Identifying Emergency Department Efficiency Frontiers and the Factors Associated with their Efficiency Performance

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Abstract

Emergency department (ED) overcrowding has been recognized as a serious concern in hospitals nationwide. In response, many hospitals have implemented various improvement initiatives, but not all hospitals have found great success. This study aimed to develop a data-driven framework for benchmarking efficient EDs and adopting their best practices. First, a data envelopment analysis (DEA) was used to identify ED frontiers that have achieved operational efficiencies. Using the Emergency Department Benchmarking Alliance database for 2012, we divided 449 EDs into six groups and evaluated the efficiency of each ED in the groups. Inputs include number of ED beds, clinical staffing working hours, and non-clinical staffing working hours in the ED. Outputs include the number of patient visits per day, average length of stay, and the rate of leaving without being treated. Using the efficiency rankings, logistic regression was performed to identify which features of EDs contributed to their becoming efficient frontiers or inefficient units. The results indicated that the proportion of admitted patients through the ED, the intake model with a mid-level provider, a fast-track area, and a patient volume had a significant impact on efficiency of the EDs. The identification of successful EDs and their profiles may provide comparable ED benchmarking and the proliferation of best practices.

Keywords
Emergency department (ED), performance measures, operational efficiency, data envelopment analysis (DEA), and logistic regression.
1. Background

In the past two decades, the number of emergency department (ED) visits skyrocketed from 105 million to 136 million in the United States [1], [2]. In addition, inpatient bed shortages forced many hospitals to hold admitted patients in the ED (boarders), which further reduced available space and staff for new ED patients. As a result of these and other factors, many EDs and hospitals have faced an overcrowding issue. In a 2010 survey by the American Hospital Association [3], 35% of hospitals indicated that their EDs are at or over capacity. ED overcrowding has caused long waiting times and frequent ambulance diversions that compromise patient safety and lower patient satisfaction [4].

In response to the challenges outlined above, many EDs have implemented various improvement initiatives, including physical plant expansion, point-of-care testing, triage protocols, and separate care paths for low-acuity patients. However, only limited numbers of EDs have successfully reduced crowding. In the meantime, healthcare organizations have pushed EDs to tackle the issues that result from overcrowding and to improve the efficiency of care. For example, insurance providers have requested hospitals to report a set of process metrics associated with operational efficiency in the ED, and offered target-based financial incentives for the level of efficiency. The Centers for Medicare and Medicaid Services (CMS) has developed a performance measure set for timely care in the ED, and made the information available publicly [5]. Using the ED performance measure developed by the CMS, the Joint Commission has defined the core measure set and used for determining hospital accreditation and certification [6]. To meet the internal and external expectations, it is imperative for EDs to understand how their own systems perform, and to develop methods to optimize the care process.

Strategies for improving the efficiency of care can be learned from other institutions that have achieved highly efficient systems. Benchmarking is a procedure by which an organization measures its own process and compares itself with those of leading organizations in a certain field [7]. Through benchmarking, an ED can discover what to learn from the frontier EDs with an efficient system, and adopt the frontiers’ best practices within its own system.

It is important for EDs to measure their performance to determine the appropriate best practices to adopt, to evaluate the effectiveness of changes they implement, and to receive the maximum amount of reimbursement and incentives from outside agencies. However, there exists no single standardized hospital performance measure. Also, hospitals have multiple objectives and complex processes. As a result, hospitals and external organizations have used many different performance metrics to assess the operational efficiency in EDs, including key time intervals (e.g., door to doctor, door to bed, and admit order to discharge) and multi-dimensional indexes (e.g., the Emergency Department Work Index (EDWI), the National ED Overcrowding Survey (NEDOS), and Real-time Emergency Analysis of Demand Indicators (READI) scores) [8]. Although the metrics can play a role in representing the efficiency of each ED in a quantitative way, a simple comparison of the numbers can lead to inaccurate conclusions because inputs consumed for the outcomes were not taken into account. In this respect, using the metrics based on only output-related information may not appropriate for ranking EDs with respect to the efficiency of a system and determining which EDs are advanced for the purpose of benchmarking.

Data Envelopment Analysis (DEA) can be a useful tool to evaluate the efficiency of each ED among a set of peer groups and compare their performance. This is because DEA shows relative performance scores of the decision-making units (DMU) and incorporates multiple inputs and outputs, while other commonly used metrics shown above provide absolute and output-based values. The DEA approach has been widely used to measure the production efficiency of organizations in the nonprofit, for-profit, public, and private sectors. Since the mid-1980s, DEA increasingly has been applied in the healthcare field to identify the most efficient units among the DMUs, and to measure the divergence of the less efficient units from the frontiers [9].

This study aimed to develop a data-driven framework for benchmarking efficient EDs and adopting their best practices. First, DEA was used to identify ED frontiers that have achieved operational efficiencies. Second, logistic regression was performed to identify the relationship between various features of the EDs and operational efficiency. In particular, this study sought to investigate the impact for advanced features, such as a physician in triage, a mid-level provider (MLP) in triage, computerized physician order entry (CPOE), and a fast-track area, on the efficiency level.
2. Literature Review
Since the first application of DEA in healthcare by Nunamaker [10], many studies have used DEA to evaluate the efficiency of healthcare services. Literature review studies demonstrate that DEA applications in healthcare have been evolving. In 1999, Hollingsworth et al. reviewed various applications of non-parametric methods used to measure healthcare performance [11]. The study showed that the majority of studies conducted in the U.S. assessed the efficiency and productivity of hospitals and nursing homes. Over 60% of performance measure studies in healthcare utilized DEA alone, and about 20% of studies used regression analysis with DEA. In the study, it was also indicated that public had higher efficiency scores than private hospitals. However, the result should be treated with caution because the scores were not calculated under the same conditions. Different inputs and outputs in the DEA model can affect the performance results. In 2003, Hollingsworth [12] added more recent studies to each of the categories included in the previous study [7]. O’Neill et al. [13] reviewed 79 hospital efficiency studies performed in 12 countries. They divided the studies into four groups by the type of efficiency measured (technical vs. allocative) and the number of time periods studied (a single time period vs. multiple time periods). The largest number of the studies measured only technical efficiency for a single time period, and the smallest number of studies included allocative efficiency for multiple time periods. Many studies employed DEA to measure hospital efficiency, but some studies, particularly those performed in Europe, used stochastic frontier analysis (SFA) and Malmquist index in conjunction with DEA. The authors also provided cross-national and methodological comparisons of hospital DEA studies. Dittman et al. [14] evaluated the performance of 105 hospitals using the American Hospital Association (AHA) data and demonstrated how DEA can provide managerial perspectives to hospital administrators. By developing three DEA models, including different combinations of inputs and outs, the study showed how the selection of the factors can affect the performance measure.

Some studies investigated how the features of hospitals affect their operational efficiency. Kerr et al. [15] estimated the technical efficiency of 23 acute hospitals for three years, and performed a tobit regression analysis to investigate the factors affecting the efficiency measure. They segmented the hospitals into two groups by size based on the total number of inpatients and outpatients and compared the inefficiency of the two groups. The DEA analysis showed that on average, about 6% of larger hospitals and 13.5% of smaller hospitals were inefficient over the period. That is, the results mean that hospitals with more patient visits were likely to maintain relatively higher level of efficiency. In addition to hospital size, factors associated with greater efficiency included higher occupancy and a lower length of inpatient stay. However, the DEA model may not be strong enough to identify a benchmarking group because about 90% of units obtained the highest efficiency score. An additional analysis incorporating a different set of inputs and outputs may provide more insight on the efficient hospitals. Kazley and Ozcan [16] demonstrated the relationship between electronic medical record (EMR) use and efficiency in acute hospitals by using several national data sources. The logistic regression analysis indicated that the use of EMR generally did not increase efficiency for medium and large hospitals, although it may be beneficial to small hospitals. Also, the longitudinal study results revealed that hospitals implementing an EMR did not experience a significant improvement in efficiency associated with the documentation over time, compared to the efficiency of hospitals without the system. Similarly, Sahin and Ozcan [17] evaluated the efficiency level of public sector hospitals and pointed out the use of excessive beds and care providers as the sources of inefficiency. This study assessed hospital efficiency in a different way than many other studies did, in that the DEA model included mortality rates of hospitals. The DEA results showed that the mortality rate affected the performance efficiency of hospitals significantly.

3. Hypotheses and Methods
3.1 Hypotheses
For this study, we established two hypotheses: 1) EDs with larger patient volumes operate at higher efficiency levels; 2) EDs with advanced features (i.e. a physician in triage, a mid-level provider (MLP) in triage, computerized physician order entry (CPOE), and a fast-track area) operate at higher efficiency levels. To test the hypotheses, this study was conducted in two phases. The first phase identified efficient ED units using DEA. The second phase identified the relationship between the efficiency and ED profiles using regression analysis.

3.2 Research design
Our study is a cross-sectional retrospective using the Emergency Department Benchmarking Alliance (EDBA) database. The EDBA, a non-profit organization, annually surveys EDs across the country to compare their performance measures. This study used a 2012 report that includes 976 EDs and 58 survey questions.
3.3 Data envelopment analysis (DEA)

DEA measures the relative efficiencies of all of the DMUs based on a set of inputs and outputs, and identifies efficiency frontiers and inefficient DMUs. A group that is assigned a efficiency score of one is considered efficiency frontiers and others that are assigned a score less than 1 are considered inefficient DMUs. Efficiency scores of relatively inefficient DMUs can be improved by (1) increasing their outputs without changing their inputs or (2) decreasing their inputs without changing their outputs. When emphasis is placed on the reduction of inputs to improve efficiency, a DEA model is called input oriented. In contrast, when emphasis is place on increasing outputs, a DEA model is called output oriented [18].

For our study, DMUs were EDs to be evaluated, and the DEA measured how efficiently each ED provided care utilizing certain inputs compared with other facilities within the same group. Because many DEA studies in healthcare intend to reduce costs and because they cannot control their output factors, they tend to adopt an input-oriented model [13]. However, this study aimed to improve the throughput and operational efficiency rather than decrease resources and associated costs so we used the output-oriented model.

In DEA, efficiency is defined as the ratio of weighted outputs to weighted inputs. To determine the set of weights that maximizes the relative efficiency of each DMU, a DEA model is formulated as a linear programming problem. The dual form of the linear programming model is as follows:

\[
\begin{align*}
\text{Max} & \quad \theta_o \\
\text{s.t.} & \quad \sum_{j=1}^{J} x_{jn} \lambda_j \leq x_{on}, \quad \forall n = 1 \ldots N \\
& \quad \sum_{j=1}^{J} y_{jm} \lambda_j \geq \theta_o y_{om}, \quad \forall m = 1 \ldots M \\
& \quad \sum_{j=1}^{J} \lambda_j = 1 \\
& \quad \lambda_j \geq 0, \quad j = 1 \ldots J 
\end{align*}
\]  

(1)

where the objective function is to maximize the efficiency of the particular ED \( (\theta_o) \) subject to \( N \) inputs, \( x_{jn} (n=1\ldots N) \) used to produce different amounts of \( M \) outputs, \( y_{jm} (m=1\ldots M) \) based on \( J \) DMUs. Note every DMU \( j \) consumes different amounts of the inputs and outputs.

Our model incorporated five inputs and three outputs for each hospital efficiency measure. Inputs included (1) the number of ED beds, (2) working hours for medical doctors (MD), (3) working hours for mid-level providers (MLPs), (4) working hours for registered nurses (RNs), and (5) working hours for technicians (non-clinical staff). Outputs included the (1) number of patient visits per day (PPD), (2) ED length of stay (LOS), and (3) the rate of leaving without being treated (LWBT). Table 1 provides definitions of these components.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Inputs</strong></td>
<td>Number of licensed beds contained within the ED including triage rooms.</td>
</tr>
<tr>
<td>Number of ED beds</td>
<td>Schedule number of work hours per day of clinical and non-clinical staff. This number represents actual worked hours, and does not incorporate administrative hours, leave hours, overtime, and other elements.</td>
</tr>
<tr>
<td>Staff working hours</td>
<td>Sum of patients who present to the ED for service and are recognized by the institution for one calendar year divided by the number of days in the year (365 days in 2012)</td>
</tr>
<tr>
<td>PPD</td>
<td>Number of minutes for each group of patients that are spent in the ED</td>
</tr>
<tr>
<td>ED LOS</td>
<td>The ratio of the annual number of patients who leave prior to completion of treatment to the annual number of patients who are recognized by the ED.</td>
</tr>
<tr>
<td>LWBT rate</td>
<td>The ratio of the annual number of patients who leave prior to completion of treatment to the annual number of patients who are recognized by the ED.</td>
</tr>
</tbody>
</table>

This study focused on efficiency that refers to the extent to which an ED produces maximum outputs from its chosen combination of inputs when compared with other EDs in a group[19]. To achieve a higher efficiency score in the DEA model, it is desirable to increase outputs when inputs remain the same. In our case, however, lower ED LOS
and lower rate of LWBT represent more efficient ED performance. To take into account the effect of the undesirable outputs, we used the inverse values of LOS and LWBT.

Selecting an appropriate benchmarking group can ensure more accurate analysis because DEA evaluates a hospital’s performance relative to that of similar hospitals. If DMUs in significantly different cohorts were to be compared, the model would likely lead to misguided results and insights. Studies have shown that the ED patient volume is highly associated with operational performance [20]. In order to obtain balanced results, we divided the EDs into 6 groups by the annual patient volume, as shown in Table 2. Six DEA models were formulated and run for each of the groups using Microsoft Excel solver and macro.

<table>
<thead>
<tr>
<th>Group Annual patient visits</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
<th>Group 5</th>
<th>Group 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Over 100K</td>
<td>80-100K</td>
<td>60-80K</td>
<td>40-60K</td>
<td>20-40K</td>
<td>1-20K</td>
<td></td>
</tr>
</tbody>
</table>

### 3.4 Logistic regression analysis

Various features of EDs can influence their operational efficiency. To investigate which features of EDs contributed to their becoming efficient frontiers or inefficient units, we designed a logistic regression model. This study chose a multivariate logistic regression over multivariate linear regression because the focus was on identifying the profiles of ED efficiency frontiers rather than determining how much each factor contributes to the efficiency score.

Logistic regression is a statistical model that determines the relationship between binary outcomes and independent variables by using a probability as the predicted value of the dependent variable [21]. The odds of the event are the ratio of the probability of the event occurring ($P$) to the probability of event not occurring ($1-P$) and is calculated as

$$odds = \frac{p}{1-p} = e^{\beta x_1 + \beta x_2 + \ldots + \beta x_p}$$

(2)

where $x_i$ is a value for each factor $i = 1 \ldots p$, and $\beta_i$ is a coefficient of factor $i$. Equation (2) shows that the odds changes by a factor of $e^\beta$. A logistic regression model describes the logit transformed probability as a linear relationship with the predictor variables as

$$ln(odds) = ln\left(\frac{p}{1-p}\right) = \beta + \beta x_1 + \beta x_2 + \ldots + \beta x_p$$

(3)

where a unit change in $x$ increases or decreases the log odds by an amount equal to $\beta$.

Note that the DEA analysis was performed for each of the six groups in order to determine the efficiency score of each DMU within a comparable group of DMUs. After the efficiency scores were determined, we combined all of the results from the six groups and performed the logistic regression analysis for the composite group. The list of variables and the coding of the variables in the model are shown in Table 3.

In the logistic regression model, the dependent variable is a binary response of whether a DMU is efficient (1) or inefficient (0). For this study, the dependent variable was coded as 1 if a DMU was an efficiency frontier whose efficiency score was 1 from DEA, and otherwise the dependent variable was coded as 0. We could classify the DMUs into the two groups using a threshold of the efficiency score. For example, if the efficiency score was greater than 0.9, they are in the efficient group (1), and otherwise there are in the inefficient group (0). However, the threshold was set to 1 for a conservative analysis.

There are nine independent variables. Two continuous variables were included to test the impact of more complex and serious illnesses or injuries on ED operational efficiency. The current procedural terminology (CPT®) is a reporting nomenclature used for medical procedures and services; High CPT acuity represents the percentage of patients with higher acuity illnesses or injuries. Admit % thru ED is the percentage of patients seen in the ED and then placed in an inpatient area of the hospital. Seven categorical variables further describe the system. Location (Urban, Suburban, Rural) and Type (Academic, Non-academic) are frequently used hospital classifiers. Physician in triage means that patients are initially screened by a licensed physician, whereas MLP in triage means that patients are initially screened by another care provider. According to a study conducted by Welch and Davidson[22] and the EDBA report, a growing number of EDs have adopted those new intake models in triage to move patients quickly to
patient care areas and to reduce the waiting time to see a physician for an evaluation. CPOE and FT represent other features of ED practices. The EDs using CPOE are more likely to have a better information technology system, which may affect patient flow and staff work efficiency. A FT is a common ED redesign for patient throughput improvement [23]. EDs with FT separate patients by their acuity levels and the required amount of resources, then route them to different care paths. Volume groups the EDs according to the annual number of patient visits.

Table 3: Variables in a logistic regression model

<table>
<thead>
<tr>
<th>Types of Variables</th>
<th>Variable names</th>
<th>Levels</th>
<th>Values in a model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable</strong></td>
<td>Efficiency</td>
<td>Efficient DMU</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Inefficient DMU</td>
<td>0</td>
</tr>
<tr>
<td><strong>Continuous variables</strong></td>
<td>High CPT acuity (%)</td>
<td>[0,1]</td>
<td>real value</td>
</tr>
<tr>
<td></td>
<td>Admit % thru ED</td>
<td>[0,1]</td>
<td>real value</td>
</tr>
<tr>
<td><strong>Independent variables</strong></td>
<td>Location</td>
<td>Urban</td>
<td>U</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Suburban</td>
<td>S</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rural</td>
<td>R</td>
</tr>
<tr>
<td><strong>Categorical variables</strong></td>
<td>Type</td>
<td>Academic</td>
<td>A</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Non-academic</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>Physician in triage</td>
<td>Yes</td>
<td>MD</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>MLP in triage</td>
<td>Yes</td>
<td>MLP</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>NA</td>
</tr>
<tr>
<td>CPOE</td>
<td>Yes</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>FT</td>
<td>Yes</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Volume</td>
<td>Above 100K</td>
<td>100K</td>
<td></td>
</tr>
<tr>
<td></td>
<td>80-100K</td>
<td>80K</td>
<td></td>
</tr>
<tr>
<td></td>
<td>60-80K</td>
<td>60K</td>
<td></td>
</tr>
<tr>
<td></td>
<td>40-60K</td>
<td>40K</td>
<td></td>
</tr>
<tr>
<td></td>
<td>20-40K</td>
<td>20K</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1-20K</td>
<td>1K</td>
<td></td>
</tr>
</tbody>
</table>

4. Results

4.1 ED efficiency frontiers from DEA

Of the 976 EDs in the original dataset, observations missing any input and output values were excluded from the analysis. As a result, 449 EDs were included in the analysis, and the EDs were grouped by patient volume. The efficiency score of each ED in the assigned group was calculated using the output-oriented DEA model. Table 4 summarizes the results of DEA analysis for each group.

Table 4: DEA results

<table>
<thead>
<tr>
<th>ED groups</th>
<th>Group 1 (Over 100K)</th>
<th>Group 2 (80-100K)</th>
<th>Group 3 (60-80K)</th>
<th>Group 4 (40-60K)</th>
<th>Group 5 (20-40K)</th>
<th>Group 6 (1-20K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficient # of DMUs</td>
<td>16</td>
<td>20</td>
<td>15</td>
<td>33</td>
<td>34</td>
<td>20</td>
</tr>
<tr>
<td>Inefficient # of DMUs</td>
<td>10</td>
<td>9</td>
<td>58</td>
<td>76</td>
<td>127</td>
<td>31</td>
</tr>
<tr>
<td>Total # of DMUs</td>
<td>26</td>
<td>29</td>
<td>73</td>
<td>109</td>
<td>161</td>
<td>51</td>
</tr>
<tr>
<td>Proportion of efficient DMUs (%)</td>
<td>61.54%</td>
<td>68.97%</td>
<td>20.55%</td>
<td>30.28%</td>
<td>21.12%</td>
<td>39.22%</td>
</tr>
</tbody>
</table>

The first question this study sought to answer was how the performance of EDs with high patient volumes differs from EDs with fewer patient visits. We hypothesized that busier EDs may be more efficient than EDs with fewer patients. The results supported the hypothesis that a greater proportion of EDs in Groups 1 and 2 provided patient care in a relatively efficient manner, compared to EDs in Groups 3, 4, 5, and 6. Figure 1 shows the difference in the proportion of efficient EDs between the high patient volume groups and the low patient volume groups.
4.2 Logistic regression model results

The logistic regression analysis was performed using Minitab. Of 449 EDs evaluated by the DEA, 11 EDs were excluded from the logistic regression analysis because they included missing values for independent variables. Of the 438 EDs, 123 EDs (28%) were identified as operationally efficient units and 315 (72%) were identified as non-efficient units. As aforementioned, the full model included nine independent variables. However, the results of the regression analysis indicated that coefficients of only five independent variables were significant at $\alpha = 0.1$: Admit % thru ED, Academic, MLP in triage, Fast Track, and Volume. We removed the insignificant variables from the model and analyzed the reduced model. The Minitab results of the reduced model are shown in Figure 2.

The odds ratio for each variable in Figure 2 indicates how strongly a given variable may be associated with the outcome. If $x_i$ is a continuous variable, the odds ratio represents the change in the odds for a unit change in $x_i$, holding all other variables constant. On the other hand, if $x_i$ is a categorical variable, the odds ratio represents the change between the corresponding level and the reference level, holding all other variables constant [21]. The odds ratios of Admit % thru ED was 0.26, which means that for each additional percent increase in admitted patients through an ED, the odds of the ED being efficient decreased by 74%. The odds ratio of Type was 1.43, which means that the odds of non-teaching hospitals being efficient increased by 43% compared with teaching hospitals. However,
p-value of Type indicated that the variable was not significant anymore in this reduced model. For EDs having the intake model of a MLP in triage, the odds of being an efficient ED decreased by 72% compared with EDs with a traditional intake model in triage. Similarly, EDs with a Fast Track area were 53% less likely to be efficient than EDs without the separate treatment area. The odds ratios of Volume demonstrated consistent results with the finding from the initial DEA analysis. Note that ED Group 1 corresponded to the EDs with an annual patient volume over 100K, and ED Group 6 corresponded to the EDs with an annual patient volume of 1-20K. The logistic regression analysis indicated that there was no difference between Groups 1 (reference level) and 2. However, the odds of the EDs in Groups 3, 4, 5, and 6 being efficient decreased by about 75-91% compared to Group 1 (reference level).

In addition to the significance of model coefficients, the appropriateness of the fitted logistic regression model should be checked to prove that the implications explained above are statistically reasonable. A low p-value of a Goodness-of-Fit test indicates that the predicted probabilities are different from the observed probabilities in a way that the binomial distribution does not predict. Figure 2 shows that the p-values of the Pearson and Deviance tests were low. We assumed that the low p-values were not attributed to the poor fit of the model to the data because the Pearson and Deviance tests have distributions greatly deviated from a true chi-square distribution when the model includes continuous independent variables that produce many classes of data [24]. On the other hand, the Hosmer-Lemeshow test groups the data into a set of classes. Since our logistic regression model included both continuous and categorical covariates, the Hosmer-Lemeshow test was expected to provide a more accurate p-value. With the p-value 0.620, we concluded that the model was a satisfactory fit to the data.

5. Discussion

This study has two main limitations. The outputs used in the DEA model were not case-mix index (CMI) adjusted values. Since outputs measured without case-mix complexity do not fully represent how hospitals perform, the use of raw values for outputs may have affected the accuracy of ED efficiency scores. However, we considered this limitation acceptable considering that the purpose of this study was not identifying specific EDs for incentives or penalties but rather providing a framework for evaluating EDs for the proliferation of best practices. The other limitation of this study was that no quality measures beyond efficiency were included in the DEA model. Quality-related outcomes are critical to evaluate the performance of hospitals because they are strongly associated with patient safety and satisfaction. The quality of care should not be negotiated in order to increase the efficiency of care. By including indicators that are associated with both efficiency and effectiveness of care such as mortality rate in the ED, the DEA may be able to provide more accurate and practical insights into the overall performance in the ED.

Given the chosen grouping and study design, DEA results demonstrated that there was a significant difference between larger patient volume EDs (80K and greater) and smaller patient volume groups (under 80K). For the two larger groups, the proportion of efficient EDs was between 61%-69%, but for the four smaller groups the proportion of the efficient EDs was between 20%-40%. Further investigation would be required to determine the cause of these results, but we can say that the large efficiency gap between the groups implies that more rapid proliferation of best practices is needed among the smaller patient volume groups for improving performance.

Based on the efficiency score, we performed a logistic regression analysis to determine which factors were associated with the efficient EDs. In particular, this study aimed to explore how four advanced features, which EDs have implemented, affected efficiency in the ED. However, there exist other advanced features as well. For example, many EDs have implemented new information technology to improve workflow of patients and staff, such as computerized physician order entry (CPOE), electronic medical record (EMR), and radio-frequency identification (RFID). Also, EDs have adopted new patient flow models, such as new triage protocols, fast track, and observation units. Some EDs showed how the implementation of the features actually affected the process performance through retrospective observational studies [25], [26]. However, these studies did not determine how much the changes actually contributed to the outcomes. Positive outcomes from the new features could be attributed to many other factors in the EDs, and the isolated contribution of the changes is difficult to ascertain. On the other hand, a logistic regression model can demonstrate whether considered factors have significant effects on outcomes and, if so, how much each factor contributes to the result when holding other factors the same.

In this study, the binary dependent variable was determined by whether an ED was efficient or inefficient, and nine explanatory variables were considered. However, the initial model showed that only a subset of the independent
variables was significant and therefore a reduced model of five independent variables was used. The final model showed several interesting results. According to the model, an increase in admitted patients through an ED may reduce the ED’s efficiency. This result was expected because the increased number of admitted patients can lead to boarding problems resulting from the lack of inpatient hospital beds. However, Intake using MLP and Fast Track revealed unexpected results. When using the MLP at triage model, or when opening a fast track program, the odds of being an efficient ED dropped by 72% and 53%, respectively. Although the results were derived from the limited data and mathematical models, they suggested important implications. The wide adoption of certain features in the EDs does not always mean that the features have positively impacted on the efficiency of care.

6. Conclusion and Future Work

Many EDs experience overcrowding issues, and are searching solutions to achieve efficient patient flow. Insurance providers and governmental organizations have required hospitals to collect ED performance efficiency indicators and have included some of the metrics in core measures. Because the scores for these core measures are associated with hospital reimbursement, EDs have tried to increase the efficiency through process improvement projects. However, since there are no standardized metrics to assess operational efficiency, organizations use different metrics, which can affect the efficiency scores. Also, since the commonly used metrics do not account for inputs utilized to produce the outcomes, it can be more challenging to compare EDs with one another.

This study proposed DEA as an effective tool to identify relatively efficient EDs in the same cohort, and to investigate which part of the systems of inefficient EDs can be improved. When benchmarking best practices, care providers and hospital managers should have a comprehensive understanding of their own processes and key metrics, and they should conduct rigorous research on the characteristics of the frontiers that achieved success through the best practices.

Future work on the study will include three steps. The first step is to analyze sources of ED inefficiency and the relationship between the sources and the levels of inefficiency. The analysis will help establish strategic approaches to determine which best practices may work better for an inefficient ED. The second step is to define the forces that contribute to speed of the adoption of the best practices. The final step is to combine the findings from the previous steps and to develop a macro model for proliferating best practices. We expect that the macro-model will help EDs disseminate and adopt best practices in a faster and more effective way, which will lead to providing more timely and effective care.

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