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Impact of cloud deployment on operational expenses of healthcare centers

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Abstract

Healthcare is among the most advanced industries when it comes to embracing and adopting modern technology in some way. Cloud computing approaches, in conjunction with the Internet of Things, are advantageous to extract information from healthcare records. In many cases, cloud computing combined with IoT and AI will pave the way for new avenues of medical innovation and insight. Cloud computing's growing acceptance in healthcare extends much beyond simply storing data on cloud infrastructure. Healthcare providers are already embracing this technology to increase efficiency, optimize processes, reduce healthcare costs. The objective of this research was to investigate whether the deployment of cloud computing can assist in reducing operational costs in healthcare centers. We used panel data ranging from 2008 to 2019 for 156 healthcare centers. The Fixed Effect (FE) model and Random Effect (RE) model have been employed. The results suggest that the deployment of cloud computing significantly assists in reducing the operational costs in healthcare centers.

Keywords: *Cloud computing, Healthcare, Operational costs*

1. Introduction

The use of cloud computing in the healthcare business began years ago, but progressed slowly due to several obstacles. It has received fresh speed in recent years as a result of technological advancements, higher client demands, and the worldwide pandemic.

Moving to the cloud offers two distinct advantages. It has been shown to benefit both healthcare providers and patients. On the commercial side, cloud computing has been shown to benefit healthcare providers by lowering operating costs while enabling them to offer high-quality, tailored treatment (Onwubiko, 2010). Patients, who have become accustomed to rapid service delivery, now receive it from the health sector as well. Additionally, cloud technology increases patient participation with their own health plans by providing access to their own health data, leading in improved patient outcomes. The democratization of healthcare data and its remote accessibility liberates both clinicians and patients and eliminates geographical obstacles to healthcare.

Cloud computing's fundamental assumption is the on-demand accessibility of computer resources such as data storage and computational power. Hospitals and healthcare professionals are no longer required to buy hardware and servers entirely (Buyya, Beloglazov and Abawajy, 2010). There are no upfront costs connected with data storage in the cloud. They simply pay for the resources they utilize, resulting in significant cost savings.

Additionally, cloud computing provides the most ergonomic environment for scalability, which is a desired characteristic in today's world. With patient data streaming in not only from EMRs but also from a myriad of healthcare applications and wearables, a cloud-based platform is ideal for expanding and undergoing significant makeover while keeping costs down (Mirza and El-Masri, 2013).

Historically, healthcare organizations have stored their data on-premises because it enables them to keep complete control over their in-house data, limit the risk of data breach, and manage their own backup and recovery systems. However, with the rising complexity of healthcare big data, which comprises several geographically dispersed healthcare institutions and an expanding variety of smart health apps, there is no "one-size-fits-all" solution available today. Managing large data storage, changing real-time data from IoT devices, Bring Your Own Device (BYOD) policies, enforcing security, compliance, and availability, and providing ubiquitous access to on-premise healthcare data storage is getting more difficult (French, Guo and Shim, 2014).

With the advancement of medical technologies, the quality and volume of medical imaging data has risen. As a result, a scalable infrastructure is required for storing the growing volume of healthcare big data. Additionally, for major healthcare organizations with care centers located in various geographic regions, data is spread across several servers located in various places. Often, though, such data must be available to multiple people from several places. Healthcare data storage should be accessible 24 hours a day, which requires a dependable and available storage solution (Magrabi *et al.*, 2015).

The healthcare business is required to invest heavily in updating and expanding storage capacity in order to make it more flexible and scalable, which can be expensive. Additionally, managing the diverse array of clinical data provided by EMR, IoT, medical imaging, and genomic sequencing can be hard (Manogaran *et al.*, 2017).

Smart healthcare systems create a large quantity of data, which is referred to as healthcare big data. These data include both traditional electronic medical record (EMR) or electronic health record (EHR) systems data.

On-premise storage is frequently inflexible. It is necessary for the storage solution to be scalable, which means that additional storage capacity may be added without requiring a total upgrade and conversion, which is not always the case. Expanding on-premise storage capacity also entails increasing physical space on-site, which may be difficult to handle. Apart from the expenses of extra storage solutions, there are also operating expenditures like as power supply, cooling of server rooms, and IT employees, which combine to make on-premise data storage a relatively expensive alternative (Herre, 2016). On-premise storage may potentially have a higher delay in recovering from an attack or failure, depending on the backup plan in place. Due to the crucial nature of healthcare data, extended downtime can have a significant impact on the quality of treatment provided to patients when patient data is not readily available.

Apart from the immediate economic benefits of cloud storage over on-premises data storage, enterprises profit in the long run from easier upgrades and lower scaling costs (Mogouie, Arani and Shamsi, 2015). Cloud storage providers for healthcare use economies of scale to help their clients – hospitals and healthcare institutions – reduce data management expenses (Kossmann and Kraska, 2010).

Additionally, cloud computing provides greater flexibility in healthcare due to the standard pay-as-you-go cost structure connected with data storage (Sultan, 2010). When healthcare institutions develop their own data storage systems, they must estimate the capacity they require and invest their own money to expand that capacity when storage space becomes scarce. With cloud-based solutions, all it takes is a simple contact to service provider to increase data storage capacity to the required levels.

2. Methodology

This research utilizes the panel data techniques to achieve the research objective. If have access to a panel of data, there are significant advantages to fully utilizing this rich structure. To begin, and probably most significantly, panel data enables us to address a broader range of topics and solve more complicated problems than is achievable with pure time series or cross-sectional data alone. Second, it is frequently interesting to investigate how variables, or their relationships, change dynamically (over time). To accomplish this with pure time series data, it is frequently necessary to run the data for an extended period of time in order to obtain a sufficient number of observations to conduct any relevant hypothesis tests. However, by combining cross sectional and time series data, one can enhance the number of degrees of freedom and hence the strength of the test by simultaneously incorporating information about the dynamic behavior of a large number of entities. Additionally, the additional variance produced by integrating the data in this manner can assist alleviate multicollinearity issues that may develop when time series are simulated separately. Third, as will become clear below, by appropriately designing the model, one can eliminate the effect of certain types of omitted variables bias in regression findings.

In empirical research, panel estimator approaches fall into two basic categories: Fixed Effects (FE) models and Random Effects (RE) models (Borenstein *et al.*, 2010). The simplest types of fixed effects models allow for cross-sectional but not longitudinal variation in the intercept, whereas all slope estimates are fixed cross-sectionally and longitudinally. While this approach is clearly more sparing than SUR models (which requires the estimation of (N + k) parameters), it still involves the estimation of (N + k) parameters.

Under the fixed-effect paradigm, it is assumed that the true effect size is identical across studies and that the only cause for variation in effect size is sampling error (error in estimating the effect size). As a result, while weighting the various research, we may basically disregard the information from smaller studies because we have more information on the same effect size from larger studies.

By contrast, the purpose of the random-effects model is to estimate the mean of a distribution of effects, not a single real effect. Because each study reports on a distinct effect size, it is required to ensure that the summary estimate includes all of these effect sizes.

To estimate the impact of cloud computing on healthcare center's operational expenses, we used the model by (Bardhan and Thouin, 2013)

$$\begin{aligned} Expenses_{Op_{it}} &= \alpha + \beta_1 Financial_{it} + \beta_2 Clinical_{it} \\ &+ \beta_3 Scheduling_{it} + \beta_4 HR_{it} + \beta_5 HospType_{it} \\ &+ \beta_6 CMI_{it} + \beta_7 Location_{it} + \beta_8 TeachingStatus_{it} \\ &+ \beta_9\, Cloud_{it} + \epsilon \end{aligned}$$

Where, the $expenses_{opit}$ is the dependent variable. It represents the operational cost efficiency index. The variables Financial, Clinical, Scheduling, HR represents the usage of IT in financial, clinical, scheduling, and HR management system, respectively. The variable HospTypes is a dummy variable. It takes zero if the healthcare center is private, and one if it is public. The variable CMI indicate case mix index of healthcare centers. Location is a dummy variable. It takes zero if the healthcare center is in rural area, and one if it is in urban area. TeachingStatus is also a dummy variable. It takes zero if the healthcare center is non-teaching, and one if it is teaching. The variable Cloud is assigned zero if the healthcare center does not deploy cloud computing, and is assigned one if it deploys cloud computing. The panel data set ranging from 2008 to 2019 for 156 centers has been collected from Dorenfest Institute for Health Information Technology Research database.

2. Results

Table 1. Fixed effect model

Dependent Variable: EX_OP
Method: Panel Least Squares

Sample: 2008 2019
Periods included: 12
Cross-sections included: 156
Total panel (balanced) observations: 1872

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLINICAL	1.005079	0.037468	26.82534	0.0000
CLOUD	0.952436	0.031070	30.65429	0.0000
CMI	1.002382	0.037672	26.60829	0.0000
FIANANCIAL	0.977306	0.037744	25.89311	0.0000
HOSPTYPE	-0.007482	0.021675	-0.345186	0.7300
HR	0.955607	0.038110	25.07510	0.0000
LOCATION	0.968391	0.030585	31.66226	0.0000
SCHEDULING	0.998143	0.038194	26.13348	0.0000
TEACHING_STATUS	0.995650	0.030548	32.59318	0.0000
C	1.080687	0.053708	20.12152	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.801847	Mean dependent var	5.009639
Adjusted R-squared	0.782809	S.D. dependent var	0.967021
S.E. of regression	0.450668	Akaike info criterion	1.327839
Sum squared resid	346.6939	Schwarz criterion	1.815678
Log likelihood	-1077.857	Hannan-Quinn criter.	1.507563
F-statistic	42.11919	Durbin-Watson stat	2.064366
Prob(F-statistic)	0.000000		

The results of Fixed effect model have been reported in table 1. With R-squared of 0.80, the model seems to be good-fit. The t-statistics and associated values indicate that all the variables are significant except hospital type. It implies that the operational costs are same whether the healthcare centers public or private.

Table 2. Random effect model

Dependent Variable: EX_OP
Method: Panel EGLS (Cross-section random effects)

Sample: 2008 2019
Periods included: 12
Cross-sections included: 156
Total panel (balanced) observations: 1872
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.

CLINICAL	0.994829	0.036330	27.38276	0.0000
CLOUD	0.967995	0.029965	32.30457	0.0000
CMI	0.999314	0.036493	27.38335	0.0000
FIANANCIAL	0.973150	0.036315	26.79727	0.0000
HOSPTYPE	-0.006957	0.021004	-0.331229	0.7405
HR	0.963443	0.036855	26.14163	0.0000
LOCATION	0.961085	0.029281	32.82320	0.0000
SCHEDULING	1.014508	0.036701	27.64288	0.0000
TEACHING_STATUS	0.999997	0.029658	33.71738	0.0000
C	1.070790	0.052103	20.55157	0.0000

Effects Specification		
	S.D.	Rho
Cross-section random	0.058419	0.0165
Idiosyncratic random	0.450668	0.9835

Weighted Statistics			
R-squared	0.780472	Mean dependent var	4.570032
Adjusted R-squared	0.779411	S.D. dependent var	0.959829
S.E. of regression	0.450803	Sum squared resid	378.4011
F-statistic	735.5353	Durbin-Watson stat	1.893845
Prob(F-statistic)	0.000000		

Unweighted Statistics			
R-squared	0.780086	Mean dependent var	5.009639
Sum squared resid	384.7678	Durbin-Watson stat	1.862508

The Random effect model also yields also similar results. Table 1 summarizes the results of the Random effect model. The model appears to be well-fit with an R-squared of 0.80. The t-statistics and accompanying values suggest that all variables except hospital type are significant. This suggests that the operational expenses are the same for public and private healthcare facilities.

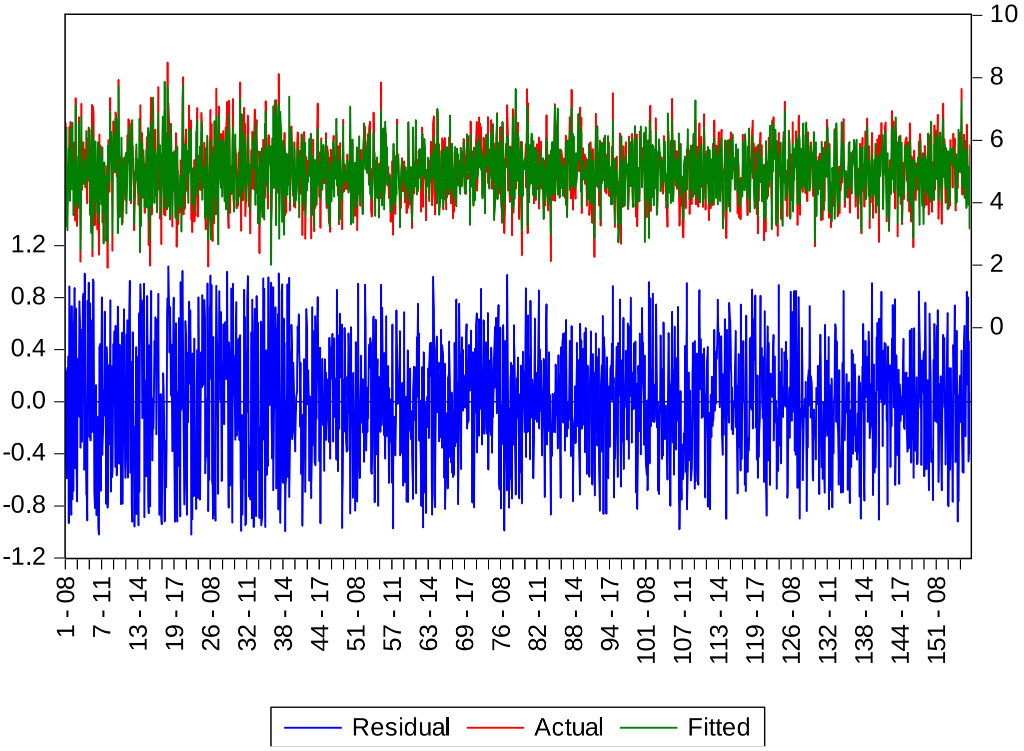
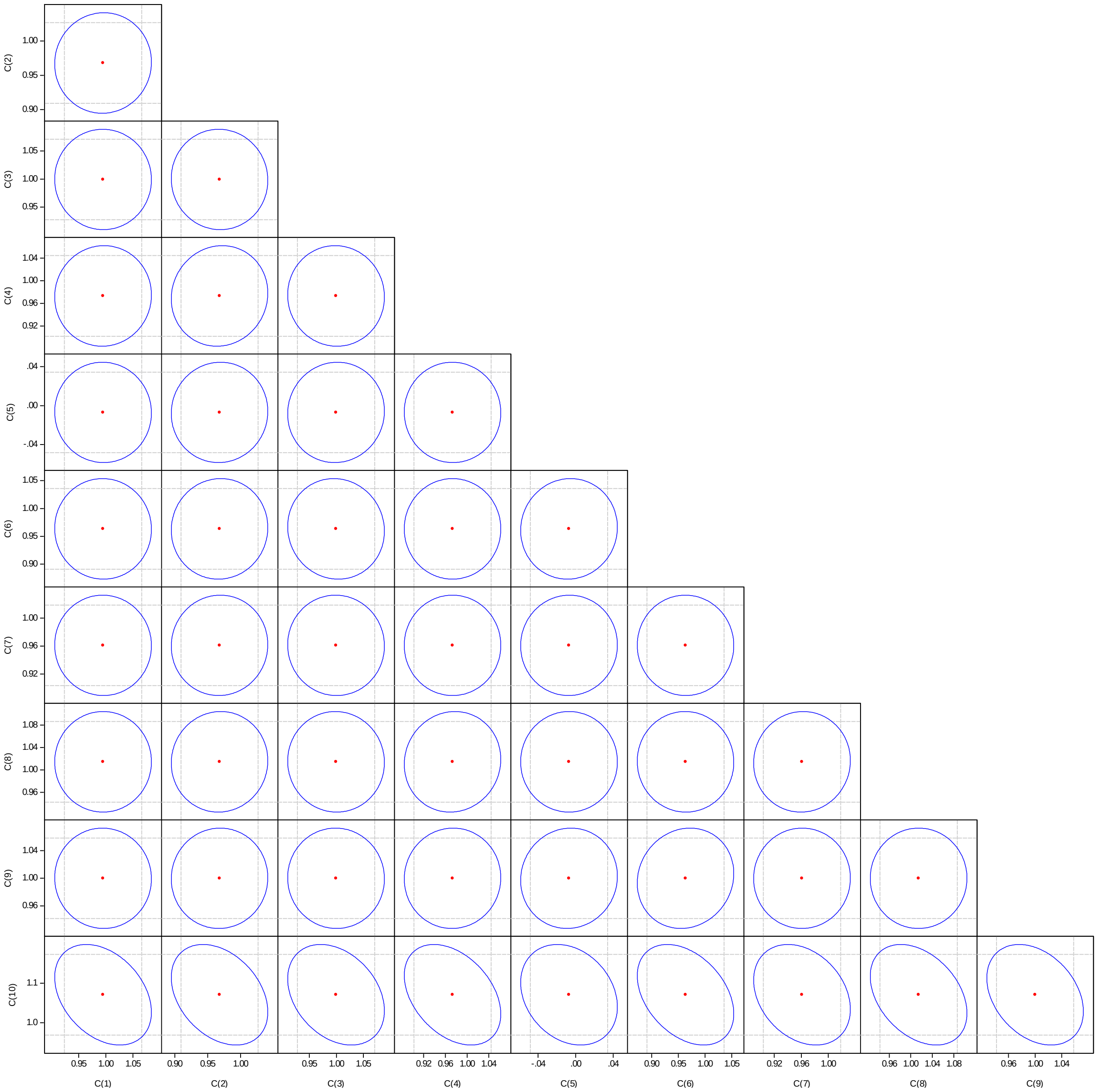


Table 3. Confidence intervals at 90, 95, and 99 percent

Coefficient Confidence Intervals

Sample: 2008 2019
Included observations: 1872

Variable	Coefficient	90% CI Low	90% CI High	95% CI Low	95% CI High	99% CI Low	99% CI High
CLINICAL	0.994829	0.935041	1.054617	0.923576	1.066082	0.901152	1.088506
CLOUD	0.967995	0.918683	1.017307	0.909227	1.026763	0.890732	1.045258
CMI	0.999314	0.939258	1.059370	0.927741	1.070886	0.905216	1.093411
FIANANCIAL	0.973150	0.913387	1.032913	0.901927	1.044373	0.879512	1.066788
HOSPTYPE	-0.006957	-0.041522	0.027608	-0.048150	0.034236	-0.061114	0.047200
HR	0.963443	0.902792	1.024094	0.891162	1.035724	0.868414	1.058472
LOCATION	0.961085	0.912898	1.009271	0.903658	1.018511	0.885585	1.036584
SCHEDULING	1.014508	0.954111	1.074905	0.942529	1.086486	0.919877	1.109139
TEACHING_STATUS	0.999997	0.951189	1.048805	0.941830	1.058164	0.923524	1.076470
C	1.070790	0.985046	1.156534	0.968604	1.172975	0.936445	1.205135



5. Conclusion

Cloud computing accelerated the development of new solutions and made them accessible to anyone, anywhere, and at any time, allowing for infinite data storage and affordable access to cutting-edge solutions for everyone. Establishing on-site storage needs an initial investment in hardware, including hard drives for data storage and other IT infrastructure to ensure that data is always secure and accessible. Cloud-based healthcare solution providers manage the administration, installation, and maintenance of cloud data storage services, allowing healthcare providers to save money up front and focus on what they do best: caring for patients. The findings of this research recommends to use cloud computing to improve cost efficiency of healthcare centers.

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