SERVICE ATTRIBUTE IMPORTANCE AND STRATEGIC PLANNING: AN EMPIRICAL STUDY

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Abstract

There is growing evidence that attribute importance is a function of attribute performance. Several studies reported that service quality attributes fall into three categories: basic, performance, and excitement. Thus, the identification of attribute importance is significantly important as a key to customer satisfaction evaluation and other behavioural intentions. According to customer behaviour literature, attribute importance can be measured in two ways: (1) self-stated importance, and (2) statistically inferred importance. The article evaluates two methods according to their impact on overall customer satisfaction measurement and, managerial implementation. A case study is conducted on the telecommunication industry for analysis.

Keywords: Customer satisfaction; Importance-performance analysis (IPA); Strategy.

1.0 Introduction

The importance of service attributes to customers is a central element to the management within the context of customer behaviour analysis, resource allocation process, and organisational behaviour. According to service marketing literature, there are two key characteristics of service quality attributes namely *importance* and *performance*. Using these two dimensions together facilitates the prescription of prioritising customer attributes when enhancing service quality and customer satisfaction [1]. In other words, measuring attribute importance and performance certainly draw a clear image for top managers to best deploy scarce resources, using importance-performance analysis (IPA).

There are several methods for measuring attribute importance in behavioural sciences such as free-elicitation method, direct rating method, direct ranking method, analytical hierarchy process, and information-display board, multi-attribute attitude methods. However, there is a lack of convergent among and nomolological validity of different methods [2]. These issues can cause inconsistent outcomes among methods. Previous research argues that the main reason of the lack of validity among methods is multi-dimensionality of attribute importance [3]. As a result, all inconsistency among methods can be interpreted by the fact that different methods measure different dimensions of importance. According to literature, key dimensions of attribute importance can be classified into three groups: (1) salience, (2) relevance, and (3) determinance [4], [5], see Fig 1.

In this article, we investigate the validity of two existing methods that are proposed to measure the determinance of service attributes in overall customer satisfaction in the mobile telecommunication industry, using statistical inferred importance and customers' stated importance. The findings show that the type of importance measure and the dynamic nature of importance to response influence management decision making. As a result, there are significant differences in nomological validity- the relationship between the importance of service attributes and overall customer satisfaction.

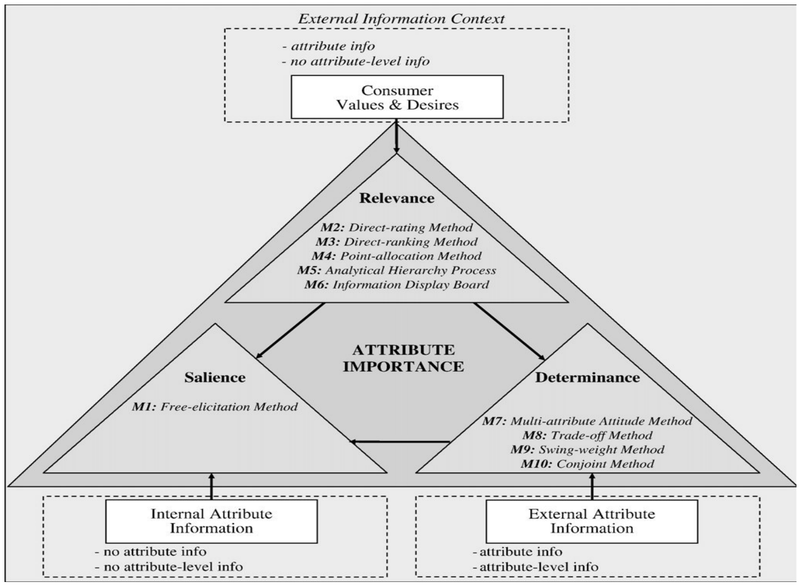

Fig. 1. The three dimensions of attribute importance (Adopted from [3])

We begin by describing the impact of attribute importance on customer behaviour and the methods we compare. We examine two different statistical methods for driving importance measures including multiple regression and regression with dummy variables. An empirical analysis of three data sets highlights interesting results.

2.0 Service Attribute Importance

Indentifying the importance that consumers place on the service attributes that affect customer satisfaction, customer retention (e.g., repurchase intention), and loyalty (e.g., feedback, and word-of0mouth) is an important element for resource allocation process. Thus, the study of importance of service attributes has been a central topic in consumer behaviour and market research for decades. Most importantly, the focus of attribute importance has shifted from traditional evaluations of service concepts within controlled settings, such as conjoint analysis [6] and choice modelling [7], to understanding the determinants of behaviours intentions [8], [9].

In this study we focus specifically on the impact of service attribute on cumulative customer satisfaction, defined as an overall evaluation of a customer perception of service performance to date [10], [11]. As previous research reported, customer satisfaction has significant impact on other customer behavioural intentions in the form of retention and loyalty. In other words, it plays as mediating attitude between service quality or attribute performance and other behavioural variables. Thus, indentifying the determinants of customer satisfaction can help managers within their long term business planning.

3.0 Methodology

Most research studies which have investigated the importance of service attributes in customer behaviour employed two methods: *customers' self-stated* or *explicitly derived importance* (direct method), and (2) *implicitly derived importance* or *statistically derived importance* (indirect method). By using explicitly derived importance, customers are asked to rate a list of service or product attributes according their importance (e.g. rating scales, constant sum scales, etc.). As a result, basic attributes usually receive the highest rating levels as they are naturally expected by customers (minimum requirements). However, they have literally no impact on overall customer satisfaction and future intentions even if they performed at a satisfactory level. For instance, consider an airline safety. Most customers would rank safety as highly important attribute. But in reality it does not contribute significantly to the prediction of airline choice, since it is more of a minimum requirement (basic attribute). So, do we need to take resources away from this kind of attributes?

It is argued that direct methods do not effectively measure attribute importance [12], [13]. The main issue with this method is that respondents may not take into account the current level of attribute performance. Moreover, there is an asymmetric and nonlinear relationship between attribute importance and performance [12], [11], [14], [15]. Therefore, the customer's self-stated importance is not the actual value for attribute importance.

Importance performance analysis (IPA) is widely used technique indentifying the relative importance of service attributes with associated performance of service attributes [16]. The technique determines where a company should focus its resources to produce the greatest impact on customer satisfaction and subsequent behavioural intentions like retention and loyalty.

3.1 Self-Stated Importance

For the purpose of the evaluation of service attribute importance (explicitly derived), we employed methodology from previous study [17]. Respondents were asked to rate just the three most important attributes; from "1=most important2 to "3=least important". In order to assign each attribute (*i*) an importance value (P_i) lying between 0 and 1, we integrate the ranked assigned by respondents, using Equation 1, to a ranking score (h_{ij}) using Equation 2. Table I lists the frequency of ranks 1, 2 and 3 for each attributes and also the aggregate importance value (using Eq. 2).

$$h_{ij} = \begin{cases} (k - g_{ij} + 1)/k \\ 0 \end{cases} \qquad (1)$$

$$P_i = (n^{-1} \sum_j h_{ij})^{k/s} \qquad (2)$$

3.2. Multiple Regression Analysis (MR)

There are various statistical methods for measuring attribute importance such as multiple regression (MR), structural equation modelling or partial correlation [18], [19], [20]. Several researchers have suggested multiple regression analysis as a suitable tool for measuring attribute importance. The method simply regresses the relative performance ratings of service attributes against dependent variable (overall customer satisfaction) to generate significant-level for individual attribute. This approach is the easiest to implement statistically. One of the advantages of regression analysis is that the method provides a model of all attributes to form the overall rating. As a result, multiple regression analysis estimates the degree of influence that attributes have in determining customer satisfaction (shown in Table I). The primary problem with this approach is multicollinearity among the independent variables.

$$Sat_{total} = \alpha_0 + \alpha_1 X_1 + ... + \alpha_n X_n + \varepsilon \quad (3)$$

3.3. Regression Analysis with Dummy Variables

In order to identify the asymmetric impact of attributes' performance on attribute importance, a regression analysis with dummy variables was used [21], [22], and [13]. Accordingly, two sets of dummy variables; the first dummy variables quantify basic attributes, and the second ones quantify exciting attributes are set. The attribute-level performance ratings are recoded as (0,1) for low ratings, (0,0) for average ratings, and (1,0) for high ratings. As a result, two regression coefficients are obtained (shown in Table I and Fig II).

$$\begin{aligned} Sat_{total} = {} & \alpha_0 + \alpha_{1Att.1} \times dummy_{1Att.1} + \alpha_{2Att.1} \times dummy_{2Att.1} + ... + \\ & \alpha_{1n} \times dummy_{1Att.n} + \alpha_{2n} \times dummy_{2Att.n} \end{aligned} \quad (4)$$

Sat_{total} is the overall customer satisfaction, and n is the number of quality attributes (n = 7), $dummy_1$ indicates lowest customer satisfaction level, $dummy_2$ indicates highest customer satisfaction levels, α_1 the incremental decline in overall satisfaction associated with low satisfaction levels, and α_2 the incremental increase in overall satisfaction associated with high satisfaction level.

4.0 Survey Methods

The survey was conducted with a random sample of 270 students of a University. Questionnaires were completed and returned either via email or were collected in face-to-face interviews. From this sample, 74.4% percent of the respondents were under 27 years old. In this study, market segmentation is highly considered in order to avoid the risk of displacement and strategy application bias.

Respondents were asked to indicate the most three important service attributes in the mobile service with the anchors of "1=Most important" to "3=Least important". In second part, the performance for each service attribute was rated using a seven-point Likert scale from "1=Poor" to "7=Excellent". Finally respondents were asked to rate overall satisfaction using a seven-point Likert scale from "1=Strongly dissatisfied" to "7=Strongly satisfied".

4.1 Findings

Table I presents the results of three methods for perceived importance. Applying the results of two methods (indirect and direct) into IPA grid shows a change in strategic outcomes for service attributes. The difference between two IPA models emphasises the influence of measurement on managerial implementation [23].

(a) R^2 = .480, F-value = 34.936,
(b) R^2 = .469; F-Value = 15.338,
***P < .01, ** P<.05, *P<.1, *ns* = not significant

More importantly, the results from regression with dummy variables accommodates the concept of change in the relative importance of attributes with change in attribute performance as a function of overall customer satisfaction, see Fig. II. Since changes to attribute performance affects the relative attribute importance, therefore, the self-stated importance is not appropriate method. However, multiple regression analysis can be an inappropriate if multicollinearly exists within independent variables [14]. In the case of multicollinearly, partial correlation analysis with dummy variables and multiple regression with natural logarithmic dummy variables are more suitable [24], [14], [22], [21], [25]. By using regression with dummy variables, we also found two types of service attribute within the mobile industry: Basic and Exciting [12].

Table I:.Attribute importance analysis

Attribute	Ranking order			Explicit derived	Regression coefficient (a)	Dummy-variable regression coefficient (b)		Attribute performance
	1	2	3			Low performance	High performance	
Network performance	82	51	52	0.81	0.302***	0.048 (*ns*)	.366***	5.44
Customer service quality	9	27	38	0.54	0.199***	-.001 (*ns*)	.221***	4.88
Service plans	87	47	31	0.79	0.141*	-.009 (*ns*)	.068 (*ns*)	5.05
Range of phones	9	22	30	0.51	-0.089*	-.130 **	-.114*	4.36
Accuracy of billing and payment	6	19	18	0.46	0.145**	-.115**	.064 (*ns*)	5.11
Value for money	56	62	43	0.76	0.222**	-.012 (*ns*)	.202***	4.92
Total	253	252	249					

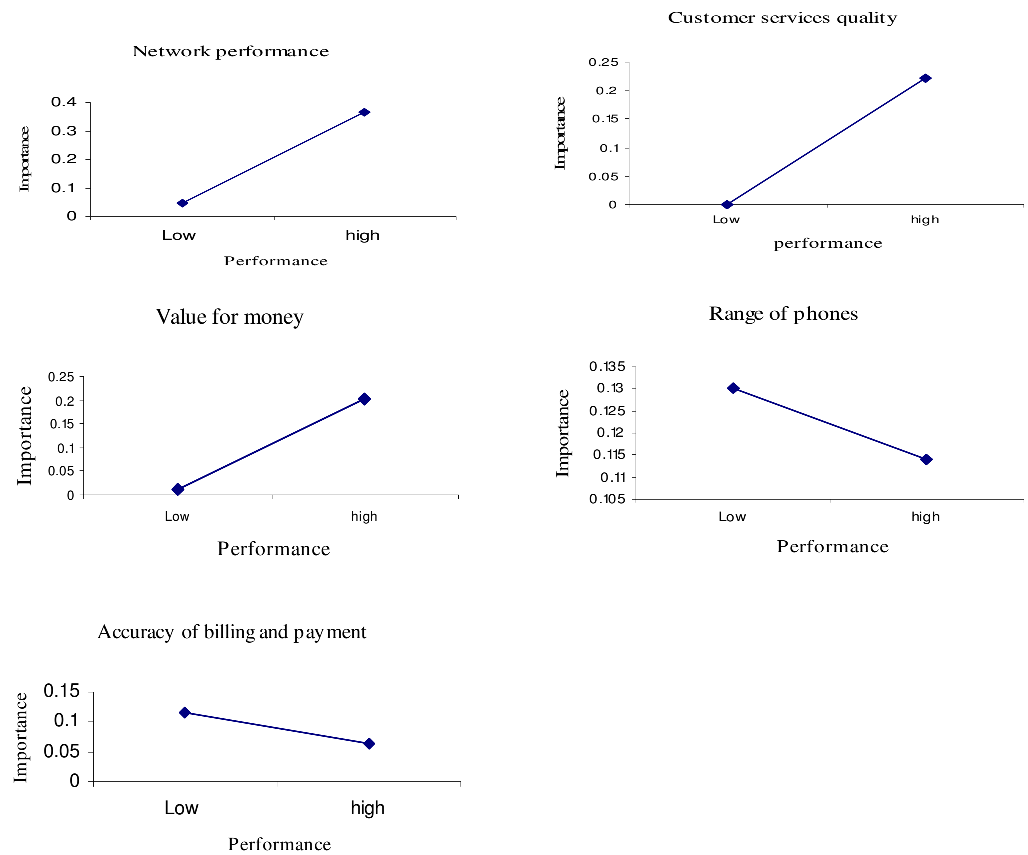

Fig. 2. Relationship between importance and performance

Fig III demonstrates two IPA models. There are some differences between two methods as some attributes located in different quadrants. However, managers must consider the relationship between importance and performance since changes in performance will affect attrite importance-level.

Statistically importance derived   Customer self-stated importance

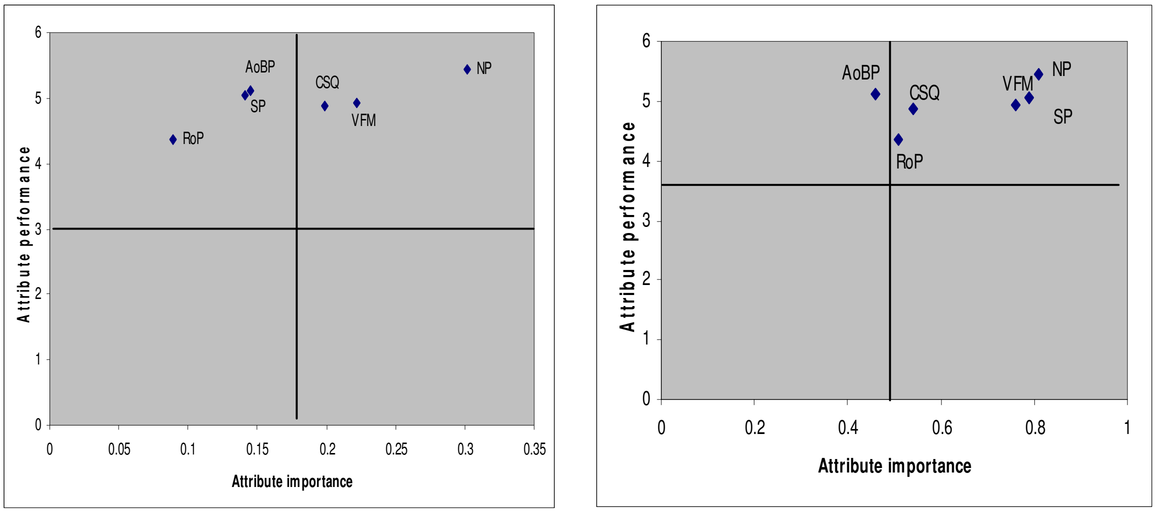

Fig. 3. IPA models

5. Conclusion and Management Implications

This article evaluates the effect of importance measurement variation on outcome strategy variance, using IPA technique. The comparative analysis of outcomes from different IPA analysis demonstrates the influence of respective importance measures. In addition, the results of regression analysis with dummy variables highlight the dynamic nature of importance relating to response variance. As a result, managers should consider the fact that changes to attribute performance are associated with changes to attribute importance since quality attributes have impact on customer satisfaction [12]. Differences between two methods of direct and indirect are particularly marked. From managerial perspective, there is absolutely no assurance that increasing scores on attributes with the highest self-stated importance will provide maximised increase in the overall measure [26].

References

[1] Matzler, K., Bailom, F., Hinterhuber, H. H., Renzl, B. and Pichler, J. (2004), "The asymmetric relationship between attribute-level performance and overall customer satisfaction: a reconsideration of the importance-performance analysis", Industrial Marketing Management, Vo. 33, No. 4, pp. 271-277.
[2] Jaccard, J., Brinberg, D. and Ackerman, L.J. (1986), "Assessing attribute importance: a comparison of six methods",Journal of Consumer Research, Vol. 12 (March), pp. 463-8.
[3] Ittersum, K.V., Pennings, J.M.E., Wansik, B. and Trijp, H.C.M. (2007), "The validity of attribute-importance measurement: A review", Journal of Business Research, Vol. 60, pp. 1177-1190.
[4] Myers, J.H. and Alpert, M.I. (1968), "Determinant buying attitudes: meaning and measurement", Journal of Marketing, Vol. 32 (July), pp. 13-20.
[5] Myers, J.H. and Alpert, M.I. (1977), "Semantic confusion in attitude research: salience vs. importance vs. determinance", Advertising Consumer Research, Vol. 4, pp. 106-10.
[6] Green, P.E. and Srinivasan, V. (1990), "Conjoint analysis in marketing: new developments and directions", Journal of Marketing, Vol. 54 (October), pp. 3-19.

[7] Gaudagni, P.M. and Little, J.D.C. (1983), "A logit model of brand choice calibrated on scanner data", Marketing Science, Vol. 2, No. 3 (summer), pp. 203-238.
[8] Gustafsson, and Johnson, (1997), "Determining attribute importance in a service satisfaction model", Journal of Service Research, Vol. 7, No. 2, pp. 124-141.
[9] Ryan, M.J., Rayner, R. and Morrison, A. (1999), Diagnosing customer loyalty drivers: Partial Least Squares vs. Regression", Marketing Research, Vol. 11 (summer), pp. 19-26.
[10] Fornell, C. (1992), "A national customer barometer: The Swedish Experience", Journal of Marketing, Vol. 56, (January), pp. 6-21.
[11] Fornell, C., Johnson, M.D., Anderson, E.W., Cha, J. and Bryant, B.E. (1996), "The American Customer Satisfaction Index: Nature, Purpose and Findings", Journal of Marketing, Vol. 60 (October), pp. 7-18.
[12] Kano, N., Seraku, N., Takahashi, F. and Tsuji, S. (1984), "Alternative quality and must-be quality", Hinshitsu (Quality, The Journal of Japanese Society Control), Vol. 14, pp. 39-48.
[13] Matzler, K. and Sauerwein, E. (2002), "The factor structure of customer satisfaction: an empirical test of the performance grid and the penalty-reward-contrast analysis", International Journal of Industrial Management, Vol. 13, No. 4, pp. 371-32.
[14] Matzler, K., Fuchs, M. and Schubert, A.K. (2004), "Employee satisfaction: Does Kano's model apply?", Total Quality Management and Business Excellence, Vol. 15, No. 9/10, pp. 1179-1198.
[15] Oh, H. (2001), "Revisiting importance-performance analysis", Tourism Management, Vol. 22, No. 6, pp. 617-627.
[16] Matrilla, J.A. and James, J.C. (1977), "Importance-performance analysis", Journal of Marketing, Vol. 41. pp. 77-79.
[17] Abalo, J., Varela, J., Manzano, V. (2007), "Importance values for Importance-Performance Analysis: A formula for spreading out values derived from preference rankings", Journal of Business Research, Vol. 60, pp. 115-121.
[18] Danaher, P.J. and Mattsson, J. (1994), "Customer satisfaction during the service deliver process", European Journal of Marketing, Vol. 28, No. 5, pp. 5-16.
[19] Wittink, D.R. and Bayer, L.R. (1994), "The measurement imperative", Marketing Research, Vol. 6 No.4, pp.14-23.
[20] Varva, T.G. (1997), "Improving your measurement of Customer Satisfaction", ASQ Quality Press, Milwaukee, WI.
[21] Anderson, E.W. and Mittal, V. (2000), "Strengthening the satisfaction-profit chain", Journal of Service Research, vol. 3, No. 2, pp. 107-120.
[22] Brandt, D.R. (1988), "How service marketers can identify value-enhancing service elements", The journal of Service Marketing, Vol. 2, No. 3, pp. 35-41.
[23] Matzler, K., Sauerwein, E. and Heischmidt, K.A. (2002), "The factor structure of customer satisfaction: an empirical test of the performance grid and the penalty-reward-contrast analysis", International Journal of service industry Management, Vol. 23, No. 2. pp. 112-29.
[24] Hair, J.F., Anderson, R.E., Tatham, R.L. and Black, W.C. (1995), "Multivariate Data Analysis", Upper Saddle River, New Jersey: Prentice-Hall (Fourth edition).
[25] Ting, S.C. and Chen, C.N. (2002), "The asymmetrical and non-linear effects of store quality attributes on customer satisfaction", Total Quality of Management, Vol. 13, No. 4, pp. 547-569.
[26] Pennings, J.M.E and Smidts, A. (2003), "The shape of utility functions and organisational behaviour", Journal of Management Science, Vol. 49 (September), pp. 1251-63.