Managing Service Quality Using Data Envelopment Analysis

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This study introduces a new managerial tool for evaluating and managing service quality. This new approach treats service quality as an intermediate variable, not the ultimate managerial goal, and makes use of data envelopment analysis (DEA), a nonparametric technique that allows for the relative comparison of a number of comparable organizational decision-making units (Sexton 1986).

Using data from 497 customer surveys collected at 13 different grocery store locations for a major supermarket chain in the southeast region of the United States, relative efficiency scores and prescriptive guidance for improvement were generated for each store. These results were then used to compare the benefits of this new approach to that of existing service quality performance evaluation techniques. The evidence suggests the DEA technique provides a unique and much needed perspective that would help a manager to obtain optimal levels of service quality dimensions that are directly linked to critical performance outcomes for the organization.

Keywords: data envelopment analysis, service quality

INTRODUCTION

Service firms have long recognized the value of monitoring customers' quality perceptions. Accordingly, much effort has been devoted to developing instruments that can be used to adequately measure such perceptions for a variety of service industries. In much the same way, there has been a lot of interest in understanding the relationship between customer service quality perceptions and firm performance. Surprisingly, though, little effort has been devoted to designing tools that allow quality managers to link such customer perceptions to desired performance outcomes so that this information might be effectively used to shape strategic decisions. While evaluative tools have been proposed that are said to help service providers get a sense of where they stand and how they might make service quality improvements, these techniques are still very limited.

The purpose of this study is to propose a new managerial tool for evaluating and managing service quality levels. This new approach treats service quality as an intermediate variable, not the ultimate managerial goal of interest, and makes use of data envelopment analysis (DEA), a nonparametric technique that allows for the relative comparison of a number of comparable organizational decision-making units (DMUs) (Sexton 1986).

In the next two sections, the primary techniques currently available for the management of service quality are described and their limitations chronicled. Then, DEA analysis is introduced, use of the technique in a retail setting is illustrated, and the results of the analysis are outlined, with the unique benefits of this new technique highlighted. Finally, the limitations of this study, directions for future research, and the conclusions that can be made based on this report are discussed.

MANAGING SERVICE QUALITY: EXISTING TECHNIQUES

Despite the difficulty researchers have had trying to model and measure perceived service quality, a few scholars have forged ahead in an effort to provide recommendations as to how service quality information might be used to shape the strategy of the firm. For example, Parasuraman, Zeithaml, and Berry (1988) make several recommendations relating directly to SERVQUAL results. One such recommendation is that a service firm might administer a SERVQUAL survey several times a year to track trends in its service quality offering. By doing this, fluctuations in service quality could be monitored and, ideally, any significant problems detected early and quickly remedied. They also suggest survey results might be used to compare service quality performance across various units within a firm (for example, different stores in a chain) or across competitors in an industry. Others have made similar recommendations (Cronin and Taylor 1994; Asubonteng, McCleary, and Swan 1996). None of these researchers, however, describes exactly how these activities might be systematically carried out so that meaningful analyses can be made.

Regression Analysis

One other, more concrete, recommendation Parasuraman, Zeithaml, and Berry (1988) make is to use regression analysis to determine the relative impact of each service quality dimension on overall service quality. This can be done by regressing the average score for each of the dimensions on the overall service quality score obtained from each individual surveyed. The estimated coefficients can then be compared. The dimension with the largest coefficient represents the most important dimension in terms of its influence on overall quality perceptions. The next largest coefficient represents the second most influential dimension and so forth. By ranking the dimensions in this fashion, this information can be used to focus a firm's efforts on improving those service quality features that have the most influence on overall service quality perceptions.

Performance-Importance Analysis

Hemmasi, Strong, and Taylor (1994) propose that "performance-importance analysis" be used to manage service quality. This would involve first measuring consumers' service quality performance perceptions using a scale that taps whatever pertinent dimensions have been identified for the given service context and measuring consumers' perceptions of the importance of each attribute. Then, each service attribute would be plotted on a matrix in terms of its performance score and its importance score to highlight where improvement efforts should be focused. Figure 1 is an example of such a map. The divisions between the four quadrants are determined using the overall mean importance rating and the overall mean performance score of the data obtained in the survey.

The basic value of this plot is that it could be used to help a firm identify aspects of its service that consumers feel are important but need improvement (that is, the quadrant labeled "Concentrate Here"). Similarly, attributes of the service the firm delivers particularly well, but consumers feel are less important, might be identified so that fewer resources could be devoted to performing these activities (that is, the quadrant labeled "Possible Overkill"). The plot might also be used to compare one firm's performance to other firms. With data from two firms plotted on the same map, one could easily determine how the two firms compare on any of the specific service attributes.

Figure 1 Matrix for a Performance-Importance Analysis.

Firm performance

Excellent	Possible overkill	Keep up the good work
Adequate	Low priority	Concentrate here
	Slightly important	Extremely important

Attribute importance

Source: Hemmasi, Strong, and Taylor (1994)

Norms

Brown (1997) recommends firms employ a technique in which one's service quality performance scores are compared to a set of norms. For example, he suggests a firm's overall mean service quality performance score could be compared to the distribution of a similar firm's overall mean performance scores. When there is a tendency for others to outperform the firm under review, this firm's performance is inadequate and the specific areas in which a firm might focus improvement efforts on are not the areas receiving the scores lowest in magnitude necessarily, but those areas in which the firm's scores rank the lowest compared to its competitors. Brown also suggests that performance at the dimension level or even the specific-item level can be similarly analyzed.

Control Charts

Jensen and Markland (1996) suggest quality control charts could be used to monitor the day-to-day service quality offered by a firm and identify those occasions when a customer was abnormally pleased or displeased with the service he or she received. With this information, then, the firm could more closely examine each of these instances to determine what made them unique, how the unpleasant experiences might be avoided in the future, and how those that were outstanding might be replicated.

Conducting such an analysis would involve looking at a series of plots. First, a plot of each individual's overall perceived service quality evaluation would be examined to identify aberrant service experiences. Then, for these outstanding cases, plots representing the firm's performance on each of the dimensions making up service quality would be examined to determine which of the attributes of the service experience made the occasion an experience that was out of the ordinary.

MANAGING SERVICE QUALITY: EXISTING LIMITATIONS

Generally, each of these approaches should be somewhat helpful to a manager trying to track his or her firm's service quality performance. Unfortunately, however, the value of the information generated from each technique for shaping specific strategic efforts to improve service quality is actually quite minimal. For instance, while regression could be used to determine the relative impact of each service quality dimension on overall service quality, such an analysis would not specifically indicate how managerial and/or firm behavior should be strategically modified. Are resources to be devoted entirely to improving performance on the most influential dimension, the two most influential, or the three most?

And, assuming the firm can, in fact, determine the number of dimensions to focus improvement efforts on, there follows a second very significant, yet unanswered, question: Should the firm attempt to maximize performance in each area by maintaining or increasing resource allocation as if there were no point of diminishing returns resulting from the resources applied? While regression analysis would, perhaps, differentiate the more important dimensions from the less important, it would not give a definitive prescription as to how much adjustment in resources should be made by shifting emphasis from relatively less important dimensions. Similarly, performance-importance mapping, norms, and control charts could also be used to identify areas where adjustments might be made, but none of these tools would indicate the specific amount by which service levels should be adjusted either.

Another important problem associated with these techniques is that the basis used for judging whether a particular service effort has been adequate is the average performance of other branches or firms. That is, each of these approaches helps to identify areas for service quality improvement using the average performance of a branch (firm) across time or average performance of a number of branches (firms) as a standard for comparison.

For instance, using norms for means of comparison involves directly comparing one's own performance to the general tendency of the rest of the group. Using control charts involves identifying instances of service delivery in which the ratings assigned to one or more dimensions fall outside of a specified range that is centered on average performance levels of the dimensions. The quadrants in performance/importance analysis that are used to label whether a particular service area is adequate or in need of attention are defined by the overall mean importance and performance ratings assigned to the attributes. Similarly, if one were to examine the residuals generated in a regression analysis, the same limitation would exist since the predicted performance levels used as a basis for comparison represent what firms can be expected to do on average. It has been suggested, however, that it is inappropriate to set performance standards based on average performance. Instead, one should use the best possible practices as targets (Golany et al. 1990). For this reason, all of these approaches are somewhat problematic.

Service Quality and DEA

Upon reflection, there is also another important limitation to the approaches outlined here that may even be more significant than those already described. Excluding performance-importance analysis, all of these techniques in one way or another incorporate an assumption that the manager's goal is to effectively manipulate various elements, or dimensions, of service quality to maximize the overall measure of service quality. Since it has generally been accepted that high levels of service quality are associated with high levels of firm performance (Bolton and Drew 1994), this is not an entirely unreasonable position to take. Realistically, however, service quality itself is generally not the ultimate managerial, or firm, goal. Instead, it has been suggested that there is an optimal level of service quality that each firm should try to obtain. Beyond this, marginally diminishing returns are encountered (Rust and Oliver 1994; Anderson, Fornell, and Lehman 1994; Parasuraman, Zeithaml, and Berry 1996). Stated in terms of the ultimate goals of the firm, at some point, the incremental costs of service quality, per se, may simply outweigh the additional benefits accruing to the firm.

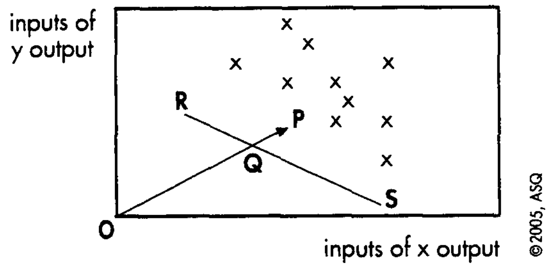
Given this, perhaps a better approach to management of the various dimensions of service quality is to link this activity directly to the ultimate goal of marketing; that is, the maintenance of a healthy business by adequately meeting customers' needs and desires (Gellings 1994). Accomplishment of this goal can be measured by firm outputs such as profitability or customer loyalty, for example. It seems important to identify efficient levels of the various dimensions of service quality that directly link to measures of specific firm outputs that firms do, unequivocally, intend to maximize. It would be useful to know where management has allocated resources to specified dimensions of service quality beyond the point of marginally diminishing returns in terms of these outputs. Importance-performance mapping begins to tap this notion, but the approach fails to link resources invested to real outputs of interest.

Data Envelopment Analysis

DEA was originally introduced by Charnes, Cooper, and Rhodes in 1978 as a tool for nonprofit and public service organizations to use for monitoring organizational performance (Austin 1986). It is a methodology that allows management analysts to measure the relative productive efficiency of each member of a set of comparable organizational units based on a theoretical optimal performance for each organization. For this purpose, the organizational units under analysis are designated as DMUs. These DMUs can be separate firms or institutions, or they can be separate sites or branches of a single firm or agency. The key advantage of DEA over other methods of performance evaluation is that it allows one to consider a number of outputs and inputs simultaneously, regardless of whether all the variables of interest are measured in common units (Sexton 1986).

The method was developed as an extension of what is known as Farrell's single-output/input technical-efficiency measure, which was introduced earlier in 1957 (Charnes et al. 1994). Farrell suggested that when assessing the productivity of an organization, at times, it is important to be able to consider more than one output or more than one input simultaneously. This is problematic because, oftentimes, the different variables of interest are not measured in common units and, thus, are not easily and meaningfully combined into some type of productivity index. As a solution, he proposed a diagrammatical approach that allows one to examine the productivity of an

Figure 2 Farrell's (1957) technical efficiency.



organization in terms of either a single input that is used to produce two separate outputs or two inputs used to produce a single output. Figure 2 depicts an example of the plot for an analysis using the latter approach (Pickering 1983).

The coordinates of each point in Figure 2 represent the amount of each input used to obtain one unit of output. By definition, the organizations closest to the origin in Figure 2 are those that are operating most efficiently, since they are producing the most output for the amount of inputs used. The isoquant RS consists of piecewise linear segments connecting these efficient organizations and defines the "efficient frontier." This is the set of possible combinations of the two inputs an organization might hypothetically use to achieve a given output and still be defined as relatively efficient with respect to the other organizations under analysis. Any organizations located on this frontier are thought to be "best performers" in terms of their efficient use of resources to obtain a desired outcome.

All organizations that fall outside the efficiency frontier are thought to be operating relatively inefficiently in some way or another. For example, the organization labeled as P on the plot is said to be operating suboptimally (since there is hypothetically a way to produce equivalent amounts of output using fewer resources) and "the extent to which P is less than optimal is given by the ratio OQ/OP" (Pickering 1983, 232). By labeling different organizations in this way, those that have been identified as relatively inefficient can look to the relatively efficient units to learn how to make better use of their resources.

Ironically, the great benefit of Farrell's approach is also its major limitation. While it allows an analyst to consider more than one input (output) at a time, it only works for two inputs (outputs) at a time. The production of most goods and services, however, typically involves multiple inputs and outputs. Building on Farrell's notion of an efficiency frontier, Charnes, Cooper, and Rhodes (1978) developed data envelopment analysis to allow an analyst to consider more than two outputs and/or inputs simultaneously. Conceptually, the efficient frontier identified by data envelopment analysis is similar to that of Farrell's. Technically speaking, however, the piecewise linear segments defining Farrell's efficient frontier, as depicted in Figure 2, are replaced with efficient "facets" since the analysis includes multiple dimensions rather than just two (Charnes, Cooper, and Rhodes 1978).

The Basic Model

Using a linear programming approach, data envelopment analysis mathematically determines the best weights for each input and output for the particular DMU under analysis so as to maximize the relative efficiency ratio while satisfying certain minimal conditions specified in the model (Sexton 1986). One general (conceptual) formula for the DEA model structured as a linear fractional program can be written as:

$$\text{Efficiency of DMU}_k = \sum_{r=1}^{s} U_{rk}Y_{rk} \,/\, \sum_{i=1}^{m} V_{ik}X_{ik}$$

where:

k = the DMU under analysis
s = the number of outputs
m = the number of inputs
Y_{rk} = amount of output r produced by DMU_k, $r = 1,...,s$
X_{ik} = amount of input i used by DMU_k, $i = 1,...,m$
U_{rk} = the unit weight placed on output r by DMU_k, $r = 1,...,s$
V_{ik} = the unit weight placed on input i by DMU_k, $i = 1,...,m$

In the application of the procedure, analysts have transformed the mathematical model into an equivalent linear program and solved for relative efficiency values using the simplex method (Sexton 1986).

The transformed linear program is:

$$\text{Maximize } H_k = \sum_{r=1}^{s} U_{rk}Y_{rk}$$

subject to:

$$\sum_{r=1}^{s} U_{rk}Y_{rj} - \sum_{i=1}^{m} V_{ik}X_{ij} \leq 0;\ j = 1,\ldots,n$$

$$\sum_{i=1}^{m} V_{ik}X_{ik} = 1$$

$$U_{rk} \geq 0;\ r = 1,\ldots,s$$
$$V_{ik} \geq 0;\ i = 1,\ldots,m$$

where:
k = the DMU under analysis
n = the number of DMUs to be analyzed
m = the number of inputs

To generate a complete analysis of the relative efficiencies for all the organizational units under study a separate linear program would be solved for each DMU. The results for a particular DMU include the unique set of weights that are used in the ratio formula to calculate the relative efficiency score for the DMU, as well as the relative efficiency score. The reader should note that while linear programming problems typically involve specifying a production function and solving for the levels of each of the various inputs to be used, the mathematics of this problem is no different from more traditional ones. The difference is, here, the levels of the various inputs used serve as the observed data, and the solution is the weights used to calculate the efficiency score.

The weights that are selected for a DMU are those that will give it the highest possible ratio of outputs to inputs while at the same time meeting several constraints. The first constraint is that no DMU can have an efficiency score greater than one. Thus, when the weights are being selected for a particular DMU, the set of viable solutions is limited to those weights leading to an efficiency score of less than or equal to one for that DMU. Since the goal of the program is to maximize each DMU's efficiency score, if this were the only constraint, the set of weights selected for each DMU would be the set that gives each DMU an efficiency score of one.

However, this does not occur because the second constraint is that the weights must be universal. That is, if the weights chosen for a particular DMU were used to calculate the efficiency of any of the other DMUs in the analysis, none of the resulting scores can be greater than one either. The logic behind this constraint is that if another DMU, say DMU_2, obtains an efficiency score of more than one using the weights of the DMU currently under consideration, say DMU_1, this would suggest that DMU_2 is more efficient. This is because the highest possible score DMU_1 can obtain with these same weights has already been limited to one. As a result, one knows a score of greater than one for DMU_2 indicates it is obtaining relatively more outputs for its level of inputs, or the same amount of outputs using relatively less inputs. If this were to occur, then, the weights for DMU_1 would be adjusted downward to give DMU_1 an efficiency score of less than one, signifying it is less efficient than DMU_2. This constraint is satisfied for each DMU in the analysis relative to all the other DMUs included in the study. The final constraint is that no weight that is selected can be negative (Sexton 1986). Only when each of these constraints has been satisfied is a solution offered for a DMU.

Once the weights have been identified, if the relative efficiency score attained by the organizational unit is one, then that DMU is labeled as perfectly "relatively efficient" and is said to appear on the efficiency frontier. Such a unit receiving a score of one would be understood as effectively maintaining ideal levels of inputs and outputs relative to the other units under study. On the other hand, those firms receiving an efficiency score of less than one are located inside the efficiency frontier and, thus, have room to improve. Specifically, an efficiency score of less than one suggests the unit might strive to use a different combination of inputs so that fewer resources are employed and/or to obtain more of selected outputs in an attempt to more efficiently achieve the organizational goals of interest. In other words, some reallocation of resources is necessary.

The Efficient Reference Set

In addition to producing the basic relative efficiency score for the DMU under study, data envelopment analysis also provides results that can be helpful in prescribing specifically what adjustments to the inputs and outputs should be made. In particular, DEA results include information that enable one to construct a hypothetical target DMU for any DMU that has been labeled as inefficient. This hypothetical DMU has a combination of inputs and outputs such that it would be rated perfectly efficient if its efficiency score were calculated using the same input and output weights as those assigned the inefficient DMU. Thus, this target DMU serves as a model of how the inefficient DMU might adjust its inputs and outputs so that it might also move to the efficiency frontier.

The hypothetical, ideal DMU for a particular inefficient DMU is located at the point where the ray connecting the inefficient DMU and the origin crosses the efficient frontier. For instance, the hypothetical, efficient DMU for DMU P located in Figure 2 is located at Q on the efficient frontier. Conceptually, the inputs and outputs of this new hypothetical DMU are a weighted average of the inputs and outputs of the efficient DMUs that define the "boundary" that makes up the envelope for the inefficient DMU. In this example, DMUs R and S make up DMU P's "efficient reference set." These DMUs are the ones to which DMU P was most directly compared to obtain its efficiency score (Austin 1986). These are also those DMUs that, hypothetically, the inefficient DMU should emulate in order to move toward efficient operations.

The information needed to construct such a hypothetical DMU is provided in the dual of the linear program (Tankersley and Tankersley 1998).

> In the theory of linear programming, every linear program has a companion linear program, which is called its dual. The dual problem, which uses a completely different set of variables, has its own set of constraints and its own objective function expressed in terms of those variables... Linear programming theory teaches that, when the simplex method is applied to any linear program, not only do we obtain its optimal solution, we also obtain the optimal solution to the dual problem. Thus, with no additional computational effort, whenever we solve the problem (DEA), we also solve its dual; that is, we obtain the values of the dual variables that optimize the dual objective function while satisfying the dual constraints (Sexton 1986, 23).

Given this, then, it is not necessary to derive and solve the separate dual problem to construct a hypothetical DMU for a particular DMU.[i]

Model Assumptions

There are just two assumptions that must be made to use the basic data envelopment analysis model in the form presented previously. These are outlined by Nunamaker (1983) as follows:

> First, the DEA approach assumes constant returns to scale for each DMU evaluated. Second, it is assumed the constructed efficient production frontier is piece-wise linear and continuous. Importantly, this second assumption implies all points along the efficient surface are practically attainable production possibilities (Nunamaker 1983, 189).

Again, these two assumptions apply to the basic data envelopment analysis model presented previously. In the DEA literature, this basic model is known as the CCR model. If either of these assumptions cannot comfortably be made, there are other modified versions that should be applied instead.

A RETAIL SERVICE QUALITY APPLICATION

The supermarket industry was selected as the setting for the present study. To demonstrate how data envelopment analysis might be used for the analysis and decision making necessary to provide adequate levels of each of the various dimensions that constitute grocery store service quality, the inputs and outputs listed in Table 1 were selected. Dimension-level service quality measures serve as the inputs to be managed, and the outputs included are measures a retail manager truly intends to maximize.

Inputs

The inputs listed in Table 1 are the dimensions Dabholkar, Thorpe, and Rentz (1996) use to define service quality in a retail setting. The specific items used to capture these dimensions of service quality are presented in the survey in the Appendix under Section B, "Grocery Store Service Quality." Physical aspects of the store include its appearance and the convenience of its physical layout (items B1-B5). Reliability is the extent to which the retail service provides *what* is promised *when* it is promised (items B6-B10). Personal interaction relates to the behavior of the store's employees (items B11, B12, and B14-B21). Problem solving refers to the store's ability to make service recoveries (items B22-B24), and policy refers to the extent to which the policies a store has adopted meet customers' needs (items B13 and B25-B29).

Table 1 Grocery store inputs and outputs.

Inputs
(adapted from Dabholkar, Thorpe, and Rentz 1996)
1. Physical aspects
2. Reliability
3. Personal interaction
4. Problem solving
5. Policy

Outputs
1. Net profit as a percentage of sales
2. Customers/labor hour
3. Customer loyalty

Outputs

The outputs included in the study are those judged to best profile the current performance of each of the participating grocery stores. "Net profit as a percentage of sales" serves as a general indicator of the profitability of each store. The output "Customers/labor hour" serves as a proxy for each store's ability to acquire customers. The participating chain provided these output measures for each store included in the study. This information was drawn from existing internal databases.

The third output, a measure of customer loyalty, was included in an attempt to measure each store's ability to retain customers. This was assessed with the two items listed under section A, "Customer loyalty," in the survey depicted in the Appendix.

RESULTS

Data Envelopment Analysis

A sample of customers from 13 different stores of the participating chain was surveyed over a six-week period during the summer of 1999. There were 497 customers

Table 2 Service quality item level summary for store 1 (Survey item number).

Dimension	Item	Item	Item	Item	Item	Item	Item	Item	Item	Row average
1	6.36 (B1)	6.38 (B2)	6.49 (B3)	5.92 (B4)	6.00 (B5)					6.23
2	6.43 (B6)	6.36 (B7)	6.06 (B9)	6.21 (B10)						6.27*
3	6.00 (B11)	6.00 (B12)	6.17 (B14)	6.04 (B15)	6.22 (B16)	6.13 (B18)	5.56 (B19)	5.98 (B20)	6.14 (B21)	6.03*
4	6.40 (B22)	6.24 (B23)	6.35 (B24)							6.33
5	6.47 (B25)	6.44 (B26)	5.96 (B27)	6.33 (B28)	6.37 (B29)	6.27 (B13)				6.31

*Readers should note service quality item numbers 8 and 17 were not included in the analysis. The purpose of these items was to assess the quality of the pharmacy in each store. Several stores included in the study did not have a pharmacy.

Table 3 Dimension-level input data and output data for all stores.

Store	Service quality dimensions* 1	2	3	4	5	GOSQ*	L*	NP*	CPH*
1	6.23	6.27	6.03	6.33	6.31	3.63	3.98	7.00	3.65
2	4.91	5.75	5.44	5.99	6.05	3.00	3.46	.00	4.93
3	6.43	6.40	6.52	6.55	6.23	3.83	3.59	7.00	4.14
4	6.05	6.22	6.14	6.35	6.51	3.68	4.00	7.00	3.95
5	6.38	6.42	6.42	6.55	6.55	3.80	3.88	5.00	4.31
6	6.06	6.21	6.00	6.42	6.20	3.55	3.38	10.00	3.65
7	5.71	5.86	6.23	6.42	6.20	3.54	3.83	6.00	4.35
8	**6.13**	**6.41**	**6.18**	**6.45**	**6.44**	**3.70**	**3.79**	**4.00**	**3.39**
9	6.18	6.26	6.21	6.76	6.69	3.76	4.27	11.00	4.46
10	6.47	6.36	6.42	6.54	6.61	3.82	4.02	9.00	3.77
11	**6.67**	**6.47**	**6.54**	**6.69**	**6.62**	**3.85**	**3.88**	**7.00**	**3.60**
12	6.44	6.38	6.53	6.61	6.63	3.84	3.92	7.00	3.80
13	6.53	6.21	6.29	6.36	6.43	3.77	4.12	12.00	3.37

***Key:**
1 = Physical aspects average dimension-level score
2 = Reliability average dimension-level score
3 = Personal interaction average dimension-level score
4 = Problem-solving average dimension-level score
5 = Policy average dimension-level score
GOSQ = Global overall service quality (dependent variable of regression)
L = Average customer loyalty score (output variable of DEA)
NP = Net profits (output variable of DEA
CPH = Customers per labor hour (output variable of DEA)

who participated in the study. Only customers age 18 and older were surveyed. For all 13 stores, the majority of customers participating in the study had been shopping at the store they completed the survey in for at least a year.

To illustrate the use of DEA, the service quality performance inputs were calculated by first averaging the responses for each service quality item across all the surveys obtained for a particular store. For example, Table 2 lists the average values of the survey responses obtained for each service quality item for store 1. Then, to create five dimension-level scores for each store, these item level averages were averaged within their corresponding dimension. The last column of Table 2 shows these values for store 1. Table 3 shows these same resulting dimension-level summary measures for all of the stores included the study. Using these measures as inputs and customer loyalty, net profits as a percentage of sales and customers per labor hour as output measures (also shown in Table 3), efficiency scores were generated for each store. The resulting DEA scores for each DMU are listed in Table 4 in order of their magnitude. As the table indicates, the efficiency scores for this set of grocery stores ranges from .917 to 1.000. This suggests all of the stores of interest are operating at least roughly at a 91 percent level of efficiency with regard to their service quality efforts. The mean efficiency score is .96 with a standard deviation of .03. Four stores attained an efficiency score more than one standard deviation above the mean, while two scored more than one standard deviation below the mean.

Table 4 DEA relative efficiency scores.

DMU	2	9	13	7	4	1	10	5	6	3	12	8	11
Efficiency score	1.0	1.0	1.0	.995	.990	.987	.961	.953	.943	.940	.931	.922	.917

Three stores were assigned an efficiency score of 1. In the context of this article, these units would be said to be obtaining, relatively speaking, the best customer loyalty levels, net profits as a percentage of sales and customers per labor hour, given each DMU's levels on the five dimensions of perceived service quality.

Those stores operating less than perfectly efficiently are thought to have room to improve. *To move up to the relative performance of their "efficient" peers, each of the inefficient stores should attain either more, or at least the same, output levels with either the same, or lower, levels (respectively) on the dimensions of perceived service quality.* In a practical sense, such results translate into two important questions for each inefficient unit under consideration. First, "Is the store wasting resources, or effort, to over-develop an unnecessarily high level on one or more dimensions of perceived service quality?" Or second, "Is it the case that some aspect of a store's perceived service quality is being taken for granted and is less appreciated by its customers such that while its perceived service quality levels are similar to the other stores, these perceptions are not translating into equivalent, desired organizational outcomes?"

The two stores that ranked more than one standard deviation below the mean for the group provide a good starting point for further examination. For instance, it might be interesting to compare the operating practices of these two stores to the practices of stores that scored at least one standard deviation above the mean. It is possible certain effective management policies and operating techniques that are easily transferable might be identified based on this comparison.

In addition to studying the procedures generally employed by those stores receiving relatively high efficiency scores, those stores with less than perfect efficiency might also look to the results of the dual problem from the DEA for guidance as to how they might improve the efficiency with which they deliver service quality to customers. As described earlier, this guidance is provided in the form of a hypothetical, relatively perfectly efficient DMU whose input and output levels can be used to identify prospective adjustments to an inefficient DMU's existing inputs or outputs that would help the DMU move toward the efficiency frontier. In Table 5, the resulting efficient reference set weights needed to construct each store's hypothetical DMU are provided. In the context of the present example, this target model actually highlights service quality dimensions where resources or service efforts are being inefficiently applied based on the ratio of perceived service quality levels to realized organizational outcomes. This information serves a diagnostic purpose: It focuses attention on areas where there is potential for useful resource reallocation, process change, or both, with respect to the identified inefficient dimension.

Table 5 DEA efficient reference set weights.

	Weights to apply to the DMUs in the efficient reference sets		
DMU	DMU No. 2	DMU No. 9	DMU No. 13
1		.4161	.5347
2	1.0000		
3	.2641	.6364	
4		.7011	.2443
5	.1956	.7502	
6		.6140	.2705
7	.2656	.6817	
8		.6099	.2878
9		1.0000	
10		.4981	.4595
11		.4407	.4850
12		.6137	.3155
13			1.0000

Table 6 Current and prescribed input and output levels.

(Current levels)
(Target levels)
(Identified excesses)

DMU	Inputs 1*	2*	3*	4*	5*	Outputs Customer loyalty	Net profit	Cust/Labor hour
1	6.230	6.265	6.027	6.330	6.307	3.980	7.000	3.650
	6.064	5.926	5.946	6.211	6.222	3.980	10.994	3.658
	-0.166	**-0.339**	**-0.081**	**-0.119**	**-0.084**	**0.000**	**3.994**	**0.008**

*(1 = Physical aspects, 2 = Reliability, 3 = Personal interaction, 4 = Problem solving, 5 = Policies)

The efficiency score assigned to store 1, .987, suggests that other stores in the reference set are getting more "bang for the buck" with respect to the utility of the perceived levels of service quality. Either they are obtaining better organizational outcomes than store 1 even though their perceived levels of service quality are similar to that of store 1, or they are obtaining similar outcomes to those observed by store 1, but have lower perceived service quality levels for some combination of the five dimensions of service quality. Whichever the case, the implication is that in order for store 1 to move to the efficiency frontier, some managerial attention to the linkage between the five dimensions of perceived service quality and resulting organizational outcomes is required. The target model identifies problem areas for consideration by management.

Based on the values in Table 5, we see that DMU 1's hypothetical, target inputs and outputs are a linear combination of DMU 9 and DMU 13's inputs and outputs. For instance, the ideal level of perceived service quality with respect to tangible features (input 1) is shown by the inputs for hypothetical DMU1 as:

$$\text{input } 1_{DMU1} = (.4161) * (\text{input } 1_{store9}) + (.5347) * (\text{input } 1_{store13})$$

Using this approach, the hypothetical target values were calculated. These values for DMU 1 are depicted in Table 6 along with the store's current input and output levels and the excesses this analysis identified.

Examining these values, one can see that excess levels are identified for each of store 1's service quality dimensions. Do these results suggest that perceived service quality should be reduced by DMU 1? After all, to increase efficiency in the traditional sense of managerial or engineering efficiency, with other things being equal, inputs should be decreased. This, however, is counter intuitive. A traditional interpretation of the typical "target model" and its prescribed adjustments would, in fact, suggest managers work to directly reduce some combination of the inputs by the amount of prescribed change while maintaining the level of outputs. Had these inputs represented actual expenditures or some other specific outlay of resources, this might make sense. Here, however, it represents a level of perceived service quality that is being compared to a theoretical construct.

Obviously, an organization would not wish to purposely reduce perceived service quality levels among its customers. Instead, the authors argue the adjustments prescribed here serve more usefully as ordinal indicators of inefficiencies ripe for change. Overall, someone is getting more "bang for the buck" in terms of efficient use of perceived service quality. Dimensions are highlighted where other DMUS have been able to get more return and, thus, DMU 1 should examine its operating procedures in these identified service quality dimensional areas to identify possible sources of inefficiency or ineffectiveness. The magnitudes of the changes prescribed by the "target model" simply serve to rank the dimensions in terms of those areas most likely to produce efficiency gains. By focusing on the most important areas, the organization is more likely to efficiently and effectively provide a service that more adequately meets customers' needs and desires while at the same time maximizing the organization's goals. From this perspective, the results displayed in Table 6 suggest the greatest efficiency gains are possible in the areas of the tangibles and reliability dimensions of its service quality offering, as these categories rank first and second in terms of the magnitude of input changes prescribed. Perhaps fewer resources should be devoted to providing modern looking equipment and fixtures or the most visually appealing signage? Are the results of these efforts actually "overkill"? There is a narrow margin between too little and too much emphasis on service quality, but these are the types of hard questions raised by the application of data envelopment analysis to reported levels on service quality dimensions. The process recognizes the presence of diminishing returns even in the area of service quality based on the results of others.

Upon closer examination of the items that constitute each of the five service quality input dimensions, it may even be the case that one or two features of the store's current service quality offering are not appreciated by the customers in the way one would expect, and a few simple adjustments would have a positive impact on the outcomes of interest. For instance, perhaps DMU 1's employees stock its shelves during the day. Since this is a highly visible activity, it is likely to attract attention and create the impression that the store is very effective at keeping merchandise available (part of the second dimension, reliability). At the same time, however, this may frustrate customers during peak traffic intervals as they find they have to struggle to move through the aisles. Ultimately, this may impact performance measures negatively as customers may tend to shop elsewhere to avoid the inconvenience. Other stores may stock their items later at night and thereby have lower perceived reliability, but, in fact, attract and maintain a larger customer base. While such a pattern could only be identified after further investigation, the DEA results provide insight into which specific areas might reveal these types of operational differences. It also suggests potential beneficial changes.

Comparison of DEA and Regression Analysis

To provide empirical evidence as to the unique results data envelopment analysis would provide, a regression analysis of the same service quality data was also generated. The general dimension-level scores for each store were regressed on a global measure of overall service quality obtained using the question in section C of the survey as prescribed by Parasuraman, Zeithaml, and Berry (1988). Table 3 displays the values used in this analysis. The following model resulted:

$$\mathbf{OSAT} = -1.103 + .241(\mathbf{PA}) + .054(\mathbf{R}) + .263(\mathbf{PI}) + .101(\mathbf{PS}) + .103(\mathbf{P}) + \text{Error},$$

where:

OSAT = the mean **overall satisfaction** performance score for each store

PA = the mean performance score each store received corresponding to the **physical aspects** dimension of grocery store service quality

R = the mean performance score each store received corresponding to the **reliability** dimension of grocery store service quality

PI = the mean performance score each store received corresponding to the **personal interaction** dimension of service quality

PS = the mean performance score each store received corresponding to the **problem solving** dimension of grocery store service quality

P = the mean performance score each store received corresponding to the store's **policies** dimensions of grocery store service quality

So that these results could be easily compared to the results of the DEA, the residuals from this regression analysis corresponding to each of the 13 stores were examined. Table 7 depicts these residuals in order of their magnitude.

Positive residuals represent above average dependent variable scores and negative residuals represent below average dependent variable scores. In the context of this study, stores with large positive residuals represent the stores with the higher levels of service quality performance because a positive residual represents the amount by which a store's average satisfaction score exceeds the predicted level from the model. This predicted level of overall satisfaction for any given set of dimension-level service quality scores represents what the stores can, on average, be expected to observe in terms of customer satisfaction. A store that reports an average satisfaction

Table 7 Regression analysis residuals

DMU	4	8	9	7	1	3	13	5	6	10	12	2	11
Efficiency score	.059	.037	.028	.023	.017	.017	.004	-.008	-.011	-.011	-.024	-.050	-.083

Table 8 Regression models using DEA outcome measures as the dependent variable

	Regression coefficients					
Dependent variable	**Physical aspects**	**Reliability**	**Personal interaction**	**Problem solving**	**Policies**	**r***
Customer loyalty	.541	-1.122	-.241	-.169	1.294	.39
Net profit as % of sales	15.880	-18.274	-12.264	11.312	-.779	.12
Customers per labor hour	-1.408	-.207	.690	1.046	.205	.31

*Correlations are between the residuals from each regression model and the DEA efficiency scores

score much larger than this predicted value is thought to be performing better than expected and, by comparison, is performing better than other stores that also have positive residuals that are not as large. Similarly, the more negative the residual, the worse the store's service quality performance.

Given this, the correlation between the DEA efficiency scores that can range from 0 to 1 and the regression residuals serves as a rough indicator of the extent to which data envelopment analysis offers relative performance evaluation information similar to that which the regression analysis offers. The Pearson's product moment correlation between the DEA efficiency scores and the residuals based on this regression model is .35. As others have suggested (Blalock 1979; Rowntree 1981; O'Sullivan and Rassel 1999), this is a relatively low correlation. Therefore, one can conclude these two performance evaluation techniques do indeed provide unique evaluations. To lend further evidence to the validity of this observation, consider DMU 2. In the data envelopment analysis, it ranks first in terms of performance, yet in the regression analysis it ranks second to last. Similarly, DMU 8 ranks second to last in the DEA results, while it ranks second to highest in the regression analysis.

Also, consider the recommendations for input and output adjustments one might glean from these two different analyses. Based on the regression model and the guidance provided by Parasuraman, Zeithaml, and Berry (1988), a manager of any of the stores in this analysis would conclude that the best way to improve service quality performance is to devote as much effort as possible to improving personnel interaction with customers and enhancing the physical facilities. These are the two service quality dimensions with the largest coefficients. This suggests they contribute most heavily to overall perceptions of service quality. In contrast, the data envelopment analysis results for DMU 1, for example, highlight tangibles and reliability as areas to examine for possible inefficiencies.

One might suggest these results are not surprising, since different outcome measures are employed in each analysis. To test further for differences in these two analytical techniques, three additional regression models were generated. In each model, the original global overall service quality measure was replaced with one of the three outcome measures employed in the data envelopment analysis. The corresponding regression models and the correlations between the residuals of each and the DEA efficiency scores are presented in Table 8.

The residuals from each of these analyses are not highly correlated with the efficiency scores of the DEA either. Not surprisingly, the managerial guidance one would draw from any one of these three models is also very different from that of the DEA. Unlike the prescription provided by the single data envelopment analysis, the varying coefficients produced across these three individual regression models paints an unclear picture as to what type of influence each dimension has on performance, which dimensions are the most influential, and which warrant the most attention. These limitations are important.

CONCLUSIONS

Discussion of the Results

The purpose of this study is to demonstrate that while useful for certain purposes, several features of the standard methods currently available for the management of service quality significantly limit the guidance these tools offer. In general, it appears the basic contribution of these existing tools is to aid in the identification of the interrelationships of the various service quality dimensions as they contribute to an overall level of service quality. While these phenomena are theoretically interesting and have, at a fundamental level, some value to the service quality manager, several limitations have been identified. They are as follows:

- Each technique uses average performance as a means of comparison, rather than identifying the "best performers" in the group. As a result, suboptimal goals may be adopted.
- No clear, prescriptive guidance is offered as to the nature and magnitude of adjustments that should be made once problem areas have been identified.
- With the exception of performance-importance analysis, their goal is to maximize service quality levels generally. Evidence, on the other hand, suggests there is an optimum level at which service quality should be offered, beyond which costs outweigh the benefits.

Important to the discussion of these limitations is the recognition that service quality, per se, is not the ultimate organizational goal. The data envelopment analysis technique provides a unique and much needed perspective that helps a manager attain optimal levels of service quality dimensions directly linked to critical performance outcomes for the organization. None of the existing techniques provides performance evaluations or prescriptions for improvement similar to that of the data envelopment analysis.

To fully appreciate the added value of this technique, consider once again the initial regression analysis conducted in this study, which included overall satisfaction with a store's service quality offering as the dependent variable. In this analysis, "good" performance is characterized by overall satisfaction performance scores that are higher than that predicted by the regression model, or what, on average, one can expect a given firm to observe. For instance, store 11 received a poor evaluation in the regression analysis because this store is characterized by very high scores for each of its service quality dimensions relative to the overall satisfaction score it reports (refer to Table 3). Based on the estimated relationship between the five service quality dimensions and overall satisfaction, the regression model predicts store 11 would observe a somewhat higher level of overall satisfaction among its customers than it actually did. For this reason, the authors conclude it has not performed as well as others in the dataset. This is reflected in the store's low negative residual of -.083.

In the data envelopment analysis, store 11 did not receive a "good" evaluation either. Relative to the rest of the stores, its efficiency score of .917 ranks last. This value is observed because relative to its high service quality dimension-level scores (the inputs to the DEA model) the store observed relatively low levels of the outcomes of interest compared to some of the other participating stores (recall the outputs in this model are customer loyalty, net profits, and customers per labor hour, refer to Table 3).

Both of these analyses provide meaningful, helpful evaluations. They both suggest given store 11's high dimension-level service quality scores, this store should be observing better outcome measures (higher overall satisfaction levels in the regression analysis and some combination of greater customer loyalty, higher net profits, and more customers per labor hour in the data envelopment analysis).

The added value of the DEA is that the results also provide poor evaluations for stores that report high levels of perceived service quality along with high levels of overall customer satisfaction but, for some reason, do not report correspondingly high levels of the outcomes that the stores ultimately need to observe in order to survive (that is, customer loyalty, net profits, and customers per labor hour). For instance, store 8 also has high marks for each of its service quality dimensions and, therefore, based on the regression model, one expects it to report a high level of overall satisfaction among its customers. The data in Table 3 reflect this is the case. In fact, unlike store 11, store 8 observes overall satisfaction levels exceeding that predicted by the regression model given its service quality dimension-level scores. On the other hand, despite this high level of overall satisfaction among its customers, and its high marks in the regression analysis, store 8 has not observed corresponding high levels of the three ultimate outcomes of interest when one considers the same measures for the other stores in the analysis (also displayed in Table 3). The regression analysis in no way captures this problem. The data envelopment analysis does. While high levels of overall satisfaction among a store's customers is an important intermediate goal to strive for, it is not going to determine whether the store meets its ultimate objectives. The relatively low correlation of .35 observed between the DEA efficiency scores and the residuals of the regression model reflects this difference in the two techniques.

Limitations of the Study

While the results of this study suggest that DEA provides additional insights into the management of service quality, it must be recognized that this research has several limitations. First, Thomas, Greffe, and Grant (1986) recommend the number of DMUs included in a study using data envelopment analysis be at least two times the number of input and output variables included in the DEA model of the study. Otherwise, they report it is likely all or most of the participating decision-making units will appear on the efficiency frontier. If this were to happen, the results will provide little helpful information as to how participants might make improvements. In this study, there is a total of eight input and output variables. Ideally, then, at least 16 different stores should have been included. Because of limited resources, only 13 stores were considered in this analysis. This had little impact, as only three of the 13 stores were assigned a perfect efficiency score leaving a large majority of the stores as candidates for improvement.

Second, this study is limited to one industry. Therefore, generalizing these results beyond this industry should be done with caution.

Third, while these findings suggest the data envelopment analysis technique does provide additional insight into the management of service quality, it is important to remember that the specific recommendations this technique will generate are prediagnostic in nature (Tankersley and Tankersley 1996). That is, the prescriptions for change must be examined in light of the specific operational context of each unit for whom changes have been prescribed to determine whether the adjustments that have been suggested are in fact feasible.

Concluding Remarks

While the purpose of this study is to illustrate the unique perspective data envelopment analysis brings to the domain of service quality management, it should be appreciated that perhaps the most valuable contribution is not to provide a new managerial technique. Instead, this study proposes a reconfiguration of the dominant paradigm with respect to the management of service quality; specifically, the recognition that service quality is not to be maximized but optimized. As was stated previously, there is an optimal level of service quality each firm should try to attain. Beyond this, marginally diminishing (and perhaps even negative) returns are encountered. While marginally diminishing returns have been recognized in the literature, this aspect of service quality has largely been ignored to date in terms of managerial tools. Furthermore, data envelopment analysis is the first service quality evaluation technique proposed to date that incorporates this aspect of the service quality phenomenon and enables the manager to link input usage to critical performance outcomes. This study has provided preliminary evidence as to the unique perspective provided by DEA and based on this evidence, it is clear, its application in service quality contexts warrants further investigation.

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APPENDIX: Survey Instrument

Dear Grocery Store Customer:

Your satisfaction is very important to us. Please take a few minutes to let us know how we are doing and how we might serve you better. Your participation is greatly appreciated.

Thank you.

A. Customer Loyalty

Please check the response that best describes you.

1. What percentage of your total grocery shopping did you do at this grocery store over the last 12 months? Please check one.
   __ All or 100%
   __ 75 - 99%
   __ 50 - 74%
   __ 25 - 49%
   __ less than 25%

2. How long have you been shopping at this store?
   __ more than one year
   __ 9 - 12 months
   __ 6 - 8 months
   __ 3 - 5 months
   __ less than 3 months

B. Grocery Store Service Quality

The following set of statements refers to your feelings about **THIS** grocery store location. For each statement, please circle the number showing the extent to which you believe **THIS** store has the feature described by the statement.

Circling a 7 means you strongly agree that this grocery store location has that feature. A 1 means you strongly disagree and a 4 means you neither agree or disagree.

You may use any of the numbers in the middle as well to show how strong your feelings are. There are no right or wrong answers—all we are interested in is a number that best shows how you feel about this grocery store.

1 — 2 — 3 — 4 — 5 — 6 — 7

Strongly Disagree — Strongly Agree

1 2 3 4 5 6 7 1. This grocery store has modern-looking equipment and fixtures.
1 2 3 4 5 6 7 2. The physical facilities at this grocery store are visually appealing.
1 2 3 4 5 6 7 3. This grocery store has clean, attractive, and convenient restrooms.
1 2 3 4 5 6 7 4. The store layout at this grocery store makes it easy for customers to find what they need.
1 2 3 4 5 6 7 5. The store layout at this grocery store makes it easy for customers to move around in the store.
1 2 3 4 5 6 7 6. When this grocery store **bakery** promises to do something by a certain time, it will do so.
1 2 3 4 5 6 7 7. When this grocery store **deli** promises to do something by a certain time, it will do so.
1 2 3 4 5 6 7 8. When this grocery store **pharmacy** promises to do something by a certain time, it will do so.

1 2 3 4 5 6 7 9. This grocery store has merchandise available when the customers want it.

1 2 3 4 5 6 7 10. This grocery store insists on error-free sales transactions and records.

1 2 3 4 5 6 7 11. Associates in this grocery store have the knowledge to answer customers' questions.

1 2 3 4 5 6 7 12. The behavior of associates in this grocery store instill confidence in customers.

1 2 3 4 5 6 7 13. Customers feel confident this grocery store will stand by its promise to guarantee satisfaction.

1 2 3 4 5 6 7 14. **Bakery** associates in this grocery store give prompt service to customers.

1 2 3 4 5 6 7 15. **Deli** associates in this grocery store give prompt service to customers.

1 2 3 4 5 6 7 16. **Check-out** associates in this grocery store give prompt service to customers.

1 2 3 4 5 6 7 17. **Pharmacy** associates in this grocery store give prompt service to customers.

1 2 3 4 5 6 7 18. Associates at the **customer service desk** in this grocery store give prompt service to customers.

1 2 3 4 5 6 7 19. Check-out associates in this grocery store always offer to carry out customers' groceries.

1 2 3 4 5 6 7 20. Associates in this grocery store are never too busy to respond to customers' requests.

1 2 3 4 5 6 7 21. Associates in this grocery store are consistently courteous with customers.

1 2 3 4 5 6 7 22. This grocery store willingly handles returns and exchanges.

1 2 3 4 5 6 7 23. When a customer has a problem, this grocery store shows a sincere interest in solving it.

1 2 3 4 5 6 7 24. Associates of this grocery store are able to handle customer complaints in a timely manner.

1 2 3 4 5 6 7 25. This grocery store offers high-quality merchandise.

1 2 3 4 5 6 7 26. This grocery store provides plenty of convenient parking for customers.

1 2 3 4 5 6 7 27. This grocery store has operating hours convenient to all their customers.

1 2 3 4 5 6 7 28. This grocery store makes it easy to pay by check.

1 2 3 4 5 6 7 29. This grocery store makes it easy to pay by credit/ATM card.

C. Overall Satisfaction

Please circle the response that best describes your feelings.

1. The OVERALL service quality of **this** grocery store is...

Excellent Good Fair Poor

D. Customer Comments

1. We encourage your comments and suggestions. Please use the space below (or the space on the front cover) to tell us how we might better serve you.