The Impact of Hospital Information Technology Adoption Process on Quality of Care

Luv Sharma (sharma.154@osu.edu) Fisher College of Business, The Ohio State University

Aravind Chandrasekaran (chandrasekaran.24@osu.edu) Fisher College of Business, The Ohio State University

Abstract:

We look at the impact of two important dimensions of the process of adoption (sequence and intensity) for Electronic Medical Record (EMR) technologies on cost and quality of care at hospitals. Sequence of adoption is captured in terms of two approaches: the depth-first approach which adopts department level integrative technologies first and the breadth-first approach which adopts organization wide integrative technologies before completing department level integration. Intensity of adoption represents the pace of addition of technologies. Results indicate that the depth-first approach performs better at lower intensity of adoption.

Keywords: Healthcare Operations Management, Information Systems in Operations,

Technology Management in Operations

Introduction

Despite having the highest spending on healthcare (\$8600 per capita) the quality of care in US hospitals remains a concern. The impact of these shortcomings in quality of care was highlighted in the Institute of Medicine (IOM) report from 1999 which pegged the number of

deaths due to preventable medical errors at 100000 (Kohn, Corrigan, & Donaldson, 1999). Since 1999 even though improvements have taken place US still lags behind its peers and is ranked the worst performing country in terms of a number of health metrics including infant mortality, heart and lung diseases and life expectancy amongst 17 high income countries (National Institute of Health, 2013).

The US Government is investing on Health Information Technology (HIT) as one of the drivers to improve quality of care by providing stimulus payments of \$27 Billion over the next 10 years to accelerate HIT adoption. A large portion of these investments are expected to be made towards the digitization of patient medical records (HITECH, 2009). The problem is that literature as well as practice is inconclusive on the benefits of HIT in improving quality of care. Studies have indicated that the answer to the link between HIT and quality of care may lie in the process used for the adoption of technologies (Agarwal et al., 2010; Angst et. al., 2011). However current studies that have looked at the process of adoption have only considered certain aspects of the adoption process and do not shed any light on the process of adoption for technologies forming Electronic Medical Records (EMRs) which are central to digitizing patient medical records.

In this study we look at the impact of two important dimensions of the process of adoption (sequence and intensity) for EMRs on cost and intermediate process of care performance at hospitals. The sequence of adoption is a representation of the approach used to adopt technologies. Specifically, we compare hospitals initially adopting department level EMR technologies (we define this as 'depth-first') against hospital adopting organization wide EMR technologies before completing department level integration (we define this as 'breadth-first'). The second dimension namely the intensity of adoption represents the pace of addition of technologies and sheds light on the manner in which the sequence of adoption of technologies was completed. The performance variables studied in this research includes:

cost – measured using the hospitals operating cost per bed, and intermediate process of caremeasured using the quality of caregiver communication with patients. We seek to answer the following research question through this study: *What is the impact of the sequence and intensity of adoption of technologies that are part of the EMR system on hospital cost and intermediate process of care performance?*

We use longitudinal data on process of adoption collected from 895 hospitals between 2007 and 2012 to investigate our research questions. Results indicate that the depth-first approach performs better at lower intensity of adoption while the breadth-first approach performs better at higher intensity of adoption. Taken together, these results suggest the importance of incorporating both sequence and intensity dimensions when studying the performance benefits from EMR adoptions.

Theoretical Background

Decades of research by operations and information systems scholars have enlightened us on topics such as the impact of information technology (IT) on performance (Brynjolfsson & Hitt, 1996; Boyer, 1999), barriers and enablers to adoption of technologies (Chatterjee et al., 2002; Venkatesh, & Davis, 2000) and assimilation of technologies (Zhu et. al., 2006; Tyre & Orlikowski, 1994). However, studies in this stream have given us limited insights on the process of adoption of multiple technologies. Although a number of studies in the IT literature have used longitudinal data to look at the impact adoption of a single technology on organizational processes (Tyre & Orlikowski, 1994), studies looking at the process of adoption (sequence and intensity) of multiple technologies are limited.

Similar to the broader literature on IT, studies on EMR have also mostly focused on issues such as the level of adoption (DesRoches et. al., 2008; Cutler et. al., 2005), the drivers of adoption (Angst et. al., 2010; Agarwal et. al., 2010) and user resistance to adoption

(Lapointe & Rivard, 2005) with studies looking at the process of adoption lacking. To the best of our knowledge, there are only two studies that look at the process of adoption of technologies (Angst et. al., 2011; Spaulding et. al., 2013).

Angst, et. al. (2011) evaluated the impact of the sequence of adoption of six cardiology department HITs for 555 hospitals. This study demonstrates that the sequence of adoption of technologies has an impact on the cost and LOS performance with cardiology departments integrating foundational technologies earlier showing better performance. Spaulding et. al., (2013) looked at the sequence of adoption of six HITs supporting a three level medication management process at hospitals. Using data from 140 hospitals two approaches for the adoption of these six technologies were evaluated: organizational and operational models of adoption. This study shows that the operational model of adoption is superior when compared to the organizational model in terms of financial benefits.

Although these studies begin to address the process adoption, they measure process using the sequence of adoption of technologies and hence ignore the manner in which the sequence was executed. Further, the two studies by Angst, et. al. (2011) and Spaulding et. al. (2013) are not directly relevant to the EMR adoption context since they do not look at technologies that constitute EMRs. We overcome this gap in literature by taking a novel approach to study the process of adoption. We measure the process of adoption using two dimensions: (1) the sequence in which EMR technologies are adopted and (2) the intensity with which these technologies are adopted. Capturing both the sequence and intensity gives us a better picture on the operational challenges when adopting these technologies.

We use the HIMSS EMR Adoption Model proposed in Furukawa, et. al. (2010) as a basis to determine the technologies to be included in our study. The criterion proposed by Furukawa, et. al. (2010) to assign an EMR maturity score to hospitals is shown in Table 1.

Based on the EMR maturity model in Table 1 we selected eight technologies that are distributed into four stages for this study.

| Stage | Criterion | Application | | | | |
|---------|-------------------------------------|------------------------------|--|--|--|--|
| Stage 0 | Not implemented ALL 3 Department | N/A | | | | |
| | Information Systems (pharmacy, | | | | | |
| | laboratory, and radiology) | | | | | |
| Stage 1 | ALL 3 Department Information | Radiology Information System | | | | |
| | Systems (pharmacy, laboratory, and | Lab Information System | | | | |
| | radiology) and a Clinical Data | Pharmacy Information System` | | | | |
| | Repository | Clinical Data Repository | | | | |
| | | (CDR) | | | | |
| Stage 2 | All EMR-S1 applications and have | Nursing Documentation | | | | |
| | started implementation of Nursing | Electronic Medication | | | | |
| | Documentation (DOC) and Electronic | Administration Records | | | | |
| | Medication Administration Records. | (EMAR) | | | | |
| Stage 3 | All EMR-S1 and EMR-S2 applications | Clinical Decision Support | | | | |
| | and have started implementation of | (CDS) | | | | |
| | Clinical Decision Support (CDS) and | Computerized Physician Order | | | | |
| | Computerized Physician Order Entry | Entry (CPOE) | | | | |
| | (CPOE) in at least one unit | | | | | |

Table 1: HIMSS Analytics EMR Adoption Model

As the hospital moves up the EMR maturity stages the complexity of technologies and their risks of implementation increases. The risk of implementation of a technology is assessed in terms of scope of the application and its degree of hospital wide impact (Premkumar & Roberts, 1999). A mix of technologies with different scope of implementation and impact (department vs. hospital wide) implies that hospitals can choose widely different processes of adoption. In this study we capture the process of adoption of these technologies in terms of the sequence and intensity of adoption. The operationalization of the process of adoption in terms of sequence and intensity as well as its impact on hospitals is discussed below.

Sequence of adoption of technologies: We define the sequence of adoption of technologies as the order in which technologies are adopted. Specifically, our sequence involves two contrasting approaches to adopt EMR technologies: breadth-first and depth-first. If a hospital completes adoption of technologies at a lower stage of the HIMSS EMR adoption model before moving to adopt technologies at a higher stage it is classified as following a depth-first approach. Depth-first approach represents a gradual change in the technology trajectory for the hospital (Dosi, 1982; Benner & Tushman, 2003). On the other hand if a hospital has adopted technologies at higher stages of the EMR adoption model before completing any of the lower stages it is classified as following a breadth-first approach. The breadth-first approach represents a steep change in the technology trajectory for the hospital (Dosi, 1982; Benner & Tushman, 2003).

Intensity of adoption of technologies: We define intensity of adoption as the pace at which EMR technologies are adopted. In other words it is a reflection of the amount of time that the hospital provides for stabilizing routines and assimilating knowledge within the organization after the introduction of the specific EMR technology.

Research Hypotheses

Process of Adoption on Operating Cost

We use hospital's operating cost per bed to measure cost performance. We argue that depthfirst approach will be associated with lower operating cost when compared to a breadth-first approach due to the following reasons.

The depth-first approach will gradually build knowledge and expertise within the organization by first adopting department level integrative technologies that have low levels of complexity. Adopting these technologies first can allow hospitals to assimilate technical knowledge that better positions them to implement more complex technologies (Levinthal, & March, 1993). On the other hand a breadth-first strategy of adoption triggers a larger change in the organization and may require additional resources and training to handle these changes

– all of which can increase costs (Levinthal, & March, 1993). A gradual knowledge and expertise buildup within the hospitals following a depth-first approach should keep the costs of implementation and training lower when compared to the breadth-first approach. This leads to our first hypothesis,

H1 (*a*): The depth-first approach will result in a better cost performance when compared to the breadth-first approach

We argue that the intensity of EMR adoption can moderate the relationship between the sequence of adoption and cost such that at higher intensity the breadth-first approach will perform better when compared to the depth-first approach.

Due to the scale of implementation as the intensity of adoption increases hospitals following a breadth-first approach are more likely to gain the benefits of economies of scale in training and coordination costs. Further, due to simultaneous implementation of technologies at different levels of the hospital coordination issues like interface design, vendor selection, etc are more likely to be addressed when hospitals are following a higher intensity of adoption (Spaulding et. al., 2013).

On the contrary, hospitals following a depth-first approach rely on the higher level of knowledge acquired from the implementation of simpler technologies to better position themselves before implementing hospital wide complex technologies. In such situations, increase in intensity can result in steeper learning curves and reduced time to learn from the adoption of these simpler technologies. Thus at higher intensities hospitals following a depth-first approach should start losing their cost advantage to the breadth-first approach. This leads to our next hypothesis,

H1 (b): The intensity of EMR adoption moderates the relationship between sequence of adoption and cost such that, higher intensity of adoption will result in greater reduction in cost for the breadth-first when compared to depth-first approach.

Process of Adoption on Experiential quality

We measure intermediate process of care in terms of experiential quality which is defined as the quality of interactions between the caregivers and patients as perceived by the patient at a hospital (Chandrasekaran, Senot, & Boyer, 2012). We argue that depth-first approach will perform better when compared to the breadth-first approach on experiential quality due to the following reasons.

Adoption of EMR will replace the existing work routines with new technology mediated routines which will need to go through an adaptation process (Tyre & Orlikowski, 1994) before they become stable and well defined processes. These new technology mediated routines will lack well defined protocols and standards which will lead to misses on experiential quality.

Adoption of EMR will also result in an increase in cognitive burden on caregivers as they adjust to their new technology mediated routines (Swensen et al., 2010). According to the psychology literature, increased cognitive burden and time pressures force people to either accelerate, avoid or filter their current routines as a coping mechanism (Miller, 1960). In a healthcare delivery, avoiding activities is not feasible due to regulatory reasons. Hence with increase in cognitive pressures, caregivers will be forced to accelerate tasks that cannot be avoided and filter the tasks that they consider as lower in importance (Miller, 1960). A number of studies have pointed out that caregivers are likely to put more emphasis on tasks that have a direct link to clinical quality of care and consider the quality of interaction with patients as a burden (Groopman, 2008). Hence they are more likely to filter or accelerate tasks related to patient experience over tasks related to clinical quality of care.

When hospitals adopt a depth-first approach, it usually translates into lower levels of cognitive burden on caregivers due to the gradual increase in technical knowledge when compared to the breadth-first approach (Dosi, 1982; Benner & Tushman, 2003). As a result,

adopting a depth-first approach allows caregivers to learn more gradually and adapt to changes in work environments without comprising on their regular responsibilities including activities related to experiential quality. These arguments suggest the following hypothesis.

H2 (a): The Depth-first approach will result in a better Experiential Quality when compared to the breadth-first approach.

We argue that the intensity of technology adoption will moderate the relationship between sequence of adoption and experiential quality such that at higher intensity the depth-first approach will perform better when compared to the breadth-first approach.

While the sequence of adoption of EMR technologies will determine the types of processes that are disrupted (e.g. nurse routines, physician routines, etc) the intensity of adoption will determine the time available for stabilization of the new technology aided routines through repetition (Tyre & Orlikowski, 1994). Hence an increase in intensity of adoption should have a negative impact on experiential quality for both the depth-first and breadth-first approaches. Increased intensity of adoption of EMR technologies will also put additional cognitive burden on caregivers as new routines are disrupted without giving sufficient time for prior routines to stabilize thus forcing them to put the quality of interactions with patients on the backburner (Miller, 1960).

Since both the cognitive burden and disruption of routines will be higher for the breadth-first approach when compared to the depth-first approach we expect the negative impact of intensity of adoption on experiential quality to be greater for hospitals following the breadth-first approach. These arguments above lead to the following hypotheses,

H2 (b): The intensity of EMR adoption moderates the relationship between sequence of adoption and Experiential Quality, such that, higher intensity of adoption will result in a greater reduction in Experiential Quality for the breadth-first approach when compared to depth-first approach.

Research Methods

Data Collection and Variable Descriptions

The unit of analysis in this study is an acute care hospital. We assembled a secondary data set from about 979 US acute care hospitals from 2007-2012. We combined data from HIMSS and CMS for this analysis. Hospitals that have completed the adoption of all the EMR technologies by 2011 were considered for the analysis. Further, hospitals that had completed stages 2 or 3 of the HIMSS EMR adoption model in 2007 were excluded from the study. This was done to provide equitable comparison across all hospitals. The description of variables used in this study is included below,

Cost Performance: This variable is calculated by dividing the net operating expenses of a hospital by the number of beds and taking a natural log of the number.

Experiential quality: This variable is calculated as the logit transformation of the average for six items from the HCAHPS survey (Chandrasekaran et al. 2012).

Sequence of adoption: Hospitals following a depth-first approach are assigned to category 1 and breadth-first approach to category 0.

Intensity of adoption: This variable represents the pace at which technologies are added. It is calculated using the following formulae,

Equation (1):

Intensity of $adoption_i = \frac{Current Year knowledge index_i - Base Year knowledge index_i}{Current Year - Base Year}$ Where,

Base Year is the first year for which EMR adoption data is available for hospital *i*.

Knowledge Index is a weighted index of the number of technologies adopted at different stages of the EMR adoption model in Table 1.

Control Variables: We control for hospital characteristics such as *teaching intensity, case mix index* (CMI), and *size* to account for hospital level differences. In addition we use dummy variables for each year and state to control for year and state effects.

Results

Table 2 gives the summary statistics on the key variables used in the analysis. We also used the correlations in Table 2 to check the validity of the data used in the analysis. Specifically the positive and significant correlations between CMI and resident to bed ratio (r = 0.45; p<0.05) reinforces the fact that teaching hospitals have higher severity of cases. In addition the correlation between number of Beds and cost (r = 0.14; p<0.05) is positive and significant reinforcing the fact that the operating cost of hospitals increases with size.

| | Mean | Stdev | 1 | 2 | 3 | 5 | 6 | 7 | 8 | 9 |
|--------------|-------|-------|--------|--------|--------|--------|--------|--------|-------|------|
| Beds | 231.7 | 202.2 | 1.00 | | | | | | | |
| Case Mix | 1.40 | 0.26 | 0.68* | 1.00 | | | | | | |
| Index | | | | | | | | | | |
| Resident to | 0.07 | 0.17 | 0.55* | 0.45* | 1.00 | | | | | |
| Bed Ratio | | | | | | | | | | |
| Current | 15.03 | 6.04 | 0.01 | 0.01 | 0.00 | 1.00 | | | | |
| Knowledge | | | | | | | | | | |
| Sequence | 0.10 | 0.30 | -0.15* | -0.14* | -0.08* | -0.07* | 1.00 | | | |
| Intensity of | 2.66 | 2.84 | -0.14* | -0.16* | -0.10* | 0.47* | 0.17* | 1.00 | | |
| Learning | | | | | | | | | | |
| Cost | 13.43 | 0.56 | 0.14* | 0.38* | 0.30* | 0.12* | -0.08* | -0.03* | 1.00 | |
| Experiential | 0.92 | 0.25 | -0.33* | -0.21* | -0.22* | 0.10* | 0.08* | 0.07* | 0.03* | 1.00 |
| Quality | | | | | | | | | | |
| * p<0.05 | | | | | | | | | | |

Table 2: Correlations between variables used in the study

| | I: Choice | II: | III: Choice | IV: Performance |
|--------------------|-----------|-------------|--------------|-----------------|
| | Model for | Performance | Model for | Model for |
| | Cost | Model for | Experiential | Experiential |
| | COSt | Cost | Quality | Quality |
| Constant | -1.504*** | 13.6491*** | -1.5356*** | .6799*** |
| Constant | | | | |
| | (.0467) | (.2255) | (.0434) | (.0827) |
| State Adoption | 4.012*** | | 4.2561*** | |
| Path | (.3157) | | (.3022) | |
| Conformance | | .0387*** | | |
| Quality | | (.0143) | | |
| Experiential | | .1992*** | | |
| Quality | | (.0483) | | |
| Beds | 0018*** | 0006*** | 0016*** | 0002*** |
| | (.0003) | (.0000) | (.0003) | (.0000) |
| Year | | Yes | | Yes |
| State | | Yes | | Yes |
| Case Mix Index | 4263* | .7951*** | 3598* | .0551*** |
| | (.2175) | (.0604) | (.1986) | (.0212) |
| Resident to Bed | .4523 | .6538*** | .3648 | 0880*** |
| Ratio | (.3150) | (.0680) | (.2831) | (.0255) |
| Years of | .0020* | .0002 | .0021** | .0002*** |
| Operation | (.0011) | (.0002) | (.0010) | (.0001) |
| Knowledge Index | 0193*** | .0056** | 0216*** | 0022** |
| e | (.0069) | (.0024) | (.0059) | (.0009) |
| Sequence | | 2652 | · · · · | .2109*** |
| (HIMSS) | | (.2182) | | (.0783) |
| Intensity of | | 0060 | | .0063*** |
| Learning | | (.0052) | | (.0019) |
| Sequence* | | .0160* | | 0091*** |
| Intensity of | | (.0094) | | (.0033) |
| Learning | | (| | (|
| Selectivity Term | | .0745 | | 1060** |
| Selectivity form | | (.1140) | | (.0409) |
| p-value | | 0.0000 | | 0.0000 |
| Observations | | 2241 | | 2729 |
| * n<0 10: **n<0.05 | . *** | 2241 | | 2127 |

Table 3: Treatment Effects model with 1 year lag on performance

* p<0.10; **p<0.05; ***p<0.01

A major concern while evaluating the impact of the EMR adoption process on hospital performance is the endogenous nature of the EMR adoption decisions made by hospitals (McCullough et al., 2010). In particular, EMR adoption decisions (breadth-first vs depth-first) may be influenced by a number of institutional, legislative and patient level factors which can also impact hospital performance thus leading to endogeneity concerns. In addition there may be a self-selection bias in the choice of the sequence of adoption as evident by the big difference in the number of hospitals following the depth-first approach (N= 87) when compared to the breadth-first approach (N= 808). This difference may be attributed to the legislative pressure on hospitals to achieve meaningful use of EMRs by 2013 thus skewing the hospitals decision towards a breadth-first approach.

To account for endogeneity and self-selection concerns with the sequence of adoption of technologies, which is a binary variable, we use a two-stage treatment effects model (Maddala, 1983). The first stage equation models the choice of the strategy for sequence of adoption while the second stage equation models the hospital performance. The results for the performance model and choice models are presented in Table 3. As seen from Table 3, 1 year forward values for cost and experiential quality have been used as dependent variables in the performance equation. This is done to account for the learning curve effects between the implementation of a technology and improvements in performance that have been observed in a number of operations management studies (Boyer, 1999). Further, conformance and experiential quality have been used as predictors in the cost model in accordance with recent research findings (Senot, et. al. 2015). The interpretations of the models are presented below,

Effect of the Process of Adoption on Cost Performance

As seen from model II, there is no difference between depth-first and breadth-first approach in terms of cost performance (β = -0.27, p>0.10) offering no support to H1a. The interaction between sequence and intensity of adoption as seen from Model II (β = 0.016, p<0.10) is positive and strongly associated with cost, offering support to H1b. The conditional effects plot in Figure 1 demonstrates that as the intensity of EMR adoption increases, cost increases for hospitals following the depth-first approach and decreases for the breadth-first approach.

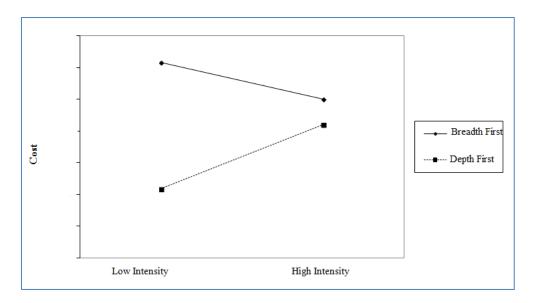


Figure 1: Two way interaction plot between Sequence of Technology Adoption and Intensity of Technology Adoption for Cost

Effect of the Process of Adoption on Experiential Quality

As seen from Model IV, the sequence of adoption (β = 0.211, p<0.01) is positive and strongly associated with experiential quality offering support to H2a. Further the interaction between sequence and intensity of adoption as seen from Model IV (β = -0.009, p<0.01) is negative and strongly associated with experiential quality, offering no support to H2b. The conditional effects plot in Figure 2 demonstrates that as the intensity of EMR adoption increases, experiential quality decreases for hospitals following the depth-first approach and increases for the breadth-first approach.

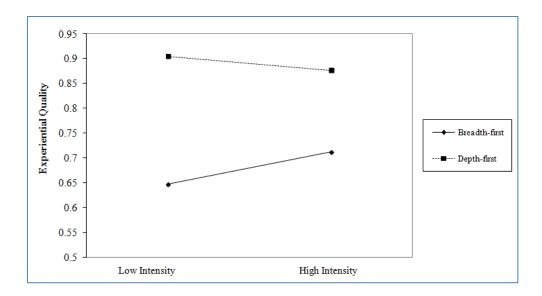


Figure 2: Two way interaction plot between Sequence of Technology Adoption and Intensity of Technology Adoption for Experiential Quality

Results from the analysis indicate the depth-first to be superior when compared to the breadth-first approach in achieving better cost and experiential quality. However, the cost and experiential quality performance of hospitals following the depth-first approach deteriorates as the intensity of adoption of technologies increases. On the other hand the cost and experiential quality performance of hospitals following the breadth-first approach improves as the intensity of adoption of technologies increases.

Conclusions

Overall, this study provides important insights for theory and practice. The clear conceptualization of the process of adoption in terms of the sequence and intensity of EMR adoption, the demonstration of the differential benefits of the depth-first and the breadth-first approaches to EMR adoption and the interactions between the sequence of adoption and the intensity of adoption are the primary contributions of this study. These contributions should go a long way to better our understanding of the relationship between process of EMR

adoption and hospital performance and help resolve the mixed research findings on the

benefits of HIT adoption.

References

- Agarwal, R., Gao, G., DesRoches, C., & Jha, A. (2010), "The Digital Transformation of Healthcare: Current Status and the Road Ahead", *Information Systems Research*, Vol. 21, No. 4, pp.796-809.
- Agarwal, R., Angst, C. M., DesRoches, C. M., & Fischer, M. A. (2010), "Technological viewpoints (frames) about electronic prescribing in physician practices", *Journal of the American Medical Informatics Association*, Vol. 17, No. 4, pp. 425-431.
- Angst, C.M., Agarwal, R., Sambamurthy, V., & Kelley, K. (2010), "Social contagion and information technology diffusion: The adoption of electronic medical records in U.S. hospitals", *Management Science*, Vol. 56, No. 8, pp. 1219–1241.
- Angst, C.M., Devaraj, S., Queenan, C. & Greenwood, B. (2011), "Performance effects related to the sequence of integration of healthcare technologies", *Production and Operations Management*, Vol. 20, No. 3, pp. 319–333.
- Benner, M. J., & Tushman, M. L. (2003), "Exploitation, exploration, and process management: The productivity dilemma revisited", *Academy of management review*, Vol. 28, No. 2, pp. 238-256.
- Boyer, K. (1999), "Evolutionary Patterns of Flexible Automation and Performance: A Longitudinal Study", *Management Science*, Vol. 45, No. 6, pp. 824-842.
- Brynjolfsson, E., & Hitt, L. (1996), "Paradox lost? Firm-level evidence on the returns to information systems spending". *Management science*, Vol. 42, No. 4, pp. 541-558.
- Chandrasekaran, A., Senot, C., & Boyer, K.K. (2012), "Process management impact on clinical and experiential quality: Managing tensions between safe and patient-centered healthcare", *Manufacturing & Service Operations Management*, Vol. 14, No. 4, pp. 548-566.
- Chatterjee, D., Grewal, R., & Sambamurthy, V. (2002), "Shaping up for e-commerce: institutional enablers of the organizational assimilation of web technologies", *Mis Quarterly*, pp. 65-89.
- DesRoches, Catherine M., et al. (2008), "Electronic health records in ambulatory care—a national survey of physicians", *New England Journal of Medicine*, Vol. 359, No. 1, pp. 50-60.
- Dosi, G. (1982), "Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change", *Research policy*, Vol.11, No.3, pp.147-162.
- Furukawa, M. F., Raghu, T. S., & Shao, B. B. (2010), "Electronic Medical Records, nurse staffing, and nurse-sensitive patient outcomes: evidence from the national database of nursing quality indicators", *Medical Care Research and Review*, Vol. 68, No. 3, pp. 311-31.
- Groopman, J.E. (2008), How doctors think, Houghton Mifflin, Boston.
- HITECH Act. (2009), *Title XIII of Division A and Title IV of Division B of the American Recovery and Reinvestment Act of 2009 (ARRA),* Pub. L. No. 111-5, 123 Stat. 226.
- Kohn, L.T., Corrigan, J.M., Donaldson, M.S. (1999), *To Err is Human: Building a Safer Health System*. National Academy Press, Washington, DC.
- Levinthal, D. A., & March, J. G. (1993), "The myopia of learning", *Strategic management journal*, Vol. 14, No. S2, pp. 95-112.

Maddala, G. S. (1983), *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press, Cambridge, UK.

- Miller, J. G. (1960), "Information input overload and psychopathology". *American journal of psychiatry*, Vol. 116, No. 8, pp. 695-704.
- National Institutes of Health. (2013), U.S. Health in International Perspective: Shorter Lives, Poorer Health. http://books.nap.edu/openbook.php?record_id=13497
- Premkumar, G., M. Roberts. (1999), "Adoption of new information technologies in rural small businesses". *Omega*, Vol. 27, No. 4, pp. 467–484.
- Senot, C., et. al. (2015), "The Impact of Combining Conformance Quality and Experiential Quality on Readmissions and Cost Performance", *Management Science. forthcoming*.
- Spaulding, T. J., Furukawa, M. F., Raghu, T. S., & Vinze, A. (2013), "Event sequence modeling of IT adoption in healthcare", *Decision Support Systems*, Vol. 55, No. 2, pp. 428-437.
- Swensen, S.J., et. al. (2010), "Cottage industry to postindustrial care The revolution in health care delivery", *New England J. Medicine*, Vol. 362, No. 5, pp.1-4.
- Tyre, M. J., & Orlikowski, W. J. (1994), "Windows of opportunity: Temporal patterns of technological adaptation in organizations". Organization Science, Vol. 5, No. 1, pp. 98-118.
- Van Merriënboer, J. J., Kirschner, P. A., & Kester, L. (2003), "Taking the load off a learner's mind: Instructional design for complex learning", *Educational psychologist*, Vol. 38, No. 1, pp. 5-13.
- Venkatesh, V., & Davis, F. D. (2000), "A theoretical extension of the technology acceptance model: four longitudinal field studies", *Management science*, Vol. 46, No. 2, pp. 186-204.
- Zhu, K., Kraemer, K. L., & Xu, S. (2006), "The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business". *Management science*, Vol. 52, No. 10, pp. 1557-1576.