Impacts of Decision Support Systems on Hospital Efficiency: A Data Envelopment Analysis Model

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This study examined whether decision support systems (DSS) matter in hospital efficiency. We used data envelopment analysis to measure the hospital's efficiency, with four inputs and three outputs - inpatients, outpatients, and total patient revenue. Results showed hospitals with more DSS were significantly more efficient than hospitals with fewer DSS. Furthermore, hospitals with fewer full-time equivalent physicians, more full-time registered nurses, and more beds had greater efficiency. For hospital efficiency, the number of beds was the highest impact factor, followed by the number of registered nurses, and the number of full-time equivalent physicians.

Keywords: Decision Support Systems, Data Envelopment Analysis, hospital efficiency

INTRODUCTION

Efficiency and appropriate resource allocation are paramount to a hospital's ability to treat patients effectively. To ensure these demands are met, hospitals use Clinical Decision Support Systems (CDSS), a subvariant of Decision Support Systems (DSS), to allocate resources based on patient needs, thereby increasing efficiency. CDSS aids health care professionals in evaluating large sets of information and making informed decisions during their clinical routines (Dramburg et al., 2020). CDSS are intended to improve healthcare delivery by enhancing medical decisions with targeted clinical knowledge, patient information, and other health information (Sutton et al., 2020).

Good Shepherd Medical Center in East Texas is a testament to the increased efficiency hospitals experience using CDSS. In 2011, Shepherd implemented a CDSS in its 425-bed acute care community. Before its implementation, clinicians struggled with administrative duties and data collection/syncretization. After implementing a CDSS, Shepherd improved communication and knowledge among staff and improved relationships with medical staff, nursing, and case management personnel. The Pharmacy Department increased its clinical interventions from an average of 1,986 per month to 4,065 per month; this represents a 105% increase in the number of interventions. The annual estimated cost savings after CDSS implementation was $2,999,508, representing a 96% savings increase per year and translating into a $1,469,907 annual return on investment (Calloway et al., 2013).

This research questions how the use of DSS in a hospital improved efficiency, accuracy, and resource allocation within the hospital. This research explores whether DSS truly makes a difference in hospital systems, and, if so, how. Additionally, if it did make a difference, was the impact measurable and certain beyond doubt, or was the effect minuscule and unmeasurable?

There have been many studies on the improvements DSS has made on hospital efficiencies. DSS facilitates determining patients' length of stay (Chuang et al., 2016). Chae et al. (2011) proved DSS improves scheduling, patient care, and treatments for stage three severe ailment cases. DSS also helps reduce the nonvalue-added-time and increase compliance with hospital guidelines (Dos Santos et al., 2014; Setijono et al., 2010). These studies used linear regression, ARENA simulation, random forest prediction models, and one-sample *t*-tests to examine the efficacy of DSS.

However, not many studies have been done on measuring hospital efficiency with DEA models for examining the impacts of DSS on hospital efficiency. No such studies have been done on the 2017 American Hospital Association (AHA) dataset. This lack of studies motivated this research project.

Therefore, we attempt to answer the research questions stated above in this study. We conducted an empirical study and investigated the impact of DSS on hospital efficiency using the 2017 AHA dataset. The results could fill the gap in the healthcare literature. In this study, we developed the research hypotheses based on the literature, collected a sample dataset, and developed a DEA model to measure efficiency, and we tested the hypotheses by running a statistical analysis of the sample data.

The outcome of this research paper will help hospital administrators identify areas of opportunity in which hospitals can become more efficient. As a result, the efficiencies gained will help lower costs associated with running the hospital, which may provide administrators with more resources in their budgets to hire more staff or improve other aspects of the hospital.

LITERATURE REVIEW

Background Information

CDSS are designed to improve hospital efficiency using faster data processing, aiding clinical decision-making, and further analyzing patient needs (Sutton et al., 2020). In this study, we concluded CDSS does have a positive role in increasing hospital efficiency, especially when used for patient care and managerial decisions because its capabilities are significantly faster, more expansive, and conversant than human decisions alone (Sutton et al., 2020).

CDSS can also be tailored to different medical fields to meet the varying needs of hospitals. For example, Antibiotic Stewardship programs that focus on the effective use of antibiotics recommend the use of CDSS to improve antibiotic therapies (Neugebauer et al., 2020). In their single-blind, randomized controlled study, Neugebauer and his team found the use of CDSS had significantly higher correct diagnosis rates compared to conventional information tools and their control, at 57.1%, 19%, and 8.3%, respectively (Neugebauer et al., 2020).

To conclude, the DSS and its derivative CDSS serve as a vital tool for increasing hospital efficiency. This is because of CDSS' rapid analytical speeds and proficiency when used in managerial decision-making (Sutton et al., 2020) and their supreme accuracy in diagnostics involving patient treatment (Neugebauer et al., 2020). Therefore, we hypothesize that, if a hospital incorporates CDSS into its operating procedures, efficiency will increase.

This research utilized Data Envelopment Analysis (DEA) and CCR-I to determine which areas of the general hospitals are inefficient, as well as which inputs and outputs are linked to inefficiency. DEA is an analytic tool that is used commonly used in the healthcare sector. For example, Ersoy et al. (1997) employed DEA and CCR-I analysis to examine the efficiency of Turkish acute general hospitals. The results indicated 90.6% of the hospitals in the research were deemed inefficient (Ersoy et al., 1997). Hospitals found to be inefficient used more inputs while providing fewer outputs. Ersoy et al. (1997) concluded that, for inefficient hospitals to become more efficient, they should decrease their inputs while increasing their outputs.

DEA is a way to research and estimate efficiencies based on a variety of inputs and outputs that are discerned in the data being studied. According to Onder et al. (2022), "Applications of data envelopment analysis (DEA) in healthcare have focused primarily on hospitals' efficiencies in terms of the number of patients they treat given available resources". Considering the availability of data in health care, it makes sense that DEA is the most consistent form of analysis being utilized in academic studies.

In conclusion, DEA is a significant tool when it comes to evaluating the efficiency of decision-making units of hospitals. It allows researchers to preselect the inputs and outputs they would like to evaluate and run the software to determine which areas are operating efficiently and which areas are not. Thus, when researching hospital inefficiency, DEA should be one of the tools used to aid the researchers.

Hypothesis Development

Chae et al. (2011) ventured to link the correlation between CDSS and hospital efficiency. The hypothesis under investigation was that CDSS would increase efficiency in the Korean hospitals in which they were implemented. To test this hypothesis, researchers deployed linear regression to compare the results between hospitals using CDSS and those not using CDSS. They concluded CDSS improves hospital performance, especially concerning scheduling, patient care, and treatment in stage three (severe ailment) cases, thereby increasing hospital efficiency (Chae et al., 2011).

The emergency room can be quite chaotic when it comes to the imbalance between supply (number of doctors available) and demand (number of patients waiting to be treated). Setijono et al. (2010) utilized DSS to allocate hospital resources to improve efficiency. They hypothesized the application of DSS would find the most efficient combination of resources, which would reduce the non-value-added time (NVAT) and total time in the system. The researchers involved simulated with ARENA by varying the number of surgeons and doctors using the data between April 2009 and June 2009 to test the hypothesis. The researchers concluded current utilization of resources in the emergency room is inefficient, but a 13% reduction of NVAT can be achieved by using the simulation results (Setijono et al., 2010).

Chuang et al. (2016) aimed to develop a predictive model to determine whether a hospital patient's length of stay fell within the average length of stay of other patients who underwent the same surgery. They separated 896 cases between urgent operations and nonurgent operations and determined the critical factors for the two groups using the gain ratio technique and discovered the most accurate, stable prediction model was using the random forest method. The most interesting finding in this study was that supervised learning is a viable method of analyzing patients' medical records, thereby allowing medical staff to predict a prolonged length of stay (Chuang et al., 2016).

Dos Santos et al. (2014) investigated the impact a new CDSS had on the CICU physician's adherence to clinical guidelines. To do so, the team performed a one-sample *t*-test on five CICU treatment options on hospital data from the national registry RIKS-HIA database from 2004 to 2008. The results indicated improvement in adherence to guidelines in all treatment options, both in the short and long term (after 5 years). Thus, using CDSS improves the efficiency of the hospital because physicians will make correct decisions more often.

In summary, DSS improves a hospital's ability to determine the patient length of stay, scheduling, patient care, and treatments (Chae et al., 2011; Chuang et al., 2016). DSS can also help reduce the nonvalue-added time by correctly allocating resources (Setijono et al., 2010). Additionally, DSS improves physicians' adherence to hospital guidelines (Dos Santos et al., 2014). Hence, all the literature reported CDSS improved the efficiency of hospitals in several metrics. Therefore, we hypothesized that hospitals using DSS are more efficient than hospitals without DSS.

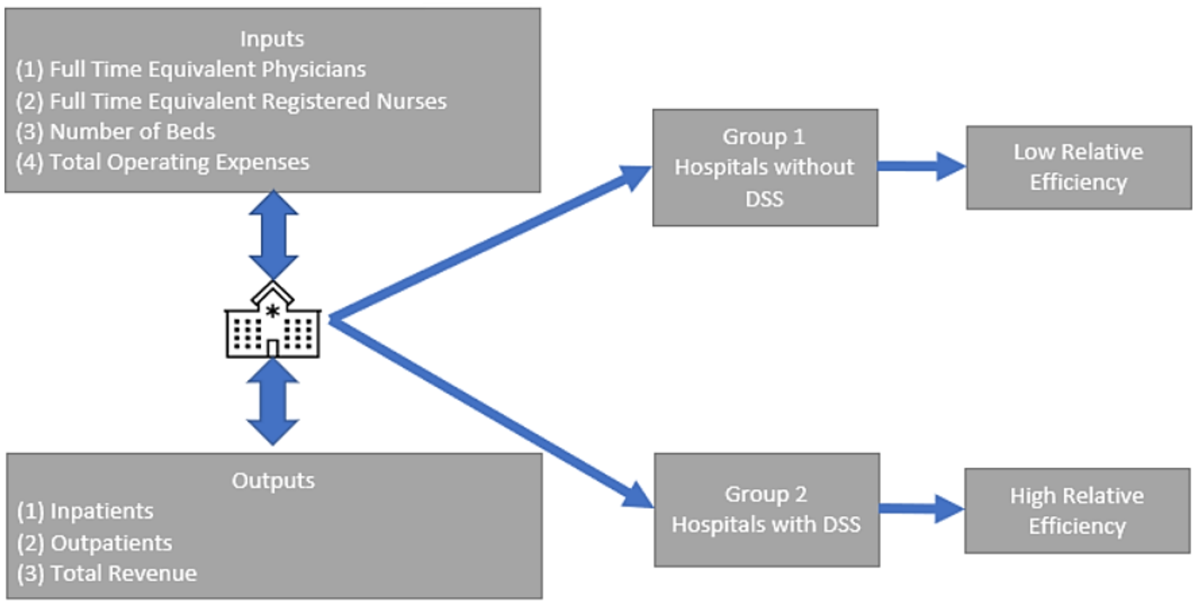
Hypothesis**:** *If a hospital implements DSS, then the hospital's efficiency will be higher than that of a hospital without DSS.*

METHODOLOGY

Conceptual Model

Figure 1 illustrates a conceptual model of this paper. It describes the four inputs and three outputs that will be used to measure a hospital's efficiency and the hospital are separated into two groups – hospitals without DSS (Group 1) and hospitals with DSS (Group 2). The conceptual model proposes that Group 2 will produce a higher relative efficiency score on average.

FIGURE 1
CONCEPTUAL MODEL



Input Variable 1: Full-Time Equivalent Physicians (FTED*)*

Many researchers have investigated the difference in efficiency between for-profit hospitals and nonprofit hospitals; Needlemen (1995) examined entry and exit decisions and pricing, which is also where hospital managers have the most independence. Many researchers argue in favor of for-profit institutions because they will be more likely to produce more efficient healthcare deliveries. Rosko et al. (2020) found a strong correlation between hospital efficiency and profitability. To explain this point, when a for-profit hospital operates at peak efficiency, the hospital decreases operating costs while raising gross margins. Higher profits allow the for-profit hospital to pay larger salaries, thereby attracting higher-tier doctors, thus increasing efficiency and proficiency (Rosko et al., 2020).

Input Variable 2: Full-Time Equivalent Registered Nurses (FTEN)

Many researchers have investigated how hospitals are offering a wide range of services and comparable quality, namely Staat (2006) noted it can give you a wide range of understanding of how efficiently hospitals are performing. To figure out which hospitals have been performing more efficiently and be able to give him more accurate results, Staat (2006) had to use the DEA model. Habib and Shahwan (2020) used a DEA model to measure the operational efficiency of isolation hospitals in Egypt. They showed that, out of 26 isolation hospitals, only 4 were found to be efficient according to the CCR model, and 12 were efficient under the Banker, Charnes, and Cooper (BCC) model. The number of nurses and beds in isolation hospitals are two common criteria found to influence their operational efficiency.

Input Variable 3: Number of Beds (BDTOT)

An important variable that will be used to measure efficiency in hospitals is the number of beds. Hospitals need to consider how to generate more return on their investment. In research done by Watcharasriroj and Tang (2004), size does influence hospital efficiency; they studied this using contingency theory, in which three elements were highlighted: communication, coordination, and integration of effort across the organization. As the hospitals increase in size, they will in turn increase the number of employees or APRNs on hand. The greater the number of beds utilized, the more APRNs will be in good use, which will result in the hospital becoming very efficient. In health care, efficiency pertains to the efficient use of resources in providing health services to patients. Aloh et al. (2020) studied hospital performance by assessing bed utilization rates. The results showed there was a low bed occupancy rate, along with a high average length of stay, which demonstrated a teaching hospital in South Nigeria was inefficient. Aloh et al. (2020) also demonstrated various health ratio indications, such as hospital bed turnover rate, along with bed occupancy rate combined with the patient's average length of stay, can be used to evaluate hospital efficiency.

Input Variable 4: Total Operating Expenses (EXPTOT)

Many studies have investigated the relationship between financial performance and efficiency, such as Watson (2000), who underlined the important variables to consider when assessing the profitability of hospital entities. Operating expenses are all costs a hospital incurs during its normal course of business. When measured against total revenue earned in a period, the researchers can gain a better understanding of how the operations of a unit are performing. Watson also considers this a measure of efficiency. Additionally, Akinleye et al. (2019) discovered clear coordination among quality, efficiency, and safety of patient care, linked to operating expenses and that, in 108 New York hospitals, composite financial scores—indicating higher expenses related to medical treatment, staff, and salaries—indicated performance scores were positively associated with decreased 30-day readmissions for all treatments performed at the hospitals involved in the study. Therefore, there is a clear correlation between increased financial expenditure, leading to increased patient care and efficiency by reducing readmission to the hospital.

Output Variable 1: Inpatients (IPDTOT)

One variable we will use to evaluate hospital efficiency is the number of inpatients that are treated based on the 2017 AHA-provided data. The use of this variable comes from Gok and Sezen (2012). However, this variable is often used as a measure of output for studies about the efficiency of a hospital. Inpatient turnover measurement allows researchers to measure the number of patients admitted, treated, and released, in comparison to the various inputs. When comparing the number of inpatients between hospitals of similar scales, we can better understand which variables are instrumental in creating hospital efficiency. Studying inpatients provides broader, more indicative data, which grants insight into factors like bed occupancy rates, the average length of stay, bed turnover rate, and turnover interval. With this in mind, Aloh et al. (2020) found that, in Nigerian hospitals, the aforementioned factors serve as ideal indicators of a hospital's performance and efficiency. Thus, measuring inpatients as output provides valuable insights into hospital efficiency.

Output Variable 2: Outpatients (VTOT)

Another variable we will use to evaluate hospital efficiency is the number of outpatients who are treated, also based on the 2017 data provided by the AHA. As with the use of inpatient turnover, the use of this variable comes from Gok and Sezen (2012). Outpatient measurement can be used to measure hospital efficiency, but unlike inpatients, it would be a measure of different services provided by a hospital, such as emergent care, which would not typically correlate with the same procedures performed on inpatients. Reflecting on the research of Caballer-Tarazona et al. (2010), who supported the segmentation of hospital services for efficiency studies, we can see it is for this reason that inpatients and outpatients will be segregated variables in our research. According to Vitikainen et al. (2010), outpatient services have a smaller impact on total cost than inpatient services. As such, one might expect to see a higher efficiency associated with hospitals that have a higher ratio of outpatients to inpatients.

Output Variable 3: Total Revenue (TPR)

Total revenue is another commonly used variable in the assessment of hospital efficiency. Watkins (2000) studied hospital performance and suggested total revenue can be used as an indicator of efficiency. Using the DEA method to determine which hospitals perform best financially based on total revenue, and by comparing the inputs through variance analysis, we can determine which inputs and control variables create superior financial efficiency. In their study, Nakata et al. (2019) determined the relationship between a surgeon's technical efficiency and revenues by using multiple regression analyses. They identified seven independent variables: revenue, experience, medical school, surgical volume, sex, academic rank, and surgical specialty. Nakata et al. (2019) found hospital revenue could be a proxy variable for a surgeon's technical efficiency due to a strong positive correlation between them.

Data Envelopment Analysis Model

Habib and Shahwan (2020) used the DEA model to assess the financial and operational efficiency of 33 Egyptian private hospitals. They collected data by visiting the 33 private hospitals and using the Egyptian Central Agency for Public Mobilization and Statistics. By using the Malmquist DEA analysis, they found there was an overall decline in financial and operational efficiency from 2014 to 2016. Additionally, Habib and Shahwan found 17 of the 33 hospitals were inefficient relative to one another. By continually using DEA models, hospitals can assess how they are performing against other private hospitals and determine what needs improvement.

In their study, Nakata et al. (2019) set out to determine the relationship between surgeons and the revenue they bring to a hospital. They collected data from all surgical procedures performed at a University Hospital from April 1 through September 30 between 2013 and 2018. They used an output-oriented Charnes-Cooper-Rhodes (CCR) model of data envelopment analysis to calculate each surgeon's efficiency. They selected seven independent variables: revenue, experience, medical school, surgical volume, sex, academic rank, and surgical specialty. Nakata et al. (2019) obtained data from a total of 17,227 surgical cases in the 36-month study period, and they performed multiple regression analyses on 222 surgeons. They found revenue had a significantly positive association with mean efficiency score, and they demonstrated an increase in revenue by 1% was associated with a 0.46% to 0.52% increase in efficiency score.

Rosko et al. (2020) set out to study the effects of a hospital's income on the quality of provided care. To achieve this, data from 1,317 not-for-profit hospitals in the United States were gathered. Using DEA analysis, and after ranking hospitals based on income levels and readmission rates by patients based on medical procedures, the researchers concluded there was an undeniable link between patient care and hospital income, whereby, as income increases, care quality increases. Using the DEA analysis models, researchers can learn and study the characteristics of successful hospitals and apply these findings to improve less successful hospitals.

There is a significant gap between public and private hospitals in India. Public hospitals, which are provided by the government at no cost, provide substandard care; therefore, government officials are pushing private hospitals to enhance their accessibility and affordability of health care services. Aradhana and Sharma (2018) utilized DEA, the Malmquist Productivity Index (MPI), and a Tobit regression to determine the performance of select Indian private hospitals. The findings showed that, for the CCR model, 14 out of 37 hospitals were deemed efficient; using the BCC model, 21 out of 37 hospitals were efficient in terms of managerial skill but inefficient regarding skill level (Aradhana & Sharma, 2018). The hospitals studied were corporate hospitals that employed some of India's top doctors and spent a significant amount of money on technology and infrastructure to achieve high-efficiency levels and attract patients from across the country.

We employ DEA to measure the comparative efficiencies of hospitals with and without DSS. DEA is a special application of linear programming based on Farrell's (1957) frontier methodology. Since Farrell, breakthroughs for developing DEA have been achieved by Charnes et al. (1978) and Banker et al. (1984).

DEA is a useful approach for measuring relative efficiency among similar organizations or objects. An entity that is an object to be measured for efficiency is called a decision-making unit, or DMU. Because DEA can identify relatively efficient DMUs among a group of given DMUs, it is a promising tool for comparative analysis or benchmarking (Mhatre et al., 2014).

To explore the mathematical property of DEA, let E_0 be an efficiency score for the base DMU *0*, then:

$$E_0 = \frac{\{\sum_{r=1}^{R} u_{r0} y_{r0}\}}{\{\sum_{i=1}^{I} v_{i0} x_{i0}\}} \tag{1}$$

Maximize
subject to

$$\frac{\{\sum_{r=1}^{R} u_{r0} y_{rk}\}}{\{\sum_{i=1}^{I} v_{i0} x_{ik}\}} \leq 1 \quad \text{for all } k \tag{2}$$

$$u_{r0}, v_{i0} \geq \delta \text{ for all } r, i, \tag{3}$$

where y_{rk}: the observed quantity of output r generated by unit $k = 1, 2, \ldots, N$,
x_{ik}: the observed quantity of input i consumed by unit $k = 1, 2, \ldots, N$,
u_{r0}: the weight to be computed given to output r by the base unit 0,
v_{i0}: the weight to be computed given to input i by the base unit 0,
δ: a very small positive number.

The fractional programming model can be converted to a common linear programming (LP) model without much difficulty. A major assumption of LP is a linear relationship among the variables. Accordingly, an ordinary LP for solving DEA utilizes a constant returns-to-scale so all observed production combinations can be scaled up or down proportionally (Charnes et al., 1978). However, when we use a piecewise LP, we can model a nonproportional returns-to-scale, such as an increasing, decreasing, or variable returns-to-scale (Banker et al., 1984). Depending on returns-to-scales and/or various modeling approaches, different types of DEA models are available (Mhatre et al., 2014; Lee & Joo, 2020).

Sherman and Ladino (1995) summarized the capability of DEA in the following manner:

- Identifies the best practice DMU that uses the least resources to provide its products or services at or above the quality standard of other DMUs
- Compares the less efficient DMUs to the best-practice DMU
- Identifies the number of excess resources used by each of the less efficient DMUs
- Identifies the amount of excess capacity or ability to increase outputs for less efficient DMUs, without requiring added resources

In this study, involving comparative measures of operational efficiencies for DMUs, we employed a CCR model. First, we measured the efficiency of DMUs using the CCR.

Sample Data

The data we used were obtained from the 2017 American Hospital Association Annual Survey dataset and the AHA IT annual survey dataset. We combined the data from both datasets into one dataset and distributed it to all hospitals in the United States and territories. We designed the voluntary survey to create a comprehensive database with information on each hospital's organizational structure, service lines, utilization, finances, insurance, and payment models, as well as staffing for the given fiscal year. Supplemental information on patients' hospital experiences was provided by the HCAHPS survey distributed by Medicare. We will use the data provided from these surveys to run the DEA models and determine which variables relate to the most efficient hospitals.

RESULTS

We merged the databases from the IT survey, general hospital survey, and financial data to provide the dataset. The survey asked hospitals, "Does your hospital currently have a computerized system that allows for clinical guidelines, clinical reminders, drug allergy alerts, drug interaction alerts, drug-lab interaction alerts, and drug dosing alerts?" Hospitals were allowed to respond to each of these decision support systems with the values 1 = Fully implemented across all units, 2 = Partially implemented across all units, and 3 = Not implemented.

The original dataset consisted of 6,798 hospitals. The dataset was adjusted to remove invalid responses. We removed a total of 3,337 hospitals because of responses of 0 and no response to the DSS question, 1,060 hospitals because of responses of 0 for full-time equivalent doctors, 68 hospitals because of a response of 0 for outpatients, and 152 hospitals because of responses of 0 for total patient revenue. This left a total of 2,181 hospitals in the dataset.

We added the sum of all the DSS responses of each hospital together to give them an overall score (DSS1) for the level of use of DSS at that hospital. We then divided the hospitals into two groups under the category DSS2. Group 1 is all hospitals with a DSS1 score of less than or equal to 6, which represents at least one or more of the DSS being fully implemented. Group 2 is all the hospitals with a DSS1 score above a 6, which indicates a lower DSS involvement. Thus, Group 1 is hospitals using more DSS, and Group 2 is hospitals using fewer DSS.

TABLE 1
SAMPLE DISTRIBUTION

	Frequency	%
Hospitals Using Fewer DSS	670	30.7
Hospitals Using More DSS	1,511	69.3
Total	2,181	100

Table 1 shows that, of the 2,181 hospitals participating, 1,511 (69.3%) used more DSS in daily operations, whereas hospitals using fewer DSS were the minority, with only 670 hospitals, or 30.7%, claiming low involvement.

TABLE 2
DESCRIPTIVE STATISTICS

	N	Minimum	Maximum	Mean	Std. Deviation
DEA Score	**2181**	0	1	1	0
(I) FTED	**2181**	1	2,669	51	171
(I) FTEN	**2181**	4	7,517	372	611
(I) BDTOT	**2181**	4	2,877	194	226
(I) EXPTOT $	**2181**	2,274,545	5,543,477,948	251,622,362	433,714,287
(O) IPDTOT	**2181**	48	761,889	47,382	64,157
(O) VTOT	**2181**	1	6,297,877	199,898	313,020
(O) TPR $	**2181**	510,769	16,863,431,079	901,141,048	1,566,600,062

Table 2 shows the descriptive statistic of each of the variables across the hospital data analyzed. As can be seen, there is wide variation throughout all the input and output variables. The mean skewed closer to the minimum values, indicating the majority of the hospitals were smaller, and a few larger hospitals with large values were extending the data to the higher end.

We ran a correlation analysis using Spearman's rho analysis. The data indicate the DEA score was significantly correlated with FED, FTEN, BDTOT, EXPTOT, IPDTOT, VTOT, and TPR ($p < 0.01$). Additionally, the data showed the input and output variables were significantly correlated with each other ($p < 0.01$). Table 3 shows the results below.

TABLE 3
SPEARMAN'S RHO CORRELATION ANALYSIS RESULTS

	DEA	**(I) FTED**	**(I) FTEN**	**(I) BDTOT**	**(I) EXPTOT**	**(O) IPDTOT**	**(O) VTOT**	**(O) TPR**
DEA Score	1							
(I) FTED	-.057**	1						
(I) FTEN	.300**	.662**	1					
(I) BDTOT	.440**	.559**	.899**	1				
(I) EXPTOT	.299**	.690**	.972**	.881**	1			
(O) IPDTOT	.563**	.545**	.879**	.976**	.863**	1		
(O) VTOT	.256**	.687**	.854**	.732**	.878**	.705**	1	
(O) TPR	.328**	.621**	.942**	.856**	.950**	.833**	.828**	1

**p < 0.05, **p < 0.01* (two-tailed)

Because the DEA scores were not normally distributed, we used the nonparametric test for hypothesis testing. To test the differences between the two groups, we chose the Mann-Whitney Test. The data analysis results showed the mean rank of a group of hospitals using fewer DSS (1,024.17) was lower than the mean rank of those hospitals using more DSS (1,120.64). This indicated the hospitals that were more reliant on DSS were more efficient than those less reliant on DSS [Mann-Whitney test statistic = 461,406.5, $Z = -3.3$, $p < .001$]. Data showed the statistical difference between the two groups was significant. Table 4 presents the results.

TABLE 4
MANN-WHITNEY TEST RESULTS

Group	***N***	**Mean**	***SD***	**Mean Rank**	**MW U**	***Z***	***p*-value**
Fewer DSS	670	0.555	0.195	1024.17	461406.5	-3.3	<.001
More DSS	1511	0.582	0.175	1120.64			
Total	2181	0.5740	0.181				

Notes: SD stands for standard deviation; MW U indicates Mann-Whitney test statistics.

DISCUSSION

Hypothesis Test Results

As the evidence shows, the hospital group with more DSS had significantly ($p < 0.001$) higher efficiency scores (0.582) than the hospital group with fewer DSS (0.555). This evidence supported our hypothesis that, if a hospital implements a DSS, then the hospital's efficiency will be higher than one without a DSS.

The results were consistent with the literature, which supported the idea that the implementation of DSS will have a positive impact on hospital efficiency (Sutton et al., 2020). Additionally, DEA and CCI-R were vital in determining which inputs and outputs were correlated to hospital efficiency, which is consistent with Ersoy et al. (1997). Additionally, hospitals that use fewer DSS had less variation in the efficiency scores than hospitals that use fewer DSS with standard deviations of 0.175 and 0.195, respectively.

Based on our findings, hospital groups that used more DSS had higher efficiency than those that used less. The findings are congruent with our hypotheses. Intuitively, it makes sense that DSS would improve operations and lead to increased efficiency, considering it excels in analyzing patient needs and assigning doctors based on appropriate skills (Dramburg et al., 2020). Additionally, based on the sample distribution, it seems hospitals are aware of this, as most incorporate DSS in their operations. Given more time to mature and adapt to hospitals' needs, DSS will undoubtedly be used in some fashion within every hospital. Additionally, the correlation tables indicate hospitals with higher numbers of full-time nurses, more beds, and greater total operating expenses had higher DEA scores. However, hospitals with a higher number of full-time equivalent physicians had lower DEA scores.

Managerial Implications

The findings have significant management implications. The results of this study indicate that, by utilizing DEA and CCI-R, hospitals can analyze which variables affect their efficiency. Furthermore, implementing DSS will lead to higher hospital efficiency. The efficiency of hospitals was higher when DSS was present in operations. Additionally, the correlation tables indicate hospitals with fewer full-time equivalent physicians, more full-time registered nurses, more beds, and more total operating expenses had higher DEA efficiency scores.

Looking at each of the input variables, the hospitals can decide which input variables to initially address. The data indicate increasing the number of beds and increasing the number of registered nurses will have the largest impact on the efficiency score, as well as the revenue and number of patients treated. Conversely, having more full-time equivalent doctors harms the efficiency score and does not affect the revenue and number of inpatients treated.

The outcome of this study provides ample evidence to support the cost to implement and utilize DSS or CDSS programs within various hospitals or healthcare organizations. DSS or CDSS can be used to increase both inpatient and outpatient turnover, strengthen the relationships between various healthcare departments, and lower costs by ensuring asset allocation is being delivered efficiently. As an example, a healthcare facility that implements a DSS or CDSS program will be able to increase its inpatient turnover rate. Therefore, it will increase its ability to treat more patients who require medical attention, and it will lower the associated costs that would come with longer-staying patients. More patients being treated would lead to a greater source of revenue, and the lower costs would allow financial resources to be reallocated to other aspects of the organization.

CONCLUSION

In this paper, we aimed to create DEA models for computing hospital efficiency scores. DEA models evaluated the effectiveness of hospitals that utilized more DSS compared to those that utilized them less. The evidence clearly shows statistical significance between efficiency scores. Additionally, the correlation values indicate hospitals with fewer full-time equivalent physicians, more full-time registered nurses, and more beds had significantly higher efficiencies. The number of beds had the highest impact, followed by the number of full-time registered nurses and then the number of full-time equivalent physicians.

Future researchers could examine the impact of DSS on hospital efficiency scores in the following way. For instance, the sample size could be increased, and the usage of the 2020 AHA dataset might provide more accurate information. Moreover, additional variables may be explored to better understand DSS' ramifications. Other efficiency measures such as capacity productivity, manpower productivity, occupancy rate, staff efficiency, and so forth can be tested in future studies. Furthermore, an alternative type of study, such as Stochastic Frontier Analysis (SFA) or regression analysis, might yield more tangible conclusions.

Controlling effects by teaching status, hospital size, hospital location, hospital ownership type, and so on could also be examined in a future study.

Looking at each of the DSS variables and the conclusion that hospitals that use DSS experience increased efficiency serve as a testament to the lucrative and innovative uses of DSS. Furthermore, DSS will work indiscriminately on the size of the hospital. By implementing DSS, managers can expect increased productivity, efficiency, accuracy, and quality of care. DSS integration will continue to benefit both hospitals and patients alike.

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