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Aligning IT Assets to Maximize Healthcare Organizational Performance

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Aligning IT Assets to Maximize Healthcare Organizational Performance

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Abstract

This study examines the impact of healthcare information technology assets on organizational efficiency. Using an econometric approach with data envelopment analysis, we examine the effect of IT asset clusters on organizational efficiency as measured relative to a peer group of healthcare organizations We observe that different IT asset clusters have varying effects on organizational efficiency based on the size of the organizations. The results of this study have implications for healthcare organizations in planning their investments across various IT asset clusters.

1. Introduction

In February 2009, US Congress signed into law the Health Information Technology and Clinical Health Act as part of the American Recovery and Reinvestment Act. The act codifies and funds the Office of the National Coordinator for Health Information Technology (ONC) and provides for the infusion of $19 billion for healthcare organizational information technology (IT) infrastructure. These technologies have the potential for improving the quality and efficiency of IT use in health care. The funding scope includes several types of healthcare organizations and provides them with a significant opportunity to expand and improve its information technology with the use of this funding. Although $19 billion is a substantial amount, allocating it among many organizations reduces the funding size and makes it imperative to wisely select the most efficient use of that funding. Furthermore, a recent study determined the market value for electronic medical record systems was $15.7 billion in 2010. It estimated that for the next two years, these systems will experience a growth rate of 18-20%. RNCOS, a market research and information analysis company, reported that healthcare IT markets in the U.S. are anticipated to grow at a compound annual growth rate of over 24 % during years 2012-2014 [37].

With the availability of justifiable funding for IT adoption, healthcare organizations need guidance for evaluating productivity impacts of IT adoptions. Specifically, which explicit technologies contribute to increased productivity and efficiency of healthcare organizations? Despite the potential benefits of information technology, it is uncertain whether healthcare organizations are investing in the appropriate IT assets and evaluating their value-adding abilities to meet organizational goals [23].

Today's businesses recognize the impact of performance by identifying and measuring organizational goals [38]. Organizational goals also function as key factors in the allocation of IT assets. However, determining "best-fit" assets becomes a process of subjective evaluation underpinned by satisficing determinants. Difficulties lie in determining evaluation criteria that exemplifies "best practice" benchmarks [19].

There is a shortage of studies that demonstrate the impact of IT assets on organizational efficiency [27]. For example, healthcare organization might implement Enterprise Resource Planning software designed to facilitate the system wide integration of complex processes and functions including patient scheduling, human resources management, workload forecasting, and management of workflow. Each process or function has the potential of impacting efficiency. However, as an IT asset portfolio, determining explicit asset efficiency is difficult. While several studies have explored the effect of IT portfolios on productivity[4, 5, 32, 40], quality and profitability, there is no research that specifically identifies the impact of IT asset portfolios on an organizations overall efficiency. IT asset portfolios are defined as combinations of software or IT hardware that serve specific functions such as clinical, business or administrative.

In summary, despite the incentive of investing in IT infrastructures, empirical evidence of the impact of large and complex IT investments on organizational efficiency is limited. Moreover, the recognition of the value of IT infrastructure investments, knowledge of value-adding capacity of IT infrastructure remains largely inadequate in explaining the outcomes of such implementation [23]. A technique to determine the

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impact of individual or specific investment will enable healthcare organizations benchmarking guideline and for implementing the most efficient information technology asset in distinctive organizational clusters.

In this paper, we investigate the impact of mobile IT assets, and administrative and clinical IT asset clusters on organizational efficiency. Administration IT asset clusters include the aggregate assets for use in the business office, financial management, human resource management, and managed care. Clinical IT asset clusters include the use of assets explicit to clinical applications and medical reporting. Accordingly, in this paper we aim to address the following research question:

> How do each of healthcare administration IT assets, clinical IT assets, and mobile IT assets impact organizational efficiency?

The next section provides the theoretical background of performance and efficiency evaluation. Section 3 provides a theoretical model for evaluating efficiency of healthcare organizations with DEA. Section 4 presents the data analysis methodology, followed by a discussion of the results and recommendations for future research.

2. Related work

The performance impacts of information technology (IT) investments in organizations have received considerable attention particularly in evaluation methodologies. Researchers have devoted a plethora of theories directed at providing a methodology of assessing the adoption impact of IT, as a resource to improve business performance. Organizational performance can be measured by the resulting outputs as affected by predetermined inputs. Extending the concept of performance, efficiency measures the impact of inputs relative to outputs. More specifically, it allows for the measuring of the balance between multiple inputs and multiple outputs.

Data Envelopment Analysis (DEA) is an approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. DEA has been applied in a number of hospital studies to evaluate organizational efficiency. Grosskopf [21], in a study to determine the differences of best practice performance for two types of hospitals, used teaching and non-teaching hospitals to establish an efficiency benchmark. The results concluded that 10 percent of the teaching hospitals can effectively compete with non-teaching hospitals based on the provision of patient services.

DEA is used to evaluate the impact IT assets on firm performance when intermediate measures are present [10]. The study extends research[45][11] where inputs are the construct of two stages of value-adding processes. The first stage use values of fixed assets, employees, and IT investments. These process contributions flow into the second stage comprised of deposits. This research concludes that IT assets can be evaluated as factors contributing to the efficiency input factor.

Electronic Medical Records (EMRs) are a health information technology asset focused on improving the quality of care and efficiency of outcomes. Kazeley and Ozcan [24] evaluate how the impact of EMR use influences hospital efficiency. Specifically, their study evaluates the efficiency of care in the context of outputs and their relationship to inputs in terms of hospital EMR use. Hospitals with EMRs at all size levels did not report a significantly greater chance of increasing their efficiency over time.

The depth of research has solely focused on evaluating IT impact as an aggregated asset. As organization move forward with asset assessment, a means of identifying explicit IT assets positions them to make more equitable use of resources.

Several studies have explored the impact of IT investments on healthcare organizations. An econometric study in the healthcare industry analyzed the impact of IT in a healthcare setting using a longitudinal sample of hospital data from 1976 to 1994[31]. They categorized production inputs into labor and capital. Labor was classified into two components, medical labor and IT labor. Capital was classified into three components – medical IT capital, IT capital, and medical capital. The results concluded that IT and medical IT capital, IT labor, and medical labor have a positive impact on output. However, medical capital appeared to be negatively associated with output during the longitudinal time period

A study explored the productivity impact of IT in the healthcare industry using regression splines (RS)-based approach on production function [34]. This study explored the interactions between the predictor variables (non-IT Capital; non-IT Labor; and IT Stock). The results suggest that under certain conditions, investments in IT stock have a positive impact on productivity, and that this impact of IT is not uniform but is conditional on both the amount invested in the IT stock and the investments in non-IT capital. Thereby identifying an optimum level of the investment in each variable may lead to higher productivity at the hospital level.

An econometric analysis of 17 not-for-profit hospitals was conducted [33]. The study had three goals; to show that a classic econometric production function is adaptable to not-for-profit hospitals, to compute and analyze the share of each input variable in the explanation of the measured hospitals outputs and evaluated the production impact of IT investments, and to compare the share of IT in the production results between two sets of hospitals split on an IT integration level basis. Using an aggregate Cobb-Douglas function the links between hospital production and three different inputs (capital stock, quantity of labor, information technologies) were evaluated assuming the constant elasticity of substitution of the inputs.

Results show that a relationship is present, thus enabling use of econometric analysis tools in not-for-profit hospitals. In addition, with a share of labor in the hospitals superior to what is generally admitted in the industrial or service sector, the elements brought by the production function stressed the importance of the human factor in explaining the hospitals' production results.

A longitudinal study of a healthcare system suggests that the impetus of IT impact is not invested technology, but the actual usage of the technology [15]. This research examines the usage and impact of individual technologies on organizational performance. The study uses data from eight hospitals that have implemented a decision support system (DSS). The study provides general support for the proposition that the greater the actual usage of technology, the better the financial and quality performance of hospitals.

The study by (Thouin, Hoffman, & Ford, 2008)[43] investigates whether specific types of IT investments can be used to predict firm-level financial performance in the health care industry. The study results indicate that increased levels of IT expenditures lead to increased financial performance. In a study to examine the effects between different kinds of IT has on hospital performance, capital depreciation of clinical IT and administration IT are related to hospital output and medical labor productivity [32]. Inputs were represented by Clinical IT and administration IT and related to hospital outputs (patient days and medical labor productivity).

A summary of the above discussed research on the impact of IT on healthcare organizations is presented in Table 1. While several studies have been conducted that explore the impact of IT on productivity, profitability and financial performance of the healthcare organizations, there is limited research that explores the effect of information technology on the relative efficiency of healthcare organizations.

Table 1. Studies of impact of IT on Healthcare

Study	IT Measurement	Performance Measurement
Menon, Lee, & Eldenburg, 2000	Medical IT capital Medical capital IT capital Medical labor IT labor	Production of services
Osei-Bryson & Ko, 2004	Non-IT capital Non-IT labor IT stock	Productivity
Meyer, Degoulet, & Omnes, 2007	Capital Stock Quantity of labor Information technologies	Production
Devaraj & Kohli, 2003	Report usage Disk I/O usage CPU usage	Profitability
Thouin, Hoffman & Ford, 2008	IT budget IT outsourcing IT personnel	Financial performance
Menon, Yaylaciegi, & Cezar, 2009	Clinical IT capital depreciation Administrative IT capital	Adjusted patient care days Labor productivity

Mobile technology in healthcare is evolving as an integral asset of healthcare information systems. As a relatively new technology, healthcare organizations adoption of the technology is slowly advancing [2, 6, 44, 46].

Wide adoption of mobile computing technology can potentially improve information access, enhance workflow, and promote evidence-based practice to make informed, effective, and efficient decisions in healthcare organizations [29]. With the inclusion of mobile devices as an organizational asset, mobile work can be defined as the use of mobile technologies in varying degrees to accomplish tasks, across locational, temporal, and contextual boundaries [30]. Mobility enables mobile healthcare workers real-time access to data and information, reduces medical errors, saves time, supports evidence-based practice [1], improves productivity and quality of care, and improves communication [9].

3. Research methodology

3.1 Theoretical foundation

In order to construct an applicable analysis model, determining the best performance factors is essential. Research models have used economic accounting factors that include both price and costs. Others have used capital and labor. According to Scott et al., (2001)[39] applying economic thinking to an understanding of resource use in healthcare is challenging given the complexities of delivering patient care services in a hospital[39]. Differences in accounting practices and inequality of pricing make it difficult to establish relative values. However, resource allocation in a healthcare organization can be analyzed by using production theory to determine efficient resource use[31].

In the paper "The Measurement of Productive Efficiency," Farrell[18] posits a decomposition of a cost efficiency index, or overall efficiency. Farrell characterized the different ways in which a productive unit can be inefficient either by obtaining less than the maximum output available from a determined group of inputs (technically inefficient) or by not purchasing the best package of inputs given their prices and marginal productivities (allocative inefficient).

The measurement of productive efficiency has important implications for both economic theory and economic policy. Measuring productive efficiency allows for hypotheses testing regarding sources of efficiency or differentials in productivity[28]. Moreover, such measurement enables the quantification of potential increases in output that might be associated with an increase in efficiency[18].

Efficiency measurement is a main component in measuring organizational business performance and related to the association between resources used and results achieved. The Cobb-Douglas production function can be simplified into an efficiency evaluation function. By evaluating the ratio of output P over inputs L and K, an efficiency function can determine performance.

$$Efficiency = \frac{Outputs}{Inputs} = \frac{Goods\ \&\ Services}{Labor,\ Capital}$$

Technical and Allocative efficiency are types of physical relationships between resources (such as capital and labor) and outcomes (such as goods and services) [35]. A technically efficient relationship is achieved when the maximum possible improvement in outcome is obtained from a set of resource inputs. It addresses the issue of static resources to maximize output. Allocative efficiency refers to the maximization of outcome by selecting the right mixture of input resources.

The purpose of the production function is to address allocative efficiency from the relationship of inputs to outputs and evaluate the weighted compositions of those inputs and derives the marginal value for each explicit input that generates the total output value.

Farrell[18] promoted the idea of specifying the production frontier or "best-fit" as the most pessimistic piecewise linear envelopment of the data and constructs efficiency measures based on radial uniform contractions or expansions from inefficient observations to the frontier.

3.2 Data Envelopment Analysis

Data envelopment analysis (DEA) was first introduced by Farrell and later developed by Charnes, Cooper and Rhodes (CCR Model)[7]. It uses an oriented radial measure of efficiency, which identifies a point on the boundary with the same mix of inputs or outputs of that of the observed unit[12]. DEA theory is grounded in the Cobb-Douglas production function and is a mathematical programming technique used to measure performance. Unlike most of the traditional econometric approaches (cost or profit), it focuses primarily on the technological (physical assets) aspects of the production function and is not dependent on assumptions about or estimates of input and output prices.

Efficiency equals the ratio of the sum of all units' weighted outputs over the sum of all the units' weighted inputs. For each production unit, DEA (a) calculates the efficiency score; (b) determines the relative weights of inputs and outputs; and (c) identifies peers for each unit that is not technically efficient. The peers of an inefficient unit are technically efficient units with similar combinations of inputs and outputs. The peers serve as benchmarks, acting as guidelines for potential improvements for the inefficient unit. The underlying concept of DEA is based on Pareto optimality [8] where a decision making unit (DMU) is considered relatively efficient if there is no other DMU or a combination of DMUs which can produce at least the same amount of all outputs with less of one input and not more of any other input. It computes the comparative ratio of outputs to inputs for each unit, with the score expressed as 0–1 or 0–100%. A DMU with a score less than 100% is inefficient compared to other units. DEA has been initially used to investigate the relative efficiency of nonprofit organizations but now, its use has spread to hospitals, school, banks, and network industries, among others.

Because of the simplicity of the DEA model with respect to its underlying production function, certain characteristics make it a valid tool for determining efficiency. Specifically,

- DEA can handle multiple input and multiple output models.
- It doesn't require an assumption of a functional form relating inputs to outputs.

- DMUs are directly compared against a peer or combination of peers.

4. Methodology

In order to compare the IT use and efficiency of different organizations, we begin by identifying sets of peer groups that function as benchmarking "best-fit" models of IT use and integration. The approach firstly uses a DEA model as an analytical methodology of calculating the most efficient organization. The results also produce a relative weighted peer group explicit to inefficient organizations. Secondly, an alignment model is constructed to identify explicitly which IT assets are implemented for each organization and determines which IT assets require implementation or reduction. Thirdly, a panel data regression analysis is performed to determine if the impact of various It asset clusters on organizational efficiency.

4.1 DEA model

The DEA model in this research adheres to only physical factors. As shown in Table 2, the outputs selected include services produced (patients serviced). The number of total patients served is represented by total number of emergency room visits, number of outpatients, and number of inpatients. To produce the patients served, inputs required are labor and capital. The inputs include the number of staffed beds as a proxy for organizational size and capital investment and represent the potential capacity to service patients. Literature has recognized organizational size as the most important factor to predict innovation adoption [25] [13]. Number of full time employees (nurse, physicians, and support staff) represents physical labor.

Table 2. Inputs and Outputs

Inputs	Outputs
Number of Fulltime Employees	Number of Emergency Room Visits
Number of Staffed Beds	Number of Outpatient Visits
	Number of Inpatient Discharges

Mathematically, the factors are computed using the performance of DMUs inputs and outputs. The efficiency scores (E_J) for a DMU (j = 1.... n), are computed for the selected outputs (y_{rj}, r = 1... s) and inputs (x_{ij}, i = 1... m) using the following linear programming model:

Maximize: $$E_0 = \frac{\sum_{r=1}^{s} u_r\, y_{r0}}{\sum_{i=1}^{m} v_i\, x_{i0}}$$

Subject to: $$\frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{i=1}^{m} v_i\, x_{ij}} \leq 0$$

$u_r, v_i \ > 0 \; for\ all\ r$ and i.

Where:

u_r = amount of output r
y_r = weight assigned to output r
v_i = amount of input i
x_i = weight assigned to input i

Prior research has employed DEA to assess the performance of information technology investments [10, 11, 41, 42]. In formulating this model, the CCR [7] DEA methodology is followed to determine the dependent variable (efficiency).

The DEA model uses multiple inputs and multiple outputs to measure efficiency (see Table 2). Data was extracted from the Dorenfest Complete IHDS+ Database [16]. It contains detailed information on technological and demographic characteristic of over 1000 integrated health care delivery systems in the U.S.

4.2 Frequency Distribution

Much of the research that supports the benefits that information technology has analyzed only single organizations, thus limiting the generalizability of any findings [14, 25, 26]. As economies of scale become a viable approach for increasing efficiency, many smaller healthcare organizations are merging [17, 20]. For example, payroll systems can be reduced to one IT technology shared by all affiliates. DEA calculates efficiency as a relative value.

To minimize the effects of size disparities it becomes necessary to divide the integrated healthcare delivery systems (IHDS) into relatively similar groups. Integrated healthcare delivery systems are segmented into a frequency distribution comprising of quartiles. Total bed size across all sub-units is used to determine the IHDS size as it represents the physical size and breadth of IT use. Table 3 shows the results of the quartile determination.

Table 3. Frequency Distribution

Year	2005	2006	2007	2008
No of DMUs	662	989	1099	511
Number of Staffed Beds				
Mean	661	559	514	554
Minimum	10	7	6	10
Maximum	38634	37311	36130	31244
Distribution of staffed beds				
	Lower	Upper		
Quartile 1	6	91		
Quartile 2	92	222		
Quartile 3	223	462		
Quartile 4	463	38634		

Each quartile group across four years is used to calculate efficiency thus preserving the homogeneity properties of the DMUs' size.

4.3 Model

To determine IT use, explicit IT applications for each hospital organization are grouped in two clusters, administration and clinical. The administration cluster represents IT applications that directly impact internal data processing such as patient registration system, billing system, and payroll processing system. The clinical cluster represents IT applications directly impacting patient care, computerized physician order entry system, electronic medical record, and pharmacy information system (Table 4).

Table 4. IT usage applications by clusters

Administration IT Asset Cluster	**Clinical IT Asset Cluster**
Administration/Business Office	Cardiology
Admissions	Emergency Department
I.S. Department	ICU
Material Management	Labor and Delivery
Medical Records	Laboratory
Medication Administration	Nursing/Point of Care
	OR/Surgery
	OutPatient/Home HealthCare
	Pharmacy
	Physical Therapy/Rehabilitation

Each hospital organizations administration IT use, clinical IT use, administration mobile IT use and clinical mobile IT use, was represented by the total of applications used in each cluster.

5.0 Results and Discussion

Data envelopment analysis efficiency results are presented in Table 5. Missing data either due to unreported inputs or outputs reduced the number of DMUs to 2062 for the four years under study. DEA was calculated by quartile and aggregated into one regression model.

Table 5. DEA aggregated results

Efficiency Statistics	
Number of DMUs	2062
Number of Frontier DMUs (=100%)	101
Number of Frontier DMUs >90%	319
Mean	0.63
Median	0.647
Standard Deviation	0.247
Minimum	0.014
Maximum	1

There were 101 of 2062 Decision Making Units (DMUs) that are considered to be on the frontier and represent the peer organizations. The remaining 1961 DMUs are evaluated as inefficient relative to the 101efficient peer DMUs.

The DEA model calculates both efficient and inefficient DMUs, and also a set of peer group efficient DMUs explicit to each inefficient DMU. The peer group represents the weighted contribution value becoming the benchmark set of IT asset applications for each of the defined asset clusters. Table 6 represents one instance of the DEA output. Hospital B is evaluated with an inefficient value of 76%. The peer-efficient DMUs are Hospital A and C having relative contribution weights of 24 and 75%. Hospital IT assets are totaled from each of the asset clusters.

The re-alignment values represent the number of IT assets for each cluster that need to be adjusted, increased or decreased. This is calculated by subtracting the inefficient Hospital B's assets from the peer group weighted mean's assets. This produced the number of IT assets that would need to be re-adjusted to move the inefficient organization to efficiency.

Table 6. Inefficient re-alignment

Inefficient Hospital	Efficiency	Administration IT Assets	Clinical IT Assets
Hospital B	0.76	30	31
Peer Member	Weight		
Hospital A	0.246	30	40
Hospital C	0.753	27	23
Peer Group Weighted Mean		28	27
Re-alignment		-2	-4

Table 7 summarizes the results of all 156 sets of peer units to deficient units. Intuitively the results indicate that to re-align inefficient organizations, the majority will need to either decrease the IT assets presently applied or improve utilization of existing IT assets.

Table 7. Re-Alignment summary

Re-Alignment	Business IT Assets	Clinical Assets
Increase	42	45
None	8	4
Decrease	106	107
Total	156	156

6. Panel Data Regression Analysis

Timewise (also known as longitudinal) observation of data from different observational units has long been common in other fields of statistics [3, 22, 36]. Panel data analysis is a dataset in which the behaviors of entities are observed across time.

For this study, we used the data provided by the Dorenfest Institute for Health Information Research and Education. The database contains IT information for more than 1500 integrated healthcare delivery systems and their sub units, approaching over 30,000 individual health care facilities. The data analyzed included sequential years starting in 2005 and ending in 2008 therefore providing a four year time span.

In the health care industry, many healthcare organizations are comprised of multiple facilities covering wide demographics comprising of an integrated healthcare delivery system. This depth of operations permits the consolidation of resources. In information systems, this may include the sharing of payroll systems, billing and receiving processes, accounting, and data warehousing. For this analysis, the multi-facilities are aggregated into one organization and IT usage reported for one facility is calculated as a single application.

6.1 Measurement of Variables

The dependent variable examined in this study is the efficiency values calculated using the DEA process. The independent variables represent the depth of IT application use. The Dorenfest database includes information pertaining to specific IT use in both administration and clinical environments. To control for disparity of organization depth (one or many sub-units or affiliated units) the number of subunits in a multi-facility organization was included. As organizations remain in service, age of organization might affect the use of IT application. Length of service could impact the use of IT by drawing from diminishing learning curves and experience. The number of full time employees controls for the influence of human resource availability. Although Number of physicians (NoPhy) was included in the DEA calculation, the DEA scores is a relative score that is based on multiple variables and is calculated in relation to peer groups. Moreover, we observed that the NoPhy variable does not negatively correlate with the DEA scores, as expected by the inverse relationship. Therefore, based on the suggestions of previous studies exploring hospital efficiency and productivity, we decided to include NoPhy as a control variable for consistency with previous studies. To control for organization output, the number of outpatient visits, patient discharges, and emergency room visits determine the quantity of services rendered. Actual physical size is accounted for by using the variables bed size and service population.

6.2 Analysis

The regression model analyzed the effect of three different independent IT variables on organizational efficiency. The first two are the depth of IT in administration applications and clinical applications. The third is the depth of mobile (in this case handheld devices) applications. Depth is determined by counting the application processes that exist in each organization and calculates the ratio of IT applications actually used for each process.

6.3 Results

The results for the panel regression (years 2005 through 2008) are shown in table 8.

Table 8. Regression results

Quartile 1 (Bedsize 0-91)			
	Coef	Pr(>|t|)	
Administration IT	1.5E-01	2.8E-02	*
Age	-2.0E-03	3.1E-02	*
Clinical IT	-1.6E-01	4.6E-02	*
ER Visits	0.0E+00	5.9E-01	
Handheld IT	-2.5E+01	3.9E-01	
No of FTE	-1.0E-03	2.2E-01	
No of Physicians	1.0E-03	2.1E-01	
No of Outpatient Visits	0.0E+00	5.5E-01	
No of Patient Discharges	0.0E+00	0.0E+00	***
Staffed Beds	-4.0E-03	1.7E-01	
subunits	-1.0E-03	7.7E-01	
Service Population	0.0E+00	4.0E-01	
Total Sum of Squares: 0.059639			
Residual Sum of Squares: 0.012046			
R-Squared : 0.79801			
Adj. R-Squared : 0.33517			
F-stat: 6.914 on 12 and 21 DF, p-value: 6.69e-05			

Quartile 2 (Bedsize 92-221)			
	Coef	Pr(>|t|)	
Administration IT	-2.9E-02	3.0E-01	
Age	-1.0E-03	0.0E+00	***
Clinical IT	1.9E-02	4.4E-01	
ER Visits	0.0E+00	0.0E+00	***
Handheld IT	9.0E-02	9.0E-03	**
No of FTE	0.0E+00	0.0E+00	***
No of Physicians	0.0E+00	0.0E+00	***
No of Outpatient Visits	0.0E+00	0.0E+00	***
No of Patient Discharges	0.0E+00	4.2E-01	
Staffed Beds	-3.0E-03	0.0E+00	***
subunits	1.0E-03	5.2E-01	
Service Population	0.0E+00	7.3E-01	
Total Sum of Squares: 0.60289			
Residual Sum of Squares: 0.068055			
R-Squared : 0.88712			
Adj. R-Squared : 0.5227			
F-stat: 92.997 on 12 and 142 DF, p-value: < 2.22e-16			
Quartile 3 (Bedsize 222-462)			
	Coef	Pr(>|t|)	
Administration IT	-4.0E-02	6.1E-02	.
Age	0.0E+00	9.3E-01	
Clinical IT	4.9E-02	1.9E-02	*
ER Visits	0.0E+00	0.0E+00	***
Handheld IT	3.0E-03	3.5E-01	
No of FTE	0.0E+00	0.0E+00	***
No of Physicians	0.0E+00	1.9E-01	
No of Outpatient Visits	0.0E+00	0.0E+00	***
No of Patient Discharges	0.0E+00	0.0E+00	***
Staffed Beds	-2.0E-03	0.0E+00	***
subunits	-1.0E-03	1.9E-01	
Service Population	0.0E+00	6.0E-01	
Total Sum of Squares: 0.86262			
Residual Sum of Squares: 0.12973			
R-Squared : 0.84961			
Adj. R-Squared : 0.51672			
F-stat: 97.921 on 12 and 208 DF, p-value: < 2.22e-16			
Quartile 4 (Bedsize 463-37,311)			
	Coef	Pr(>|t|)	
Administration IT	4.2E-02	2.0E-01	
Age	0.0E+00	3.6E-01	
Clinical IT	-1.8E-02	6.2E-01	
ER Visits	0.0E+00	1.0E-03	***
Handheld IT	-1.0E-03	8.5E-01	
No of FTE	0.0E+00	5.4E-01	
No of Physicians	0.0E+00	8.4E-01	
No of Outpatient Visits	0.0E+00	3.5E-01	
No of Patient Discharges	0.0E+00	2.1E-01	
Staffed Beds	0.0E+00	0.0E+00	***
subunits	0.0E+00	6.7E-01	
Service Population	0.0E+00	2.9E-01	
Total Sum of Squares: 1.1413			
Residual Sum of Squares: 0.95178			
R-Squared : 0.16602			
Adj. R-Squared : 0.1073			
F-stat: 5.093 on 12 and 307 DF, p-value: 9.231e-08			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

The analysis finds significance in the Quartile 1 (Bedsize 0-91) group. Administration IT applications show a positive benefit and clinical IT applications show a negative impact. The mobile IT applications had no significant relationship to efficiency.

The analysis finds minimal significance in the Quartile 2 (Bedsize 92-221) group. Administration IT applications had minimal negative (-0.029) significance and clinical IT applications show a minimal positive (.019) impact. The mobile IT applications had minimal positive (.090) significant relationship to efficiency.

The analysis finds minimal significance in the Quartile 3 (Bedsize 222-462) group. Administration IT applications had minimal negative (-0.040) significance and clinical IT applications show a minimal positive (.049) impact. The mobile IT applications had minimal positive (.003) significant relationship to efficiency.

The analysis finds minimal significance in the Quartile 4 (Bedsize 463-37,311) group. Administration IT applications had minimal positive (.042) significance and clinical IT applications show a minimal negative (-.018) impact. The mobile IT applications had minimal negative (-.001) significant relationship to efficiency.

Although the tests do not strongly support the notion that IT assets impact organizational efficiency, it does indicate organizational size as determined by bed size can be used as a guideline when determining the most efficient applications for IT integration. The smallest group (Q1) analysis results purports that funding be applied first to administration IT applications or improving the negative effects of clinical IT applications. The data in Tables 6 and 7 clearly represent a disparity of the sum totals of IT assets. This implies that allocative imbalances could exist when IT assets are applied excessively in one area and deficient in others. These disproportional applications could lead to inefficiencies.

7.0 Conclusion

7.1 Implications

The results of our study present an approach to identifying specific IT assets that contribute to higher organizational efficiency compared to a relative peer groups. Using DEA to measure relative efficiency, benchmarked organizations provide insight to the impact specific IT assets contribute to performance. A priority list of potential IT investment improvements is identified to best utilize available funding.

Although there has been research on IT asset as aggregate sets, there are no studies on individual IT applications. The proposed model identifies organizations that are relatively efficient to homogeneous organizations. The peer organization serves as a model for re-aligning the IT assets of inefficient organizations. It can be useful in specifying which IT asset(s) to implement, where to implement the asset, and quantify the contribution. The contribution value can be used to justify IT assets based on impact levels and costs. The results also suggest that smaller and very large organizations first invest in Administration IT to improve efficiency, whereas for mid-sized organizations, investment in clinical IT can result in efficiency improvements.

Identifying the impact of specific IT assets will guide organizations in the appropriation, implementation, and use processes. In this study, specific IT assets were clustered into administration and clinical applications. Although this approach can narrow the determination of target IT assets, this approach can also be used to include more specific IT assets within each cluster. This will enable a more granular view of IT assets value contribution.

As technology has been embedded in organizations for many years, IT becomes aged showing effects of obsolescence and misuse. Better systems could be available which perform more efficiently and are less costly. Old systems might lack support both technical and physical. Exploring the temporal effects of IT assets applications could help identify both the weak and the strong IT assets.

7.2 Limitations

Alternate DEA models need to be developed from a combination of databases. The Dornfest database focus is on IT applications and lacks inputs that could better define that efficient peer group relative to the inefficient organization. In future research we will explore datasets with more detailed information that can help perform a more in-depth analysis of the impact of IT on efficiency.

Most organization production processes deal with activities in which some outputs and / or inputs are intangible. This makes efficiency analysis difficult, compounded by aggregating benefits and costs in accounting terms. Since the relationship of output to inputs is non-monetary; that is, a production function relates physical inputs to physical outputs, prices and costs are not reflected in the production function. The function's purpose is to address allocative efficiency in the use of factor inputs in production and does not address technical efficiencies.

The study objective is to determine the impact of information systems on the organizations ratio of inputs to outputs. It is assumed that the intent of integrating IT is to change physical labor by reductions in process time and errors (thus minimizing correcting and repeating tasks). Relative pricing and costs are difficult to determine. The demographic cost differential (wages, utilities, insurance, etc.) and organizational type (profit or non-profit centers) do not relate equally and skew comparable relationships. The selection of the analysis inputs in this study was determined by matching factors that directly affect outputs.

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