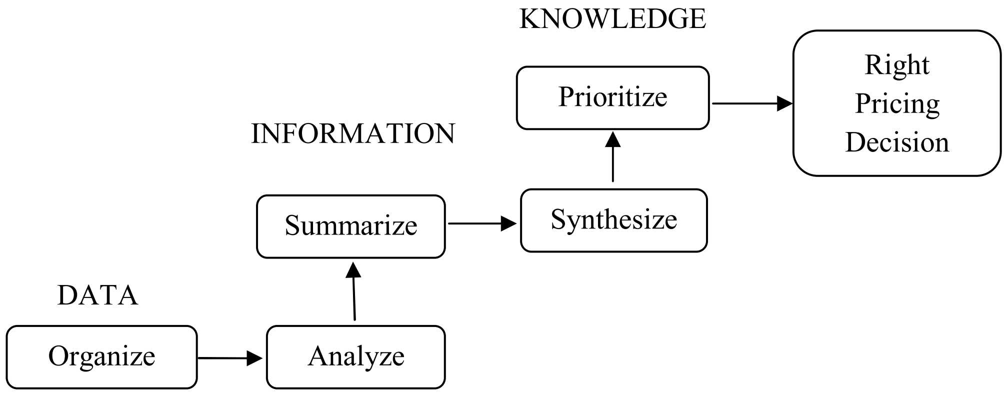


Figure 1: Summary of data-driven pricing decision-making process

Managers use systems that depend on present and historical data to support their decision making. At the point when the tasks are performed frequently that can positively influence access to the data and help administrators pick up understanding into organizational procedures, customer activities, and association wide performance measurements (Power, 2002). Yang (2012) found the significance of organizational effectiveness and market segmentation.

Business intelligence (BI) is defined as IT applications that help associations make decisions by utilizing innovation for reporting and data access, as well as analytical applications (Power, 2007). Commonly, BI applications retrieve and control information stored in databases to help knowledge workers plan choices by analyzing accessible data. It is essential that this data is as accurate as possible so that statistical inferences can be made accurately to show trends and other important information (Hedgebeth*,* 2007).

Firms could support customers through connecting their previous purchasing practices with their present site visit data not only in real-time, by promoting specific services during the customer's visit, but also by targeting them later through other means, such as e-mail. When comparing the high cost of adopting traditional methods of segmentation to target customers, then the cost-effectiveness of web-based segmentation approaches seems very appealing (Iyer *et al.,* 2002).

Data gathered through the web or a database generated from different web sources can then be subjected to further examination. A basic form of analysis includes utilizing past deals and customer behavior data to connect different purchaser attributes to anticipate customer/purchaser conduct (Mena, l999). The accessibility of customer data and increasingly sophisticated analytical tools empower critical increases in profit through price optimization. Hotels which have traditionally used RM have begun to use advanced pricing techniques to enhance the sales of their products and increase their profits (Rusmevichientong *et al.,* 2005).

Hotels store many different types of data like arrivals, reservation data, folio history, occupancy rates. The definitions and accessibility of these data may vary among hotels. El Gayar *et al.* (2011) reported three types of data: *historical arrivals* which are the number of customers in a specific period; *reservation records* that contain each of the parameters that depict a reservation like arrival date, reservation date, and length of stay. Records must contain as a mechanism the above expressed three parameters to be of value. Other parameters, like cancelation date, customer type, and room type, can also be helpful, e.g. *a booking matrix* is a compact version of reservation data. Considering all the arrival dates in the past in addition to those that will occur later on and placing them chronologically, generates the booking matrix.

Intelligent Pricing Identification

Hotel revenue managers usually offer special deals, tailored for different segments of customers, and calculate the right price for a particular customer at the right time. This change has been largely due to wiring the economy through the Internet. Customers are now able to quickly and easily compare services and prices, putting them in a better bargaining position. At the same time, the technology allows hotels to collect detailed data about customers and their preferences, so they can customize their services and prices accordingly (Narahari *et al.,* 2005). There are two major models used to achieve price intelligence: A) Multi-product pricing; B) Dynamic pricing.

A) Multi-product pricing means quoting different prices to different market segments for the same product that enables an organization to increase market share and profitability (Smith *et al.,* 2001). This is through giving an understanding of interactions and substitutions among products and assigning prices to these products that maximize profit according to interdependencies and consumer preferences (Aggarwal *et al.,* 2004; Rusmevichientong *et al.,* 2005).

B) Dynamic pricing is the dynamic adjustment of prices to consumers depending upon the value these customers attribute to a product or service (Reinartz, 2002). Dynamic pricing includes two aspects: price dispersion and price discrimination. First, price dispersion can be *spatial* price dispersion in which several sellers offer a given item at different prices or *temporal* price dispersion; a given seller varies his/her price for a given product based on the time of sale and supply-demand situation. Second, price discrimination relates to offer up different customer prices for the same product (Varian, 1996).

Dynamic RM depends on optimal pricing policies that are typically computed on the basis of an underlying deterministic demand price. These policies need a new approach to provide capacity-constrained hotels with integrated capabilities to implement optimal pricing decisions in real time while providing key stakeholders relevant and timely information to analyze the observed purchases of behavior of customers, and identify the attractiveness of offered products with respect to those of the competitors (Mehrotra, 2013). Data through e-business web sites has opened up enormous opportunities for revenue enhancing measures. E-business sites accumulate huge amounts of data about customers which they can use to improve their revenues and profits (Narahari *et al.,* 2005).

With the incorporation of sophisticated information technology approaches and their blending with machine learning, data mining, statistics, organizational theory and business experience; new models of hotel revenue management systems can be created to give hotel managers viable approaches to accomplishing an optimal level of revenue by offering hotel rooms at different price levels to distinct classes of customers (El Gayar *et al.,* 2011; Choi and Cho, 2000).

Thus, RM is characterized in the hotel business as the procedure of specifically accepting or rejecting customers by rate, length of stay and entry date to expand revenue (Vinod, 2004). The use of RM frameworks is accounted for building hotel revenue systems. Programming products for RM, like IDeaS, Rainmaker Group, PROS pricing software, Easy RMS, Optimism RM solutions, etc., have appeared in the recent years and give helpful and important backing to hotel RM practices. Be that as it may, experts and practitioners trust that further improvements and upgrades in hotel RM models are required and can be relied upon to have significant effect on the tourism business (El Gayar *et al.,* 2011; Chiang *et al.,* 2007).

Methodology

A review of literature on the current studies of RM, data-driven decisions and the nature of this study required a quantitative approach. A questionnaire was distributed in hotel revenue management to explore their DdDM attitudes, perceptions and practices. There is one overarching question underpinning this study; Do data-driven decision-making plays an effective role in leveraging hotel RM? To answer this question, the following hypotheses were tested as shown in Fig. 2 (Conceptual Framework):

H1: The wider use of data sources, the more likely the use of DdDM efficiently.
H2: The wider use of data types, the more likely the use of DdDM efficiently.
H3: The wider use of data distribution methods, the more likely the use of DdDM efficiently.
H4: The more concern of revenue managers, the more likely the use of DdDM efficiently.
H5: The wider use of DdDM, the more likely to affect intelligent pricing efficiently.

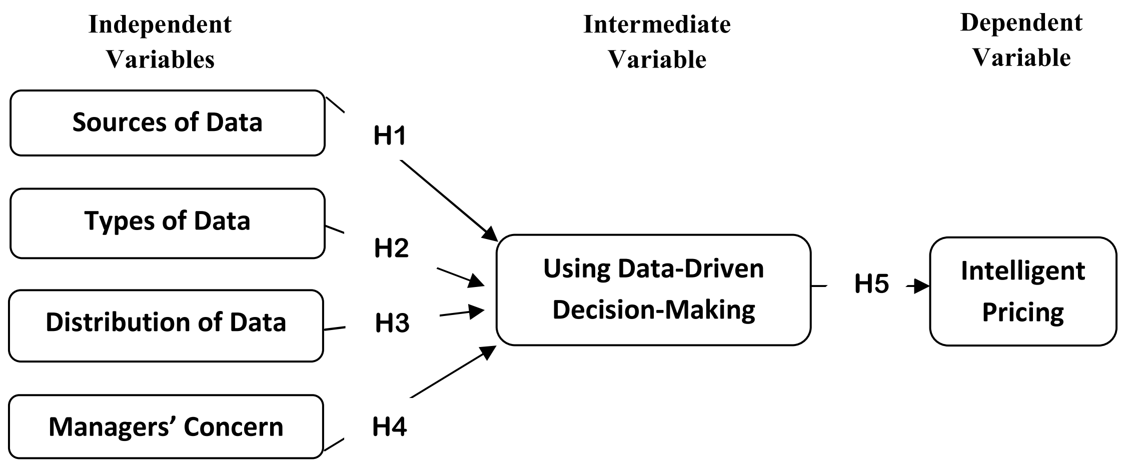


Figure 2: Conceptual framework for data-driven decision-making

Data collection

Measuring instruments

A questionnaire was based on a number of different models and measures that have been developed to measure data-driven decision-making and RM. It is divided into two main sections discussing sources, types and distribution of data; managers' concerns and using data driven decision-making; pricing decisions as shown in Table 1. Managers were required to choose the most suitable answer and indicate the extent to which each statement was true. A five-point scale (1=strongly disagree/don't use, to 5= strongly agree/use) was used.

Table 1: The main sections in the research study

Sections	Sample Reference
Section One:	
Sources of data: Traditional data, digital data, neuro-physiological data	(Kumar *et al.,* 2013)
Types of data: Transactional data, marketing data, firm data, historical data	(Talón-Ballestero *et al.,* 2014; Kumar *et al.,* 2013; Magnini *et al.,* 2003)
Distribution methods	(Kimes, 2011)
Section Two:	
Assessing managers' concerns about using data-driven decision-making	(Power, 2008; Mandinach *et al.,* 2006; Dunn *et al.,* 2013a, Dunn *et al.,* 2013b; Harvard Business Review Analytic Services Report, 2012; Brynjolfsson *et al.,* 2011; Kimes, 2011)
Pricing decisions	(Talón-Ballestero *et al.,* 2014)

The Target Population and Data Analysis

The target population of this study was revenue managers in fifteen five-star hotels in greater Cairo, Egypt. This category of hotels was chosen as they seemingly more knowledgeable and of better understanding and acquaintance with the topics of the research in order to obtain meaningful data. Also, greater Cairo has been selected as the studied area because it is convenient for the researchers due to time and cost concerns. A random sample is appropriate to be used where every hotel is given equal opportunities of being selected.

Different statistical techniques using SPSS 20 were applied to analyze the data. The reliability analysis was performed to assess the internal consistency of the measurement scales. Moreover, descriptive statistics such as means and standard deviations were computed according to the studied variables. In addition, Spearman correlation analysis and simple regression were conducted to examine the associations among the studied variables. Finally, statistical significance was considered for P values less than 0.05.

Results and Discussion

Reliability and Validity

Computed Cronbach's Alpha demonstrated an acceptable reliability with an average reliability of $\alpha = 0.60$ which matches the reliability level recommended by Nunnally and Bernestein (1994). As for validity, each scale showed a significant correlation ($p < 0.01$), which provided preliminary evidence for validity.

Descriptive Statistics

Descriptive scores for each subscale of section one (sources and types of data, distribution methods) and section two (assessing managers' concerns about using data-driven decision-making, and pricing decisions) were calculated (Table 2).

Table 2: Mean and std. deviation of measurement model

	Subscales	Mean	Std. Deviation
	Sources of data	**4.05**	**.2133**
	Traditional data	3.76	.2959
1	Surveys	2.63	.4901
2	Observations	4.56	.5040
3	Focus groups	4.50	.5085
4	Structured interviews	4.06	.9071
5	Unstructured interviews	3.33	.9589
6	Transactions (Scanner data)	3.46	.5713
	Digital data	4.07	.1835
7	Surveys	4.63	.4901
8	Search engine queries	4.53	.5074
9	Click-stream (Clicking behavior of a customer on hotel webpage)	4.43	.6260
10	Social media (e.g. Face book)	4.33	.4794
11	Blogs (Websites that display postings by one or more individuals)	4.20	.4842
12	Community forums	2.66	.4794
13	Incentivized referrals (Online membership size)	3.73	.4497
	Neuro-physiological data	4.31	.4449
14	Eye-tracking	4.46	.5074
15	Facial Electromyography (Emotional valence)	4.16	.5920
	Types of data	**4.41**	**.2128**

	Transactional data:	4.55	.3559
16	Profit	4.76	.4301
17	Time of Purchase	4.33	.4794
	Marketing data	4.23	.4299
18	E-mails	4.60	.4982
19	Direct mails	3.70	.7943
20	Promotions	4.40	.4982
	Historical data	4.45	.2792
21	Different type of customers	4.20	.7143
22	Occupancy rates	4.80	.4068
23	No. of denials (Room reservations rejected by the hotel)	4.36	.6686
24	No. of no-shows	4.33	.6608
25	No. of walk-ins	4.36	.7184
26	Lengths of stay	4.66	.4794
	Hotel distribution sources	4.40	.2183
27	Hotel website	4.53	.5074
28	Smart phone	4.13	.6814
29	Integration with reservation system	4.66	.4794
30	Social networking	3.73	.7849
31	Global distribution system (GDS)	4.60	.4982
32	Third party intermediaries (e.g. OTAs)	4.43	.5040
33	Hotel reservation centers	4.70	.4660
	Assessing using data-driven decision-making (DdDM) in relation to price decisions	**4.67**	**.1589**
34	DdDM can be customized to meet the requirements of this hotel.	4.33	.4794
35	It is easy to exchange information with other hotel information systems.	4.90	.3051
36	I am comfortable using the key assessment terms and concepts of the DdDM.	4.36	.4901
37	I identify data-driven goals and develop action plans to accomplish these goals.	4.63	.4901
38	Data is sufficiently integrated so that we are able to combine multiple data sets for analysis.	4.80	.4068
39	I depend on data to support my decision-making activities.	4.90	.3051
40	I have the data I need to make decisions.	4.53	.5074
41	I can use the technology system tools to retrieve charts, tables or graphs for analysis.	4.93	.2537
	Managers' concerns about data-driven decision-making (DdDM):	**4.60**	**.2318**
42	I would like to know more about using DdDM and intelligent pricing.	4.36	.4901
43	I would like to know how my hotel prices are supposed to be changed.	4.56	.5040
44	I don't feel confident about DdDM.	4.76	.4301
45	I would like to manage all that DdDM requires.	4.70	.4660
46	I would like to help other hotels in their use of DdDM.	4.63	.4901
	Pricing decisions	**4.69**	**.1793**
47	The sales department is involved in pricing decisions.	4.60	.4982
48	The revenue management department is involved in pricing decisions	4.56	.5040
49	Different rates are applied to different market segments.	4.80	.4068
50	Restrictive criteria are applied to the lowest rates.	4.46	.5074
51	Package deals (room plus other services) are offered.	4.76	.4301
52	Rooms are differentiated by installing facilities that entail no significant extra cost.	4.90	.3051
53	Agreements with tour operators and corporate accounts contain provisions for varying rates.	4.83	.3790
54	The BAR (best available rate) model is used.	4.33	.4794
55	Pricing parity is in place for all distribution channels.	4.76	.4301
56	Discounts are subject to compliance with pre-established requirements	4.70	.4660
57	The effect of local events is taken into consideration when revising rates	4.86	.3457

Descriptive Statistics of Sources and Types of Data

The descriptive statistics reveals high perception of using the different sources of data. It was noted that observations, focus groups and structured interviews achieved the highest using perceptions which their values were 0.91, 0.90 and 0.81, respectively as shown in fig. 3.

Many of the traditional data sources now overlap with digital data since they can be sourced over the internet as well. Such as observational data collection that takes place when consumer behavior is recorded through direct and contrived observation, physical trace measures, and behavior recordings devices (Aaker *et al.,* 2012).

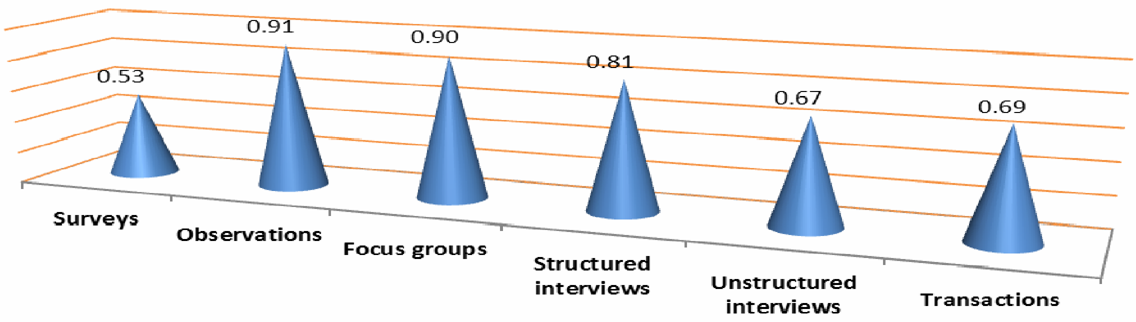


Figure 3: Traditional data descriptives

When describing digital data as shown in Fig. 4, it is noted that electronic surveys, search engine queries and click stream approximately represent high degrees of using perception. Their values were 0.93, 0.91 and 0.89 respectively.

Digital data is defined as the data produced through human interaction with services provided by the internet (e.g. search and clickstream data), and human interaction with others on the internet (e.g. data from social media, blogs, community forums, and incentivized referrals) (Skiera and Abou Nabout, 2012).

In details, search engine queries are important for marketers by paying attention to keywords that are being used to search for services that they offer (Skiera and Abou Nabout, 2012). Clickstream data is generated by cataloguing the clicking behavior of a customer once they access a webpage. Analyzing clickstream data provide the opportunity to understand visitor traffic by collecting information on customer behavior (Moe and Fader, 2004).

Also, social media is a powerful tool which can be used to inform consumers about provided services. Managers are working to understand how they can harness the vast amounts of information found in social media and target it to meet the needs of their brand. Social media is among the topics at the forefront of marketing with 85 percent of marketers across industries marketing through their own brand accounts on social networks (Rogers and Sexton, 2012).

In the same line, e-business web sites provide preference data on a large number of consumers. These online buyer preference data provide new opportunities to understand consumer behavior and to customize item prices to meet the customer needs. However, routines for acquiring and securing data are frequently expensive and time-consuming, limiting the size of the data set (Rusmevichientong *et al.,* 2005).

Intelligent display technology enables to gather and profile data on what customers view on the company web site. The data is then used to support the decision making. Marketers can reach out to customers using different channels and send out customized messages, thus transforming their digital space into a tailored offering to each customer's tastes (Kumar *et al.,* 2013).

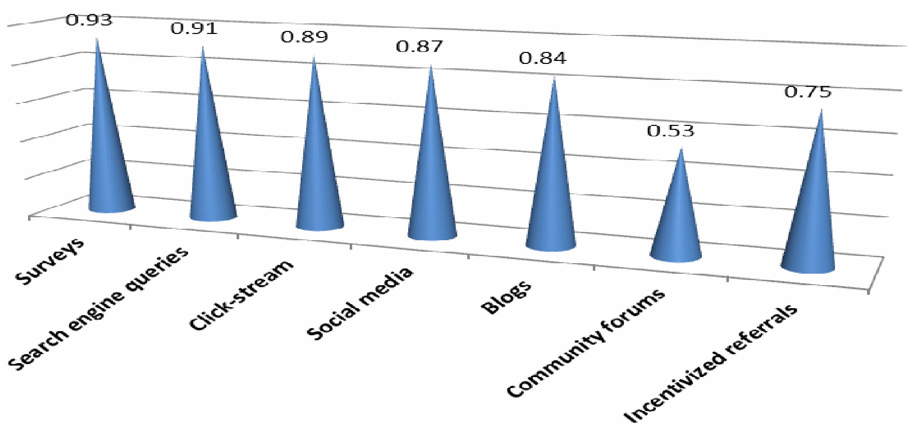


Figure 4: Digital data descriptives

For the last source of data, eye-tracking data represents higher degrees of using perception (0.89) than facial electromyography one (0.83) as shown in Fig. 5.

Eye tracking records the movement of the eyes, which include short rapid movements and short stops (saccades) and motionless gaze (fixation). It is considered a valid tool for measuring visual attention (Ohme *et al.,* 2011). Chandon *et al.* (2009) found that eye tracking was more effective in capturing actual visual attention to brands in a supermarket shelf than consumers' self-reports.

Also, facial electromyography (FEMG) offers a physiological measure of emotion and engagement. FEMG measures muscle activity in the face through small electrodes that track the contraction of muscle fibers from two main dimensions (frowning and smiling) (Peacock *et al.,* 2011). FEMG has been effective in measuring consumers' emotional response to service recovery behaviors (Boshoff, 2012) and consumer-brand relationships (Reimann *et al.*, 2012).

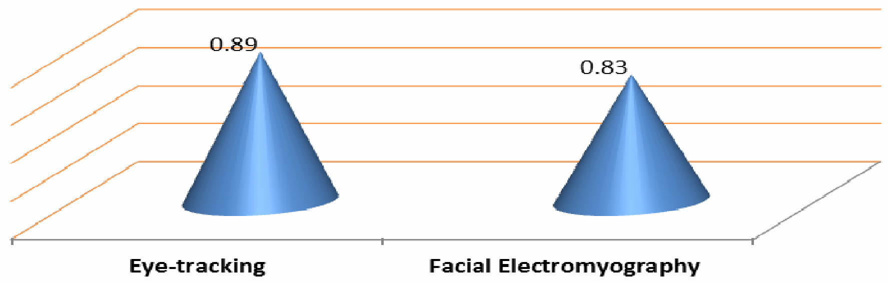


Figure 5: Neuro-physiological Data

As shown in Fig. 6 the descriptive statistics of types of data; transactional, historical and marketing data approximately represent high degrees of using perception which their values were 0.91, 0.89 and 0.85, respectively. These results agreed with Bijmolt *et al.* (2005) who pointed to the importance of historical data. They assured that price elasticity is fundamental to measuring and anticipating customer reaction to changes in value. It is a measure of the historical change in demand in respect to change in price. Taking into account normalized demand, price elasticity is more robust if it is based on several historical prices that have been tested in the business-model and its yield must be as powerful as the data on which it is based.

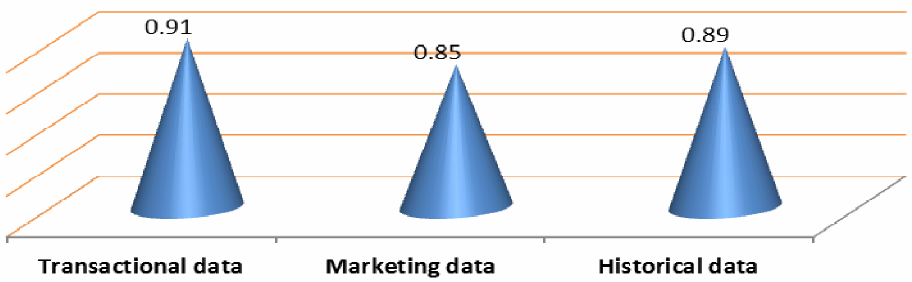


Figure 6: Types of Data

Hotel Distribution Sources

The descriptive results of hotel distribution sources revealed of the approximately perception to all sources. It was noted that hotel Res centers, integration with Res system, global distribution system and hotel website represent the highest degrees with values of 0.94, 0.93, 0.92 and 0.91, respectively as shown in Fig. 7. Advances in electronic identification help firms to better focus on targeting promotional offers. Rather than broadcasting communications and mass-media advertising (Iyer *et al.*, 2002).

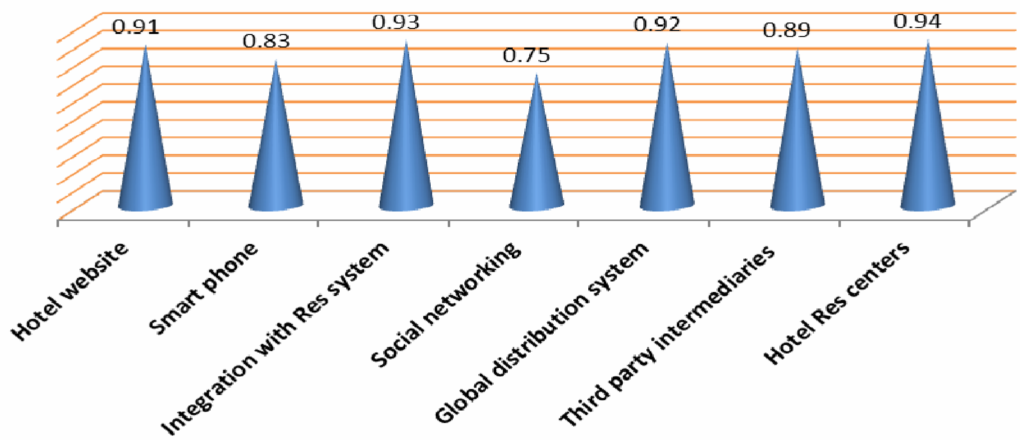


Figure 7: Hotel distribution sources

Similarly, a significant number of hotel webpages services are connected to GDS distribution channel or to an in-house inventory system with a comparable functionality to GDS. Also, airline systems depend not only on the internet but also on the GDS distribution. Internet distribution shows a reliable accessibility and offers a comparable intelligence between customer and airline inventory system, in any event with respect to availability and via travel agent and GDS. In this manner reliable accessibility offers another powerful mechanism for differential value pricing (Isler and D'Souza, 2009).

According to Braverman (2015) data-driven marketers, technologists and service providers were loud and clear in their consensus on a number of key issues:

Customer data is a valuable resource: Representing a relationship (or potential relationship) that must be both supported and defended if it is to flourish over time. Data-driven marketing and advertising (DdMA), then, is a method for giving advantage to the leveraging of a wide range of delivery channels, keeping in mind that the end goal is to build up, and develop relationships that benefit marketer and consumer alike.

It is about customers: Demand for more relevant communications that are more customer-focused was among the most essential elements driving interest in DdMA.

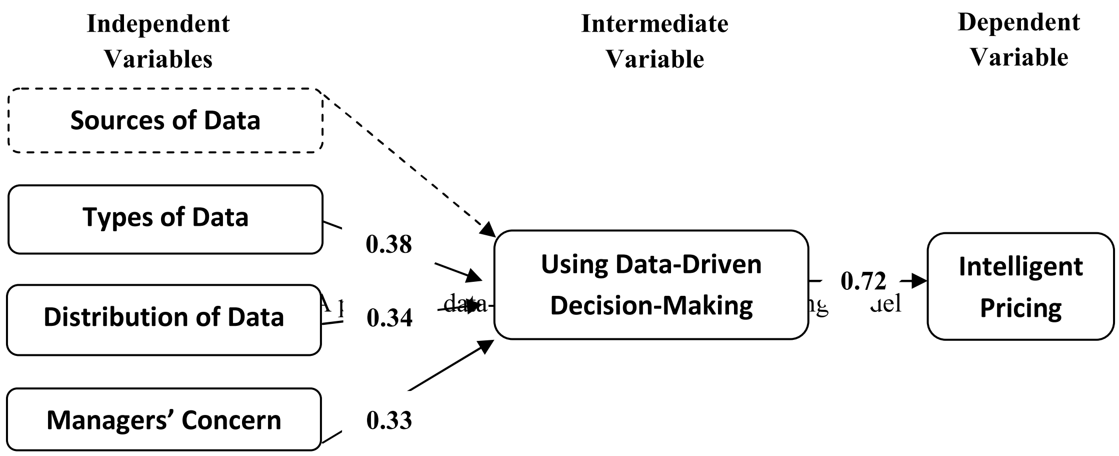
It is a bull market*:* More than 77.4 percent of global respondents had confidence in DdMA and its prospects for future growth.

The revenue management concern about data-driven decision-making, their perception of using DdDM, and pricing decisions were 4.67, 4.60 and 4.69, respectively that present a high perception as shown in table 1. Previous research has found that managers who use high-quality analytic, model-based decision support systems make objectively better decisions than do decision makers who only have access to generic decision tools such as Microsoft Excel (Lilien *et al.,* 2004).

Correlation and Regression Analysis

Regarding the relation between the independent, intermediate and dependent variables, the correlations were calculated. Unexpectedly, there was no significant relation between sources of data and using data-driven decision-making. On the other hand, the types of data, hotel distribution sources and managers' concerns about DdDM have positive and moderate relations with using DdDM. The correlation values were 0.57(**), 0.52(**) and 0.42(*), respectively. This may be due the high importance of the data necessity and convenience than their sources. The results showed also, in line with expectations, a significant and positive correlation between using DdDM as an intermediate variable and pricing decisions (r= 0.63, P value <0.01).

To find significant predictor variables, a regression analysis was used. The results revealed that types, distribution of data and managers' concern about DdDM were significantly contributed to the use of DdDM efficiently. It was noted that the types of data achieved the highest score (Coefficients = 0.38, P< 0.05), distribution of data represented the second variable (Coefficients = 0.34, P< 0.05) and managers' concern about DdDM was the least one (Coefficients = 0.33, P< 0.05) as independent variables. Finally, using data-driven decision-making had a high significant prediction of intelligent pricing (Coefficients = 0.72, P< 0.05) as shown in Fig. 8.



Conclusion

Having an effective revenue management system represents a vital element in creating a competitive advantage for hospitality management. In hotel business it has become evident that the wider usage of the data has enhanced the effectiveness of data-driven pricing decision-making. The findings of this study assured that using traditional, digital and neuro-physiological data is important from the revenue management perspective. Moreover, the findings stated that transactional, historical and marketing data had approximately high degrees of using perceptions. Also, the importance of using hotel distribution sources was obvious especially using integration with Res systems and GDS.

In addition, the data analyzed sheds light on the types of data, hotel distribution sources and managers' concerns about DdDM that have positive and moderate relations with using DdDM. The results showed also, in line with expectations, a significant and positive correlation between using DdDM as an intermediate variable and pricing decisions. On the other hand, the results show that although the high perception of using different sources of data, there was no significant relation between sources of data and using DdDM.

Finally, the proposed model provides a number of contributions to hotel revenue management such as: the classification of sources and types of data, and hotel distribution channels; the importance attached to the development of RM through its inputs and outputs which are essential to pricing decision making process; the need to be periodically reviewed and updated to adapt to continuous management changes.

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الملخص العربى

التكامل بين توجيه البيانات واتخاذ القرار فى صناعة الفنادق المصرية: من منظور إدارة الإيراد

عماد عبدالعال

يمثل وجود نظام فعال لإدارة الإيرادات عنصرا حيويا في خلق ميزة تنافسية لإدارة الفنادق. فقد أصبح من الواضح أن الاستخدام الواسع للبيانات يعزز من فعالية اتخاذ القرارات التسعيرية الذكية. وتركز الدراسة الحالية على تطبيق عملية اتخاذ القرارات المبنية على البيانات (DdDM) كمنهج جديد لإدارة الإيراد الفندقية. وتهدف الدراسة إلى التعرف على مصادر وأنواع البيانات المختلفة، وأساليب توزيع مدخلات البيانات التي يتم استخدامها من قبل مدراء الإيرادات في الفنادق وعلاقتها بكفاءة استخدام (DdDM) ، وأخيرا تقييم العلاقة بين وعي مدراء إدارات الإيراد واستخدام (DdDM) للوصول إلى التسعير الذكي. وقد أشارت النتائج إلى أهمية استخدام البيانات التقليدية والبيانات الرقمية حيث تمثلت فى درجات عالية من الإدراك لدى المدراء. كما حققت أيضا البيانات الفسيولوجية كأحد مصادر البيانات (ملاحظة حركات عيون العملاء) درجات عالية من إدراك الاستخدام. أما عن أنواع البيانات مثل البيانات التاريخية والتسويقية والمعاملات وكذلك مصادر توزيعها فهى الأخرى تمثل درجة عالية من إدراك المدراء. ولتحديد العلاقات الارتباطية لمتغيرات الدراسة فقد تم استخدام معامل اسبيرمان للارتباط وأكدت النتائج عدم وجود علاقة معنوية ذات دلالة إحصائية بين مصادر البيانات المختلفة وكفاءة استخدام(DdDM)، بينما وجدت علاقة إيجابية بين أنواع البيانات ومصادر توزيعها وعلاقتها بكفاءة استخدام (DdDM). وقد يرجع ذلك إلى أهمية نوعية ودقة البيانات المطلوبة لملائمتها تحقيق الهدف بغض النظر عن مصدرها. كما وأظهرت النتائج، تمشيا مع التوقعات، وجود علاقة معنوية إيجابية قوية بين كفاءة استخدام (DdDM) كمتغير وسيط وقرارات التسعير الذكى كأحد المخرجات.

وأخيرا، تقدم الدراسة نموذج مقترح قد يسهم في إدارة إيرادات الفنادق مثل: تصنيف مصادر وأنواع البيانات، وقنوات التوزيع الفندقية؛ أهمية تطوير إدارة الإيراد من خلال المدخلات والمخرجات التي تعتبر أساسية للوصول إلى التسعير الذكى؛ ضرورة الحاجة إلى استعراض وتحديث البيانات بشكل دورى للتكيف مع التغيرات المستمرة في الإدارة.

الكلمات الدالة: توجيه البيانات، اتخاذ القرار ، إدارة الإيراد، صناعة الفنادق.