Validating a DEA-based Menu Analysis Model using Structural Equation Modeling

Dennis Reynolds  
Washington State University, der@wsu.edu

James Taylor  
University of Mississippi, jtaylor@olemiss.edu
INTRODUCTION

A restaurant’s menu is its operator’s fundamental strategic vehicle. As McCall and Lynn (2008) noted, the menu ultimately influences how customers perceive the operation. The menu communicates the offerings, indicates the type of service to be expected, and reflects the amenities that coalesce to become the guest’s dining experience. Most important, the operator’s success ultimately depends on how the restaurant offsets the costs of its offerings through an associated pricing scheme that returns a profit.

Researchers have therefore sought menu-engineering models that optimize the menu’s offerings. Such models are intended to enhance efficiency, increase guest satisfaction, and maximize profit. Unfortunately, the majority of menu-engineering approaches are more art than science; they typically include too few variables to be reliable and fail to represent fundamental aspects of food preparation (Reynolds, Merritt, & Pinckney, 2005). For example, the prevailing matrix models (e.g., Kasavana & Smith, 1982; Miller, 1987; Pavesic, 1983) are predicated on only food-cost related data and sales velocities. Moreover, these models suffer from variable interdependency, a problem created by the central intersection between vectors in the matrix.

In response to these issues, researchers have begun to integrate other fundamental variables into menu analysis. For example, Cohen, Mesika, and Schwartz (1998) conceptualized a multidimensional approach that included food cost, price, labor cost, and sales velocity, although they did not discuss how these might be computed. Seeking to include all related costs, Raab and Mayer (2007) adapted a menu engineering model that includes activity-based costing methodologies in an attempt to trace all costs to individual menu items, but noted that this approach is difficult to apply because items must be continually assessed and data collection can be laborious.
In an effort to create a more holistic analytic model that is not constrained by problems associated with matrix models, Taylor, Reynolds, and Brown (2009) identified various surrogates for labor-related issues and employed data envelopment analysis (DEA), a non-parametric statistical approach that alleviates many of the shortcomings of other techniques such as a dependency on mean values or ordinary least squares. DEA also permits assessment of contingent efficiency and measures the performance of each menu item while accounting for their differing characteristics. Furthermore, the Taylor et al. study expanded the application of DEA as a valuable method for a wide range of service-business analyses, as recommended by Keh, Chu, and Xu (2006). The researchers proposed a viable model but because they tested it only through simulation it has yet to be fully validated.

The purpose of this study is, then, using DEA, to test a multi-dimensional holistic model that includes multiple variables and to assess its validity using structural equation modeling (SEM). In particular, we applied DEA to test the model proposed by Taylor et al. (2009) using data from a single unit of a three-unit full-service restaurant chain. Next, building on the methodology outlined by Fornell and Larcker (1981) and Garver and Mentzer (1999), among others, we used SEM to test the fit to the aforementioned DEA-based model, using data from the other two units, replicating the analysis separately for each of the two units.

BACKGROUND

As noted, early menu analysis models, as first introduced by Miller (1980), employed a four-quadrant matrix with vectors associated with sales and popularity (measured as sales velocities). Kasavana and Smith (1982) later incorporated gross profit. Pavesic (1983) modified these matrix models using food cost and weighted average gross profit, the latter variable reflecting both popularity and gross profit. This model was noteworthy as it introduced an indirect third variable.
In addition to the variable interdependency issue, which limits the utility of matrix models, researchers have noted other problems with the matrix approach. For example, gross profit may serve as an indicator of net profit but fails to reflect labor cost (which may be a restaurant’s largest expense). Horton (2001) expanded on this point, noting that labor is not a differential cost. Reynolds and Biel (2007) argued that, in assessing the functionality of various aspects of a restaurant operation, including the menu, critical items that lead to profitability must be considered. Finally, matrix models assume incorrectly that all indirect costs are equally related to all menu items (Morrison, 1996).

Attempting to circumvent these shortcomings, Hayes and Huffman (1985) developed an individual profit-and-loss statement for each menu component in an effort to allocate all costs, including labor and fixed costs, to individual associated menu items. Next, Bayou and Bennett (1992) developed a profitability analysis model designed to assess the profitability of menu items, which included the consideration of labor. More recently, Raab and Mayer (2007) adapted a matrix model to include activity-based costing methodologies in an attempt to trace all costs to individual menu items. Each of these models solved many of the traditional matrix-model issues, but introduced a new problem: difficulty in gathering the requisite data. Such analyses, while interesting from an empirical perspective, were not practical because the information analyzed is not readily available to operators.

Proposing an approach that is both inclusive of fundamental economic indicators and realistic in terms of application in either individual units or chains, Taylor et al. (2009) introduced a model with output variables including gross profit and sales velocity and input variables including those that serve as surrogates for labor-cost-related measures. They also introduced DEA as an analytic technique for menu-item efficiency. However, because the analysis was conducted via a
simulation the findings were not validated. Still, the introduction of DEA as a menu management and analysis technique is provocative and merits validation through direct testing.

**DEA and SEM**

DEA, first developed in 1978 to evaluate governmental and non-profit operations’ efficiency across units, has been applied in a variety of service-business sectors including hotels (Morey & Dittman, 1995), chain restaurants (Reynolds and Thomson, 2007), service productivity (Johnston & Jones, 2004), services marketing (Donthu, Hershberger, & Osmonbekok, 2005), and tourism (Wober & Fesenmaier, 2004). Operationally, DEA is a nonparametric statistical approach that considers the ratio of the weighted sum of outputs to the weighted sum of inputs, ultimately identifying the most efficient units within the given set and in consideration of the variables included in the analysis. It is considered superior to other means of evaluating efficiency, most of which assess units relative to an average unit; DEA is an extreme-point method that compares each unit with only the ‘best’ real or virtual producers.

In the context of menu-item analyses, DEA looks at the efficiency of $n$ menu items as a set of $n$ linear programming problems. Stated another way, DEA assesses $\lambda$ as a vector describing the percentages of other units used to construct the ideal or virtual menu item. It considers $\lambda_x$ and $\lambda_y$ as input and output vectors for the analyzed units, resulting in values for $x$ and $y$ that describe the virtual inputs and outputs, respectively. The resulting $\theta$ is the menu item’s efficiency.

Using DEA as a menu analysis method yields additional benefits: The approach can include multiple inputs and outputs; inputs can be identified as controllable or non-controllable (i.e., within or beyond management’s control); there is no functional form relating inputs to outputs; individual menu items are compared directly against another item or combination of items with similar attributes; and inputs and outputs do not require an *a priori* relationship (Charnes,
Cooper, Lewin, & Seiford, 2001). Nevertheless, DEA has its limitations. One of the most important of these is that, since DEA is a nonparametric technique, statistical hypothesis tests are difficult to conduct, and assessing the strength or fit of the resulting model is correspondingly difficult.

Some researchers have responded to this shortcoming by integrating a cross-model approach. For example, Sohn and Moon (2004) suggest applying models with goodness-of-fit measures on a post hoc basis. One such approach that offers goodness-of-fit indices and includes flexible assumptions (particularly allowing interpretation even in the face of multicollinearity) is structural equation modeling (SEM). Furthermore, SEM is usually viewed as a confirmatory rather than exploratory procedure (Anderson & Gerbing, 1988; Bollen & Lennox, 1991).

The objective of the present study is to replicate the DEA approach reported by Taylor, et al. (2009). The model we propose includes a holistic set of variables including those pertaining to labor. After conducting the DEA we will assess this relatively complex menu analysis model using SEM.

**METHODOLOGY**

The aforementioned model used the following inputs for each menu item: preparation difficulty as measured on a four-point scale, where ‘1’ reflects the simplest preparation method; number of purveyors; and number of stations used to prepare the item. Preparation was treated as a controllable variable, and the number of purveyors and number of stations used to prepare items were treated as uncontrollable as the unit managers cannot readily alter them. Output variables include gross profit per item and sales velocities (as an indicator of popularity).
Associated data were collected from three units of a small full-service restaurant chain located in the southeastern US. Each of the units offers the same menu with 65 items using similar preparation methods and the same purveyors. (Note: While proper input and output identification is critical—as noted by Sigala, 2004—we do not go through the exercise of justifying the selection process here as the goal was to replicate and test a previous model.)

With regard to the SEM, sample size is important because related tests are sensitive to both sample size and differences in covariance. Bentler and Chou (1987) asserted that researchers should use a sample of five subjects per parameter estimate in SEM analyses, but only if the data are normally distributed, with no missing data or outlying cases. Data that are not normally distributed or are flawed in some way require larger samples. Since measured variables typically have one or more path coefficients associated with other variables, with potential residual term or variance estimates, these recommendations also support approximately 10–15 cases per measured variable. Thus, the number of menu items (n = 65) is adequate.

Menu item data were evaluated using Frontier Analysis 4.0, a product developed by Banxia Software that facilitated the DEA. However, unlike the Taylor et al. (2009) study, which used the CCR model of DEA, we opted for the BCC model, the variable-returns-scale model that is more widely used today (cf. Donthu et al, 2005). The BCC model also features convexity, an attribute that allows for a convex combination of menu items in constructing the virtual ideal menu item. Finally, we also diverged somewhat from the previous study in that menu items were not grouped by category (e.g., appetizers, entrées). This is justified in that the overarching goal is to test the fit of the model and we wanted it to be as robust and portable as possible. As for the SEM, we used AMOS 16.0 to construct the models and test the fit.
RESULTS

First, the variables were analyzed to assess any relationships that might compromise the DEA. Reynolds and Thompson (2007) demonstrated that input variables should not be related to one another, nor should output variables be related to one another. Donthu (2005) noted that input variables should have a significant impact on output variables.

Table 1 shows the results of the correlation analysis with Pearson correlation values and 2-tailed significance levels along with means and standard deviations. There is no concern for collinearity between any pair of inputs or between the two outputs. There is also a connection between the input ‘preparation difficulty’ and the output ‘popularity.’ Additionally, the input ‘number of stations’ is significantly correlated with the output ‘gross profit.’ It is interesting that the input ‘number of purveyors’ does not have a significant relationship with either output variable (although the \( p \)-value of .106 suggests there is some strength, even with the weak \( r \) of .159). Nonetheless, we left this input variable in the model so as to be consistent with the replication.

Table 1: Correlation Matrix with Means and Standard Deviations

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Preparation Difficulty</td>
<td>1.36</td>
<td>.645</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B. Number of Purveyors</td>
<td>1.13</td>
<td>.331</td>
<td>-.143</td>
<td>.257</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C. Number of Stations</td>
<td>1.67</td>
<td>.560</td>
<td>-.059</td>
<td>.638</td>
<td>.060</td>
<td>.636</td>
<td>1</td>
</tr>
<tr>
<td>D. Gross Profit</td>
<td>5.82</td>
<td>3.039</td>
<td>.008</td>
<td>.949</td>
<td>.159</td>
<td>.368</td>
<td>.003</td>
</tr>
<tr>
<td>E. Popularity</td>
<td>634.94</td>
<td>456.592</td>
<td>.204</td>
<td>.003</td>
<td>-.076</td>
<td>.545</td>
<td>.040</td>
</tr>
</tbody>
</table>

N = 65; bold font indicates a correlation is significant at the 0.01 level (2-tailed).

While the findings for each menu item are not important, it is worth noting that 7 of the 65 items are 100% efficient, meaning the inputs result in maximizing velocity and gross profit for those...
menu items. Also, ‘preparation difficulty,’ at 39.52%, represents the area with the most room for improvement.

Using the three-input, two-output model, we constructed the SEM model to test data from each of the other two units. Figure 1 shows the standardized coefficients and related indices for unit #2 and Figure 2 show the results for unit #3.

![Figure 1: SEM with Unit #2 Data](image-url)
The large $p$-values show considerable causality along with the significant path coefficients that support the model fit. This is underscored by the comparative fit index (CFI). CFI is a baseline fit index and is widely considered a good overall indicator of fit (e.g., Cheung & Rensvold, 2002). Hu and Bentler (1999) suggested a minimum CFI of .90 and note that CFI values close to 1.0 indicate a very good fit, which is the case with both model applications shown here.

**DISCUSSION**

The replicated DEA model offers evidence that the original was valid, as demonstrated by the correlation matrix output. This is especially noteworthy in that items were not categorized by menu type, as in the previous study. Of greater interest are the SEM results. The strong CFI provides excellent evidence of model fit or, more aptly, evidence that the data fit the models. Thus, we now have empirical evidence supporting DEA as a viable menu analysis tool, one that is not plagued by the many constraints of the matrix approach.
The path coefficients also provide food for thought. For example, difficulty in preparation has an inverse causal relationship with popularity. We see in the DEA results, too, that preparation difficulty is the strongest input in terms of potential improvement for increasing outputs. Thus, it may be that more complicated dishes are not as popular in this restaurant chain.

This alone is a good example of how operators can utilize menu engineering. Since preparation difficulty is linked to increased labor cost for a menu item, these results suggest that the restaurant chain should consider offering fewer such items or replacing them with simpler fare. This is further demonstrated by the small standardized regression weight (0.05) for preparation difficulty and gross profit.

Regarding the fit index, the strong correlations and significant standardized regression weights support the quality of fit, which is verified empirically by the CFI of 1.0. We recognize that with samples of less than 200, all measures tend to overestimate goodness of fit in SEM. However, as Fan, Thomson, and Wang (1999) demonstrated, CFI is less sensitive to sample size than other fit indices. Another potential limitation is the small number of restaurants in the chain. If the markets for these units are especially homogeneous, then these results may be less generalizable.

Still, the implications of our work for new menu modeling and analysis techniques are noteworthy and provide valuable information for operators and researchers. Just as we use advanced approaches for labor management, inventory management, and operations management, we can now apply promising new techniques to menu management. The next step would be to add variables to the DEA model, continuing to test fit using SEM, until we identify a complex model that offers utility across foodservice segments. Thus, much as the matrix model changed our view of menu management in the 1980s, we know realize that by integrating more variables and applying DEA, we can embrace the menu not just as a strategic vehicle, but
also as the basis for formulating, implementing, and evaluating cross-functional decisions that ultimately lead to profit maximization.

REFERENCES


