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Emergent Research Forum (ERF)

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Abstract

The healthcare industry has yet to harness the full potential of data analytics in administrative and clinical care operations. Indeed, evidence of data analytics impacts on hospital operations is sparse. This study helps close this research gap by examining the effect of data analytics on hospital clinical operations. A conceptual model is proposed, anchored to dynamic capabilities theory. Using ten years of secondary data for more than 2,500 US hospitals, econometrics analyses provide evidence of a positive impact of clinical data analytical systems (CDAS) on patient experience. However, no similar evidence is found with overall hospital operational performance. Thus, while data analytics can have a targeted impact, organizational-wide effects appear to be more complex. Implications for practitioners and academics are discussed.

Keywords

Clinical Data Analytical Systems (CDAS), Patient Experience, Total Performance, Dynamic Capabilities

Introduction

The data and analytics revolution is driving change throughout firms, from internal operations to external customer relationships. New forms and sources of data are providing the foundation for these advanced insights. Data analytics, the process of raw data transformation, management, and modeling towards meaningful information for better decision making (Chen et al. 2015), builds upon this foundation and provides the engine for identifying new opportunities. Indeed, to remain competitive today, firms need a set of analytic capabilities to strengthen the data to the knowledge extraction pathway, identify disruptive innovations, and harness the competitive benefits of new strategic transformations.

In the context of hospitals, data analytics, and the relevant capability refers to the extrapolation of actionable insights from sets of treatment and patient data by clinical data analytical systems (CDAS). The CDAS constitutes a set of data warehousing, archiving, and mining tools; applications to help in population health management; systems that can help in the diagnosis and treatment of patients by physicians; and other clinical intelligence relevant tools and applications (Wang et al. 2018).

CDAS has the potential to provide useful insights into healthcare practice and delivery. It can help to improve healthcare performance outcomes by making processes more efficient, eliminating adverse events, reducing readmissions, and simplifying administrative processes (Wang et al. 2018; Wamba et al. 2017). Digitization has enabled hospitals to store large amounts of data from different sources and through different means. However, the value potential of the data can only be obtained when the data can provide information, knowledge, and intelligence to hospitals (Khuntia 2020). Hospitals can use the analysis to plan patient treatment based on symptoms. They can coordinate and schedule staff based on patient flow and volumes, thereby acting on operational data in the business intelligence integration process to improve performance (Ning 2020). Hospitals can transact and coordinate with supply chain partners for the smooth flow of medicines and equipment. Alerts from analytical systems can inform providers of patient service needs and care provisions, thereby avoiding multiple visits or calls. Hospitals can identify and follow-up with patients to provide effective post-procedure care. Finally, hospitals can create and track their scorecards against readmission rates to keep revenue plans intact (Wang et al. 2018; Tanniru 2020).

Thus, the use of analytics in healthcare can unravel insights and provide a unified view of patient care that is not possible with legacy systems. Analytical capabilities will enable hospitals to make use of millions of patient records and allow researchers to uncover drug interaction side effects digitally, reducing the need for long, costly medical trials —a significant life and money-savings for healthcare (Fredrickson 2020). Hospitals administrators are mostly concerned with performance indicators, such as readmission rates, hospital infection rates, and staffing shortages. Analytical capabilities can provide these indicators in real-time dashboards, saving time, shorting the lifecycle of inefficiencies, and aligning the hospital goals with performance.

Irrespective of the benefits of data analytics, empirical research on how such capabilities can be developed, integrated, and lead hospitals to higher levels of performance are nascent. This current study is a step to address this gap. Specifically, we examine the research question: How does CDAS affect performance and patient experience outcomes of the hospitals?

A conceptual model consisting of two sets of testable hypotheses is developed, anchoring to the concept of dynamic capabilities. We use econometrics analysis to analyze ten years of panel data for more than 2,500 US hospitals. Results of a fixed effect estimation model show a positive impact of CDAS on patient experience, but no significant impact on operational performance. We discuss the implications and contributions of the findings.

Theoretical Background

Data Analytics and Dynamic Capabilities

Dynamic capabilities are a widely used and established theoretical lens for research that provides linkages and mechanisms around firm capabilities and firm performance (Côrte-Real et al. 2017). Chen et al. (2015) used an organizational information processing capability framework, specific to the use of dynamic capabilities theory for the research around the effect of data analytics. They argued that organizational readiness, such as needed IT infrastructure, is crucial to grasp the full potential of data analytics. Wamba et al. (2017) provide a data analytics capability model and examine the direct effect of data analytics on 297 Chinese firm performance. Côrte-Real et al. (2017) provide a data analytics model based on surveying 500 European firms and conclude that data analytics helps firms to create organizational agility, achieve competitive advantages, and improve performance. In the healthcare context, Wang et al. (2018) provide data analytics capability model through case analysis. They demonstrate how healthcare organizations can utilize data analytics as an IT artifact to transform IT for higher performance and creates capabilities. However, empirical analysis of data analytics-enabled transformation in the healthcare context is sparse, that the current study tries to fulfill.

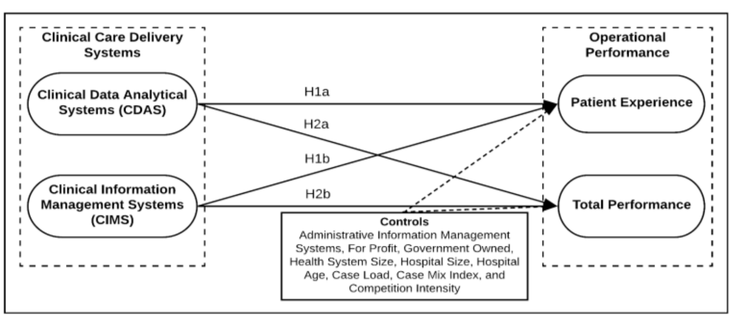

Figure 1. Research Model

Drawing on the above literature and specifically Wang et al. (2018) findings, this study proposes the conceptual framework shown in Figure 1. We conceptualize clinical care delivery systems as the construct could impact hospital operational performance. Clinical care delivery systems consist of two components, namely, clinical data analytical systems (CDAS) and clinical information management systems (CIMS) (see Table 1 for further descriptions of these variables).

Hypotheses

CDAS provide analytical knowledge, support the strategic planning, extract insight from operational and treatment data, enable patient-related information analysis in a customized way, and improve clinical decision-making for higher patient experience. CIMS supports the diagnosis, treatment planning, and medical outcomes assessment. CIMS can also enable hospitals to integrate, manage, store, and aggregate treatment data sources in the healthcare delivery process, which can result in higher patient experience (Zabada et al. 2001). Therefore, we hypothesize:
H1a: The higher the usage of CDAS within a hospital, the higher will be its patient experience.
H1b: The higher the usage of CIMS within a hospital, the higher will be its patient experience.

CDAS and CIMS can affect hospital operational outcomes. There is evidence from prior studies demonstrating that CIMS and CDAS can reduce cost (Borzekowski 2012) and improve care quality, hospital efficiency, and patient experience (Menon et al. 2009). Overall, CIMS and CDAS have the potential to impact different components of total performance. Therefore, we propose the hypotheses:
H2a: The higher the usage of CDAS within a hospital, the higher will be its total performance.
H2b: The higher the usage of CIMS within a hospital, the higher will be its total performance.

Methodology and Results

Research primary data sources are the American Hospital Directory (AHD), HIMSS Analytics, and Centers for Medicare & Medicaid Services (CMS). Table 1 shows the study variables.

Variable	Description	Source
Patient Experience	An average of 10 HCAHPS measures on care quality and efficiency, communication, and satisfaction dimensions. (5 is the best score). CMS developed the measure and used it to compare hospitals.	CMS
Total Performance	It is measured by four domains (each has 25% weight, 100 is the best score): Clinical care, the person and community engagement, safety, and the efficiency and cost reduction performance scores.	CMS
Clinical Data Analytical Systems (CDAS)	The total number of clinical analytical systems. These systems are involved in the patient care process and provide analytical knowledge and insight: Data Warehousing/Mining–Clinical, Population Health Management, Physician Assessment Software Tool, and Business Intelligence–Financial, and Business Intelligence–Clinical	HIMSS
Clinical Information Management Systems (CIMS)	The total number of clinical information management systems. The aggregated result can be considered as the hospital's clinical capability. They support the diagnosis, treatment planning, and medical outcomes assessment for providing health care for patients: Clinical Decision Support System, Respiratory Care Information System, Clinical Data Repository/EMR, OR Scheduling, Emergency Department Information System, Clinical Documentation, Operating Room (Surgery), Intensive Care, and Home Health Clinical	HIMSS
Administrative Information Management Systems (AIMS)	The total number of administrative information management systems. The aggregated result can be considered as the hospital administrative information management capability. They support the coordination among hospital functions: Accounts Payable, Benefits Administration, Budgeting, Contract Management, Cost Accounting, Credit/Collections, Customer Relationship Management (CRM), Encoder, General Ledger, Home Health Administrative, Materials Management, Patient Billing, Payroll, Patient Billing, Personnel Management, Practice Management, Time and Attendance	HIMSS
For-Profit	If the hospital is a for-profit organization. (1=Yes; 0=No).	HIMSS
Govt. Owned	If the government owns the hospital. (1=Yes; 0=No).	HIMSS
Health Sys. Size	The total number of hospitals performing under a similar healthcare organization	HIMSS
Hospital Size	The logarithm of the total number of hospital beds	HIMSS
Hospital Age	Hospital years of operations from the opening year	HIMSS
Case Load	The logarithm of the total number of annual inpatient visits per full-time employees	AHD
Case Mix Index	The average relative DRG weight of a hospital's inpatient discharges = sum of (Medicare Severity-Diagnosis Related Group weights)/ Total by the number of discharges.	CMS
Compt. Intensity	Square of the total number of hospitals per zip code. Higher value implies intense competition	HIMSS

Table 1. Description of Variables

<u>*Estimation Equation:*</u> Because of the panel nature of data, with 2,575 hospitals from the years 2006 to 2015, we use the equation:

$$Y_{i,t} = \beta X_{i,t-2} + u_i + \varepsilon_{i,t} \qquad (1)$$

where Y represents a dependent variable; X is a vector of hospital-related information, ß are the coefficients; i shows hospitals and t indicates time; u_i demonstrates unobserved time-invariant fixed factors, and ε is the error term.

The Hausman test to assess the endogeneity of independent variables rejected the null hypothesis (Wooldridge 2016), thereby indicating the appropriate use of a fixed-effect panel estimation model. Because the role of CDAS on any firm-level performance will take time, and often two or three years. Analytics tools and applications need to be assimilated and integrated, staff need to be trained, and the value propositions need to be aligned to the intended outcomes. Thus, like other IT investment-performance study (Loveman 1994), we use a two-period time lag (t-2) time-tagged CDAS variable in our model than the dependent variables.

We used White's test and Breusch-Pagan test for homoscedasticity checking, leading to rejection of the null hypothesis. Therefore, we use the robust standard error to address the heteroscedasticity concern (Wooldridge 2016). The check of multicollinearity by calculating the variance inflation factor (VIF) showed a value of less than 2.0; therefore, our models will not have a multicollinearity issue. Table 2 presents the correlations and descriptive statistics of the study variables, and Table 3 shows the main results of the Fixed-Effects analysis. As hypothesized in H1a, there is a significant and positive relationship between CDAS and patient experience (Table 3, column 1, β= 0.037 p<0.01). Therefore, the higher the usage of CDAS, the higher will be its patient experience, and **H1a is supported**. Also, as hypothesized in H1b, there is a significant and positive relationship between CIMS and patient experience (Table 3, column 1, β= 0.012, p<0.01). Therefore, the higher the usage of CIMS, the higher will be its patient experience, and **H1b is supported**. In contrary to H2a, there is a none-significant relationship between CDAS and total performance (Table 3, column 2, β= -0.072, p>0.1). Therefore, **H2a is not supported**. Also, as hypothesized in H2b, there is a significant and positive relationship between CIMS and total performance (Table 3, column 2, β= 0.119, p<0.05). Therefore, **H2b is supported**.

	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
Patient Experience	3.0	1.2	0.0	5.0												
Total Performance	39.5	8.8	2.7	95.5	0.24											
CDAS	0.9	1.2	0.0	10.0	-0.06	-0.10										
CIMS	5.2	2.7	0.0	16.0	-0.08	-0.14	0.51									
AIMS	10.8	2.2	0.0	19.0	-0.04	-0.08	0.26	0.43								
For Profit	0.2	0.4	0.0	1.0	-0.08	-0.05	-0.12	-0.02	0.02							
Government Owned	0.2	0.4	0.0	1.0	0.03	0.00	-0.07	-0.07	-0.07	-0.19						
Health System Size	21.6	41.8	1.0	203.0	-0.07	-0.10	-0.02	0.10	0.03	0.65	-0.20					
Hospital Size	2.3	0.4	0.6	3.3	-0.15	-0.33	0.15	0.16	0.17	-0.12	-0.10	0.00				
Hospital Age	41.7	37.0	9.0	197.0	-0.01	-0.02	0.03	0.04	-0.06	-0.30	0.12	-0.29	0.12			
Case Load	6.5	0.8	-0.4	12.1	0.05	0.14	-0.10	-0.12	-0.13	-0.18	0.08	-0.15	-0.34	0.10		
Case Mix Index	1.5	0.3	0.6	3.5	-0.12	-0.17	0.23	0.23	0.13	0.00	-0.15	0.07	0.64	0.01	-0.39	
Competition Intensity	23.3	40.1	1.0	484.0	-0.08	-0.06	0.07	0.08	0.06	0.02	-0.03	0.01	0.11	-0.02	-0.13	0.10

Table 2. Descriptive Statistics and Correlation Matrix

	(1)	(2)
Variables	Patient Experience	Total Performance
Clinical Data Analytical Systems (CDAS)	**0.037*** (0.007)**	-0.072 (0.115)
Clinical Information Management Systems (CIMS)	**0.012*** (0.004)**	**0.119** (0.051)**
Administrative Information Management Systems (AIMS)	0.008** (0.003)	0.052 (0.049)
For Profit	0.095 (0.087)	1.754* (0.982)
Government Owned	-0.133** (0.055)	-2.160** (1.067)
Health System Size	-0.001*** (0.000)	-0.019*** (0.007)
Hospital Size	-0.143 (0.115)	-5.371*** (1.650)
Hospital Age	-0.000 (0.001)	-0.025** (0.012)
Case Load	0.005 (0.008)	-0.081 (0.122)
Case Mix Index	0.078 (0.081)	2.444** (1.224)
Competition Intensity	-0.001** (0.000)	-0.004 (0.005)
Constant	3.107*** (0.296)	46.926*** (4.416)
Observations	17,931	17,931
Year	2008-2017	2008-2017
F-Statistics	1208.65***	63.05***
R-squared	0.677	0.117

Note: Robust standards errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3. Fixed-Effects Estimation Results

Discussion and Conclusion

This study concentrates on the impact of CDAS applications. Future research will consider the comprehensive clinical care delivery system and investigate its effect on operational performance. The interactive effects of CDAS and CIMS will also be considered. Previous studies demonstrate that hospital ownership type and the type of care delivery services may cause efficiency and cost differentiation among hospitals. Thus, we may expect to see different operational effects when these two factors are considered concurrently. Investigating the impact of data analytics on total performance and patient experience dimensions separately may also lead to unique findings and implications. We will address these questions in our broader project.

Healthcare managers must understand that data analytics, by itself, does not affect performance outcomes at the operational level. Appropriate design of a comprehensive clinical care delivery system that integrates CIMS and CDAS would be more effective than concentrating on any one of these factors. Also, as data analytics technologies and infrastructure are readily available to all organizations, investing in these technologies will not alone provide positive operational impacts of competitive advantage. Comprehensive systems should form the foundation of a unique digital capability firm built from multiple complementary factors and to maximize the benefits of data analytics,

This study sheds light on the effect of data analytics applications on clinical care operations in U.S. hospitals. Results of the econometrics analyses support the positive contributions of CDAS on patient experience. However, the positive impact of analytics systems may be targeted and not extend to across the organization. Despite this, patient satisfaction and a patient's view of their treatment, two critical factors of the patient experience, would go a long way in motivating patients to return for future care across their lifetime.

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