The Use of Information Systems in Emergency Departments: the Effect of Task Complexity

Regular Paper

Ofir Ben-Assuli[1], Ofer Arazy[2], Itamar Shabtai[3], Nanda Kumar[4] and Moshe Leshno[5]

[1] Ono Academic College; [2] University of Haifa; [3] College of Management Academic Studies; [4] Baruch College; [5] Tel-Aviv University

Introduction

Lately, there has been a renewed push to bring down costs and improve quality of medical care using information technology (IT) as a key enabler (Dentzer 2009). The assumption is that information technologies will improve medical processes and reduce costs through the integration of patient data and its immediate accessibility to physicians and medical staff (Lenz et al. 2007). In particular, large investments are made in developing Electronic Health Records (EHR) systems. Medical history retrieved by EHR allows physicians to have a more comprehensive view of the patient and improve the quality of decision-making, thus reducing some of the risks and uncertainties that stem from lack of information (Hripcsak et al. 2007). Recent studies provide evidence suggesting that EHR systems can improve physicians' performance and quality of care (Ben-Assuli and Leshno 2013; Ben-Assuli et al. 2014). However, there are variations in how EHR is used across multiple contexts. For example, emergency departments (EDs) are characterized by urgency and high stress, often resulting in medical errors in almost every area of emergency care (Lecky et al. 2013) thus requiring careful examination of how EHRs are used in this setting. The objective of this paper is to fill-in these gaps in the literature, shed light on the use of EHR in the ED settings, and study the extent to which the adoption of EHR systems leads to improved hospitalization outcomes. The EHR system we investigated, called “OFEK”, enables health care organizations to share medical information. OFEK connects health care providers, which ensures the system's interoperability within the organization itself and with other organizations. OFEK collects medical information from the participating systems (distributed health care providers, external labs, pharmacies, hospitals, medical institutes and community clinics) and shares it between the health care providers. The information include prior hospitalizations, prior diagnoses, medication lists, etc. In this study we employ a particular care quality metric: re-admission rate - the percent of released patients that are re-admitted within a pre-determined time window (Nahab et al. 2012). We investigate how the effect of system use is moderated by the contextual factor: the complexity of the medical diagnosis task.

Background

EHRs were expected to streamline the health care sector and improve the quality of care and assistance provided to patients (Sittig et al. 2014). However, despite effort to deploy EHR over the last decade, the transition from paper-based records to computerized health records has been fraught with practical, legal, medical and financial difficulties. These difficulties in the acceptance of information technologies in health care facilities have attracted the attention of information systems scholars, who systematically investigated the adoption of EHR (Holden and Karsh 2010; Lapointe and Rivard 2005). Critically, the topic that has attracted the most interest has been the link between the use of health information systems and hospitalization outcome (e.g. care quality). Evidence in this area has been inconclusive, with some studies showing a clear association between EHR use and care quality improvement (Ben-Assuli and Leshno 2013), while others have failed to do so (Poon et al. 2010). Baron (2007), for example, pointed out that an improvement in care quality via EHR use is definitely achievable, but certainly not automatic, and needs to be accompanied by certain changes and reforms at the system's organizational level.

EHR in Emergency Department: Challenges Magnified

ED represents a distinctively challenging environment. The tight time constraints and the lack of a prolonged doctor-patient relationship, have serious implications for physicians' ability to accurately diagnose patients. Diagnosis is often highly complex, requiring substantial work in accessing various forms of information and demanding making difficult decisions, especially in light of the severe mortality and morbidity risks. Hence, the implementation of information system in the ED must take these special characteristics into account (Ozkaynak and Brennan 2012). When failing to do so, EHR deployment could actually impede hospital's performance. In the ED settings, one of most common metric used to characterize care quality is the re-admission rate. The discharge decision is only made after ensuring that the condition has been diagnosed and proper treatment administered. If the patient re-appears in the ED shortly after the discharge decision, it is considered an indicator poor quality of care.

Complexity of the Medical Diagnosis Task

The complexity of the medical diagnosis task could affect the extent to which a physician needs to use the EHR. Historically, a complex task is defined by the number of processes that need to be executed (Wood 1986). Campbell (1988) highlighted the difficulty of conceptualizing complexity and especially argued that uncertainty and degree of task structure played an important part in making a task more or less complex.

Building on the complexity indicators fleshed out by Gill et al., (2006) and by guidelines provided by Center for Medicare and Medicaid (CMS) in evaluating clinical complexity, we developed a measure of diagnosis task complexity. Namely, our study focuses on three dimensions of diagnosis complexity: (a) diagnosis difficulty (e.g. a diagnosis could be harder to arrive if the patient presented symptoms that suggested multiple candidates for diagnosis); (b) the amount of work in diagnosing (for example, the amount of work is high when the diagnosis required the physician to communicate with the patient and other clinicians/staff or order multiple diagnostic tests); and (c) risk of complications/co-morbidity. In the medical context, clinicians utilize a disease classification system called “International Classification of Diseases” (ICD) to diagnose the condition of the patient. Notwithstanding the usefulness of the ICD categorization system, it does not provide a direct mapping between ICD codes and constructs such as diagnosis task complexity. However, we use it as a raw material to derive complexity in the medical domain. A secondary objective of this paper is, thus, to develop a working translation between ICD diagnosis codes and the complexity constructs discussed above.

Research Questions and Hypotheses

There is a long history of investigation in the information systems field on the drivers of system adoption. However, there seems to be a scarcity of research that focuses on the factors that drive effective system use (Burton-Jones and Grange 2012).One exception to this general scarcity of research on the outcomes of system use tends to use variations of task-technology fit either at the individual level (Goodhue et al., 1995) or at the group level (Zigurs and Buckland 1998). Just as Benbasat et al., (2003) argued for the need to elaborate more on what makes the system useful at the contextual level (rather than focusing on the impact of perceived use on system adoption), we believe that we need to identify domain specific knowledge about the drivers and outcomes of effective system use. In this research, we focus specifically on the adoption of information systems within the context of ED in hospitals. Traditionally medical histories were almost always obtained through medical interviews. Clearly, the clinician can make better decisions about their patients if they have timely access to medical information about their patients (Henriksen and Brady 2013). Previous studies have reported a significant association between EHR use and better medical care

(Kern et al. 2013). For example, Shachak et al. (2009) surveyed 14 prior studies and found that often EHR increases the satisfaction of the medical staff (because of the information it provides). Hence, we posit that:

H1: The use of EHR system will have a positive impact on the quality of medical care in EDs.

Complexity is directly related to human information processing (Miller 1956). A complex task is defined by the number of processes that need to be executed (Wood 1986), where a higher level task requires more interpretation and analysis before reaching a conclusion (Jarvenpaa and Dickson 1988). In our work, we consider complexity in terms of three components – amount of work, difficulty of arriving at a diagnosis and severity of condition. We conjecture that a patient encounter that increases the diagnosis task complexity via an increase in any of these three components will likely decrease the care quality outcome. Formally stated:

H2: The complexity of the clinical diagnosis task will have a negative impact on the quality of medical care in EDs.

Notwithstanding the evidence brought above for the potential positive effects of EHR system use on the quality of care (Ben-Assuli and Leshno 2013), the evidence of the impact of EHR use in the ED setting is not conclusive. Early studies of task complexity appeared in Performance research and mainly focused on the role of complexity in goal setting and decision making (Maynard and Hakel 1997). In the information systems literature, too, task complexity has shown to play a moderating role. For example, McKeen et al. (1997) found that task complexity moderated the relationship between user participation in system development and success of the development effort, and Sharma (2007) showed that task complexity moderates the relationship between end-user training and IS implementation success. Hence, we posit that:

H3: Diagnosis task complexity will moderate the relationship between the use of EHR system and the quality of medical care in EDs, such that the effect of system use on care quality will be stronger for high-complexity tasks.

The proposed research model is illustrated in Figure 1 below.

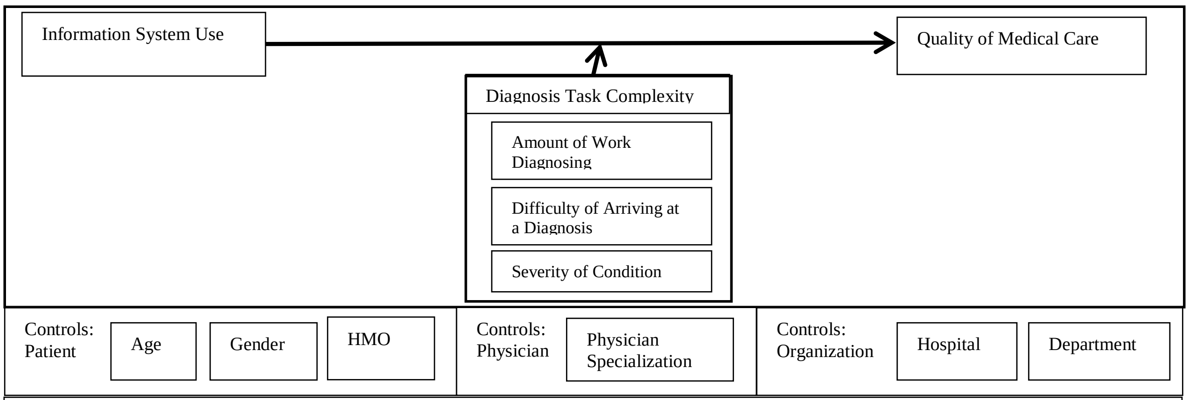


Figure 1: the proposed model

Methodology

Log File Analysis

A large database of ED referrals was analysed, collected from seven main hospitals, all owned by the primary Health Maintenance Organization (HMO) in Israel. As we asked in several meetings with the top management of the HMO, there were no implementation guidelines on how to use the EHR no instructors showing how to use it just solving problems. In addition, there were no instructions from the top management of the HMO to the hospitals on the subject of how much to use the OFEK EHR. Given our interest in diagnosis task complexity and our reliance on the ICD (version 9) codes for extracting complexity measures, we screened the log files for records containing valid ICD9 codes. Our log-file consisted of above than 3 million records, of which 42% did not include the ICD9 code categorizing the diagnosis. Of the remaining records, 46% included generic descriptions that could not be mapped into the complexity constructs, leaving us with 968,945 patient encounters with valid ICD codes. Considering that the mapping of ICD codes to complexity measures was labour intensive, we restricted the number of codes to the second level of ICD9 code hierarchy and selected the 10 most common code groups in our dataset (Table 1), leaving us with 549,108 records.

Measurement of Dependent Variables

Quality of Medical Care – Likelihood of Re-admission

We use likelihood of readmission as an indicator of quality of care in the ED setting, given that one of the most important decisions a physician has to make based on medical information in an ED is whether to admit a patient or not. The readmission measure is widely used to monitor the efficiency of critical care pathways (Adeyemi et al. 2013; Axon and Williams 2011). We operationalize care quality through the likelihood of readmission, using the metric of readmission within seven days to the same hospital after a discharge decision (coded as: not re-admitted = 0; re-admitted = 1). 36,676 out of the 549,108 records (6.67%) were recorded as re-admissions.

Measurement of Independent Variables

EHR System Use: The EHR system log file recorded access to the system by the medical staff. For each patient record, the log file indicated EHR system use as a dichotomous variable (0 = none of the system screens was accessed; 1 = at least one of the screens was accessed).

Diagnosis Task Complexity: Our operationalization of diagnosis task complexity relied on the ICD-9 codes associated with each patient record. We worked with the 10 most common codes in our dataset (Table 1). We conceptualized complexity as a multi-dimensional construct, and our operationalization provided measures for the: amount of work done; diagnostic difficult; and risk of complications. The mapping of ICD-9 codes onto these complexity dimensions was performed through a labor-intense manual procedure, employing the AHP technique. AHP is a multi-criteria method for organizing and analyzing complex decisions (Saaty 1996). For our study, AHP used pairwise comparisons of each of the ICD-9 code combinations, indicating which of the ICD-9 codes is higher on a particular complexity dimensions (on a scale of -9 to +9). We have used this procedure to aggregate the three complexity dimensions onto a single aggregate construct. The pairwise comparisons of ICD-9 codes were performed by senior physicians with extensive ED experience in the particular hospitals included in our sample. The physicians were asked to compare each combination of codes and record their comparisons on a paper questionnaire. These pairwise comparisons were repeated for the three complexity dimensions. After verifying satisfactory consensus, we calculated the AHP complexity score for each ICD-9 code as the average of the four assessors (Table 1).

Table 1: ICD9 Code Groups in Our Data Set (sorted by the frequency of their occurrence)

ICD9 Code Group	Description	# records	**Diagnosis Complexity**
920-924	Contusion with Intact Skin Surface	160,487	6.30%
840-848	Sprains and Strains of Joints and Adjacent Muscles	63,250	4.42%
360-379	Disorders of the Eye and Adnexa	58,236	8.42%
810-819	Fracture of Upper Limb	57,928	4.57%
380-389	Diseases of the Ear and Mastoid Process	42,986	7.52%
958-959	Certain Traumatic Complications and Unspecified Injuries	38,142	26.43%
720-724	Dorsopathies	33,896	8.13%
590-599	Other Diseases of Urinary System	31,855	9.14%
880-887	Open Wound of Upper Limb	31,674	5.78%
555-558	Non-infective Enteritis and Colitis	30,654	19.30%

Measurement of Control Variables

We use the following control variables based on prior literature (Ben-Assuli and Leshno 2013).

Patient confounders refer to personal characteristics that may impact the physicians' decision to use the EHR IS, namely Age, Gender, and HMO. The HMO dichotomous variable was created to control for major discrepancies in the quality and the amount of medical information between patients insured by different HMOs (1 for the primary HMO in the country and “0” in cases where the patient was insured by a different HMO).

Physician Confounders: physician specialty indicates whether the physician has a surgical specialty versus internal medicine specialties. It was coded as a binary variable (1 for surgical physician and 0 for an internist)**.**

Organizational Confounders included Hospital and type of unit in which the patient was treated.

Results

Multivariate logistic regression analyses were performed on the dependent variable: Quality of Care (operationalized as the likelihood of not being re-admitted). The blocks of variables were: EHR use, diagnosis task complexity, the interaction between system use and task complexity, and the various control variables. Table 2 presents the correlation between constructs (organizational cofounders omitted from the table).

Table 2: inter-construct correlations

Construct	System Use	Diagnostic Complexity	Age	Gender	HMO	Specialization
System Use	1					
Diagnostic Complexity	.165**	1				
Age	.178**	-.008**	1			
Gender	-.053**	-.035**	-.145**	1		
HMO	.054**	.005**	.161**	-.071**	1	
Specialization	.275**	.184**	.250**	-.096**	.040**	1

The results of the logistic regression are summarized in Table 3 (statistical significance is indicated by: '†' for $p < 0.1$; '*' for $p < 0.05$; '**' for $p < 0.01$; and '***' indicating $p < 0.001$).

Table 3: Results for regressions on the quality of medical care

	Model M1		Model M2		Model M3	
	Beta (signif.)	Odds ratio (CI)	Beta (signif.)	Odds ratio (CI)	Beta (signif.)	Odds ratio (CI)
(Constant)	(***)		(***)		(***)	
System Use			0.174 (***)	1.189	-0.065	0.937 (0.865-1.016)

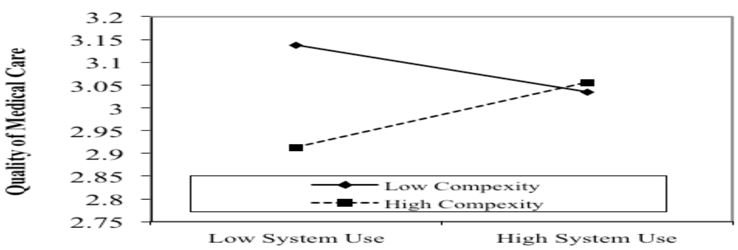
				(1.140-1.241)		
Diagnostic Complexity			-0.002 (*)	0.998 (0.996-1.000)	-0.005 (***)	0.995 (0.993-0.997)
System Use x Diagnostic Complexity					0.021 (***)	1.021 (1.015-1.027)
[control: Patient] Age	-0.009 (***)	0.991 (0.991-0.992)	-0.009 (***)	0.991 (0.990-0.991)	-0.009 (***)	0.991 (0.990-0.991)
[control: Patient] Gender	-0.016	0.984 (0.963-1.006)	-0.017	0.983 (0.962-1.005)	-0.016	0.984 (0.992-1.006)
[control: Patient] HMO	-0.189 (***)	0.828 (0.807-0.849)	-0.190 (***)	0.827 (0.806-0.848)	-0.190 (***)	0.827 (0.806-0.848)
[control: Physician] Specialization	-0.061 (**)	0.941 (0.900-0.983)	-0.092 (***)	0.912 (0.871-0.955)	-0.089 (***)	0.915 (0.874-0.957)

Table 3 shows the regression results using three models: M1, M2 and M3. M1 shows the results with just the control variables entered into the model, whereas M2 shows the results with main effect of the independent variables: System Use and Diagnostic Complexity. The results of M2 show that both System Use (positive effect; confirming H1) and Diagnostic Complexity (negative effect, confirming H2) have a significant impact on the quality of care. The results of M3 show that this interaction is significant thus confirming hypothesis H3[1]. Although main effects should not be interpreted in the presence of the interaction, the fact that system use (having a highly significant effect in model M2) is no longer significant in model M3. To plot the interaction using the composite score for complexity (based on the analysis presented in the results section), we followed the procedure recommended by Aiken and West (1991). In order to gain a better understanding for the nature of the interaction, we split the data set into low- and high-complexity diagnosis tasks (with 235,769 and 152,852 records in these two data sub-sets respectively; codes 920-924 fell on the median and we excluded 160,487 observations with those codes for this analysis), and ran tested the effect of system use on the quality of care for each set independently

[1] Please note that we also ran the same analysis with a slightly different variation of our dependent variable – depth of system use (operationalized based on the number of different system screens accessed). The general pattern of results remained similar for all models when employing the alternative metric, thus further increasing our confidence in the stability of this model and the choice of our dependent variable.

(running a logistic regression, including all of the control variables). Our results demonstrate that for highly complex tasks (ICD9 code groups: 360-379; 380-389; 555-558; 590-599; 720-724; and 958-959) an increase in system use is associated with *improved* quality of care (effect size = 0.230; $p < 0.001$; illustrated by the dotted line in Figure 2); in contrast, for low complexity tasks (ICD9 code groups: 810-819; 840-848; and 880-887) an increase in system use is associated with *a reduction* in the quality of care (effect size =-0.124; borderline significant: $p = 0.086$; illustrated by the solid line in Figure 2).

Figure 2. Diagnosis task complexity moderates the effect of system use on the quality of medical care



Discussion

The objective of this study was to advance our understanding of the contextual factors moderating the effects of system use on the quality of care in the ED setting. While the availability of medical information is crucial to the success of medical care in the ED (Hripcsak et al. 2007), the cumulative results regarding the effect of EHR use in the ED setting on the quality of medical care have been inconclusive (Ahmed et al. 2011; Ben-Assuli and Leshno 2013; Mack et al. 2009; Pickering et al. 2013). To date, empirical studies examining the effects of EHR use on medical care quality failed to provide conclusive evidence one way or another.

Our study was able to mitigate these concerns by employing the *complete hospitalization record* from seven large EDs over a four-year period, and multiple measurement methods (log analysis for system use and care quality; manual coding for diagnosis complexity).

In addition, our finding regarding the positive effect of EHR use on medical care quality has also implications for the ongoing debate regarding the economic value on investments in information technologies (IT) (Brynjolfsson and Hitt 2003). Our findings imply that using an appropriate methodology (contextualized, hard data, large-scale) has the potential to further elucidate the value of IT (McAfee et al. 2012).

Our second important finding relates to the negative effects of diagnosis task complexity on the quality of care. In this study, we have adopted a similar approach and worked to develop a methodological procedure (employing AHP) and measures (three dimensions of complexity) for the complexity of the medical diagnosis task. We now have reliable complexity scores for the ten most common diagnoses in EDs, representing nearly 50% of all encounters. The development of the complexity scale represents a significant, but secondary contribution of this study.

The most important finding from this study concerns the moderating effect of diagnosis task complexity on the relationship between EHR use and quality of care. In our work, we have considered the complexity of the medical diagnosis task in the ED setting in terms of three components – amount of work, difficulty of arriving at a diagnosis and severity of condition. Our findings show that for highly complex task the positive effect of system use is more pronounced (supporting H3; effect size = 0.021; $p < 0.001$). To demonstrate the robustness of this moderation effect, we note that it persists (and remains statistically highly significant) when using the specific diagnosis task complexity dimensions (diagnosis task difficulty, amount of work, and risk) instead of the high-level task complexity construct (running independent regression analyses with each one of the measures in turn). Considering the particular medical context, we are not aware of any prior studies that have considered the moderating role of diagnosis task complexity.

While the results of our interaction analysis demonstrate that system use is most beneficial in complex tasks, there is one particular result that is very intriguing: the finding that for low-complexity tasks system use is actually detrimental. In explaining this result we need to consider the unique characteristics of the ED setting: fast pace, time pressures, unpredictability, and high stakes for outcomes. It is possible that for simple tasks, the poorer result is an indication of other factors, such as the need for better interaction with patients especially when the task is too simple potentially leading clinicians to allocate more of their attention to patients with complex diagnostic needs. Notwithstanding the merits of our study, this research suffers from some limitations which we hope to address in future work. First, while the use of logs to examine a large number of data points (about 3.1 million to start with; 500,000 patient encounters for this study) is a strength of the study, it also requires us to work with the data that is available in the logs. While likelihood of readmission is indeed a very critical indicator of care quality and is used by insurers for reimbursing providers, one also needs to measure quality indicators at the point of care during the patient encounter. Further research should include more fine-grained indicators of system use, beyond the ones discussed in our study.

The results of our study have several implications for the practitioners. Given the unique characteristics of the ED, hospitals might want to consider a fine grained approach to pushing the clinicians to use the EHR system. As the discussion of the interaction effects in our previous section clearly shows, there is a clear benefit to the use of EHR for diagnoses that are complex. Surprisingly, the use EHR system for simpler tasks shows a negative impact on hospitalization readmission rate. While this is one of the first studies to show a negative trend for simpler tasks, more empirical research should be undertaken and the reasons for this drop should be teased out.

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