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Measuring Success in Interorganizational Information Systems: A Case Study

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Abstract:

We report results of a longitudinal case study in which an emergency medical service replaced a paper-based medical record with an electronic medical record system. The new systems electronically transmitted patient information to various other agencies for reporting, medical quality control, and billing purposes. As expected, the time required for the paramedics to document the medical record increased immediately after system implementation. As a result, operational performance of the paramedics declined. An unexpected consequence of system implementation was that operational performance never reached the level achieved prior to system implementation. However, the benefits attained by all organizations involved outweighed the prolonged decrease in operational performance of the paramedics. Therefore, we advise organizations implementing technology crossing organizational boundaries to consider both the direct and indirect benefits of a system implementation and to evaluate both operational and organizational performance.

Key Words: interorganizational information systems, operational performance, learning curve, information technology adoption, interorganizational collaboration

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I. INTRODUCTION

The term "interorganizational system" was first used by Cash and Konsynski [1985] to refer to an automated information system that extends traditional boundaries of an organization. Interorganizational systems rely upon information technology to enable the flow of data and information between two or more organizations. These systems were initially based on strategic alliances to achieve either competitive advantage [Johnston and Vitale 1988; Ibbot and O'Keefe 2004; Saeed et al. 2005] or cooperative advantage [Williams 1997; Horan and Schooley 2005]. More recently, they have also been employed to achieve operational alliances in which two or more organizations work together to improve operations [Hong 2002; Kaplan and Hurd 2002; Bunduchi 2005]. Instead of being strategic [Varadarajan and Cunningham 1995], current interorganizational systems focus on day-to-day operations and/or collaborative advantage among competitors [Ferratt et al. 1996]. Hong [2002] describes these alliances as either operational cooperation with links among a homogenous group of organizations or operational coordination with links among different organizations formed to add value to an existing product or service. Our focus is on operational coordination alliances.

Organizations typically invest in information technologies (IT) in order to improve productivity and/or performance. Although the two terms are often used interchangeably, they are not the same. Productivity is measured at the organizational or industry level for comparative purposes. It is a measure of the relationship between resources used and quantity produced. A simple definition of productivity is the ratio of outputs per unit of input [Greenberg 1973]. Conversely, performance is measured at the production or work unit level and is often based on time. It is a measurement of the time required to create or process work units [Brinkerhoff and Dressler 1990]. For the purpose of this research, *operational performance* is defined as the time required to chart a patient medical record. This is similar to a study by Poissant, Pereira et al. [2005]

With few exceptions, the vast majority of research concerning the impact of information technology has focused on the economics of organizational productivity rather than operational performance of the business unit [Melville and Kraemer 2004; Mahmood and Mann 2005]. While economic research at the firm level is important, it often fails to examine the business unit that is implementing information technology [Barua et al. 1995; Priem and Butler 2001]. Additionally, some organizations may be more concerned with functional results, i.e. emergency response, safety, or life and death situations rather than costs [Ferratt, Lederer et al. 1996; Coskun and Grabowski 2005]. However, operational performance of one or more subunits is not always indicative of the overall performance of the organization or groups of organizations which collaborate in utilizing a given technology. Organizations may willingly form some operational alliances with other organizations, while others may be required by law.

The purpose of this research was to study the implementation of a new technology and determine its operational performance impact. Specifically, we report on the results of a longitudinal case study in which an emergency medical service (EMS) organization transitioned from a manual method of patient charting to an electronic medical record system. Operational performance of the paramedics was based on the time required to document a patient record both prior to and after implementing the electronic medical record system. Documentation time, termed *completion time*, was measured over a 118-week period. This included 50 weeks prior to system implementation, six weeks of training, and 62 weeks post-system implementation. We used the learning curve as a tool for measuring the new information technology's effect on performance. Based upon the unexpected results, we delved further into the electronic tool's impact at the organizational and interorganizational levels.

This system was created because state law mandated that all EMS agencies submit trauma-related data so that efficacy of patient care prior to arrival at the hospital could be studied by emergency departments in medical schools. The required data set was captured in medical records created by the EMS agency. The data recorded on patient charts was then transmitted to other organizations for various purposes, including insurance billing, medical quality control, and the state trauma database. Thus, an interorganizational system which provided data to multiple agencies was based on operational coordination.

When IT is implemented, operational performance often shows an initial decline. This is attributed to the learning curve. However, it is expected that operational performance will eventually be better than the level prior to system implementation. Research related to operational performance, IT, and the learning curve in a nonprofit collaborative setting is scarce. Although researchers often refer to the learning curve following information technology implementations, little research in this area has been conducted concerning performance and interorganizational relationships based on operational alliances. This exploratory study focused on the following research questions:

How does implementation of a new system impact operational performance? Does operational performance decrease immediately post system implementation, yet eventually stabilize? How long is the learning curve when converting from a manual method of patient charting to an electronic method? How does an interorganizational medical system benefit the organizations?

II. PRIOR RESEARCH

Operational Performance

Fudge and Lodish [1977] conducted a field experiment to assess the operational performance of an airline sales force unit after implementing a system designed to improve sales. A control group manually estimated call frequency and anticipated sales based on policy, while a treatment group used the implemented computer system. The researchers compared performance measures and evaluated differences in sales forecasts. Results indicated that the treatment group had, on average, 8.1 percent greater sales than their counterpart in the control group.

In another example of operational performance research, Banker et al [1990] conducted a pilot study of a new point-of sale system for Hardee's, Inc. Their study approximated a controlled experiment analyzing the business unit for operational efficiencies introduced by the system implementation. The authors argue that efficiency measurements for IT should use intermediate production processes to understand how IT affects business performance rather than economic measures. By doing this, researchers may determine if conversion of IT investment is occurring within the business unit involved with implementation, rather than some other segment in the value chain. The authors utilized data-envelopment analysis and a nonparametric production frontier hypothesis test to determine if restaurants using the new system performed better than the control group. Results indicate information technology deployment at Hardee's positively affected operational performance.

Mukhopadhyay et al. [1997] researched operational performance over a longer period of time. They studied 46 mail processing centers over a three-year period to determine the impact of information technology on performance output and quality. Variables considered included measures of work volume, delivery time, labor hours, and machine hours. Using a production function, they estimated several models to test their assumptions. Results indicated that IT affects output and that increases in automation improve operational performance. Operational performance among firms that rely upon supply chain technologies has also been shown to improve when information integration among customers and suppliers is intensified [Rosenzweig et al. 2003; Devaraj et al. 2007].

Other researchers [White and Prybutok 2001; Bonavia and Marin 2006] have noted that although operational performance may improve in one area of operations, the improvement is not necessarily noted in other areas of the firm. The impact of technology may also not be equal when compared across different technologies. Bhattacherjee et al. [2007] surveyed 96 hospital CIOs to determine the relation between technology adoption and operational performance. Results showed that clinical health information technologies (HITs) had the greatest impact on operational performance. While positive, strategic and administrative HITs were not statistically significant.

Learning Curve Literature

Learning curve phenomena reveal the rate at which learning from repeated usage takes place. This phenomena was first documented by Wright [1936] while working in the aircraft construction industry. Wright noticed that as assembly workers repeated work functions their speed or unit rate increased. His learning curve measures revealed how people's performance improved with repeated tasks. Since that time, measurement of learning of skills is similar to productivity, i.e. learning costs. Learning costs can be calculated as a function of the length of time for tasks to be learned if other variables remain fixed [Kilbridge 1962]. This phenomena and its associated cost have been found to exist when new information systems are implemented [Waldman et al. 2003].

Researchers have studied the learning curve phenomenon in efforts to enhance production, reduce costs, and predict manufacturing events. Womer [1984] suggested that the learning curve model was valuable both for description and prediction. Studies in this area have explored different units of analysis in a multitude of settings using an assortment of populations. Units considered in studies included individuals [Mazur and Hastie 1978], groups [Leavit 1951; Epple and Argote 1991], and organizations [Argote and Epple 1990; Ramsay et al. 2001]. Researchers have reviewed airframe production [Wright 1936], automobile manufacturing [Levin 2000], chemical industry [Lieberman 1984], construction [Norfleet 2004], health care [Waldman, Yourstone et al. 2003], industry [Argote and Epple 1990], project management [Waterworth 2000], service organizations [Darr et al. 1995], shipbuilding [Yelle 1979], and strategic management [Lieberman 1987]. Within these contexts, populations represented have included mechanical, service, and technical workers, as well as a variety of professional groups. Thus, a review of the research concerning learning curves reveals widespread academic and practitioner acceptance of the initial concept with replication and extensions into many domains and populations [Lieberman 1984].

Operational Performance and The Learning Curve

The concept of a group learning curve was first approached during WWII as a means of assisting in predicting labor and monetary costs of building ships and aircraft [Yelle 1979]. These activities led to the use of aggregated individual learning curves in assessing group learning. Figure 1 shows the relationship between individual learning curves, individual variance, and the group learning curve. It shows a potential distribution of performance time as the number of units completed increases. Aggregating individual scores to produce a group learning curve similar to the example is an acceptable method of determining and comparing group performance [Ramsay et al. 2000]. Following are examples of studies involving operational performance and the learning curve.

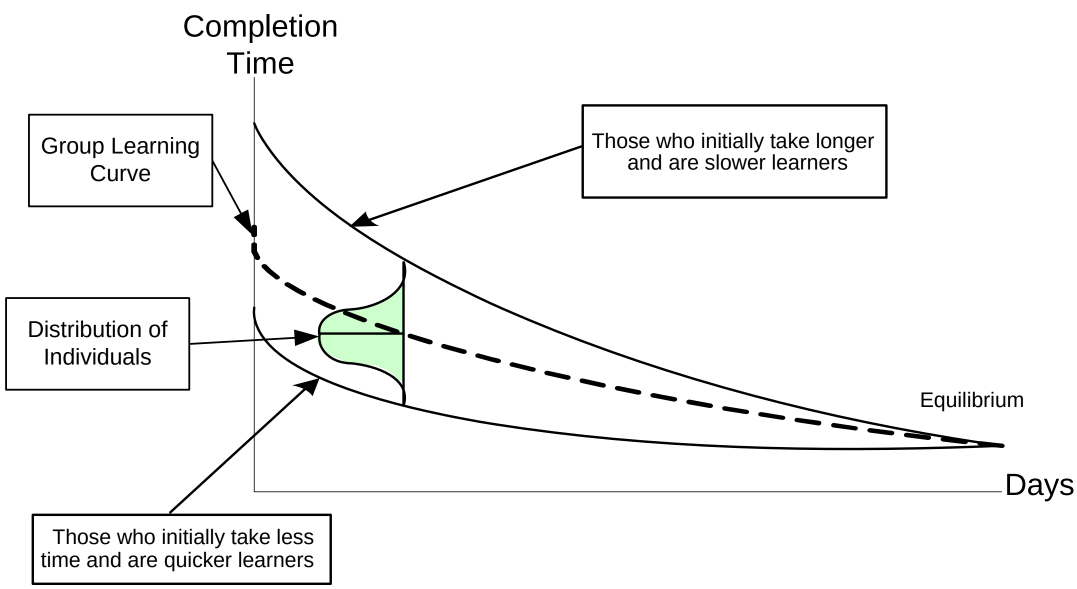

Figure 1. Group Learning Curve

Pisano, Pierra et al. [2001] examined the impact of using a new technology for performing minimally invasive cardiac surgery. They measured the learning curve of time to perform cardiac operations on 660 patients at 16 different hospitals. On average, the learning curve reached stabilization after 50 cases, and reduced procedure time from approximately 280 minutes to 220 minutes. However, there were significant differences in the slope of the learning curve across organizations. The most significant difference was seen in the hospital that reduced its average procedure time from approximately 500 minutes to 132 minutes (across 50 cases). Although its procedure time was significantly greater than average at Case 1, its time at Case 50 was significantly less. Procedures and operating rooms were similar, but the physician team with the lowest average procedure time after 50 cases worked more closely with other members of the surgical team and hospital staff, encouraging cooperation, communication, and team empowerment.

Wiersma [2007] studied the learning curve at 27 regions of the Royal Dutch Mail. She studied four factors that may impact the rate of learning: temporary employees, heterogeneity of products, capacity of workload, and task variability. The operational variable (based on cost) was the weighted average of the number of products delivered times standard rate for each product type. Although decreasing, the learning curve had yet to plateau after a two-and-a-half-year period. In addition, although the average rate of learning was flat, and the regions were homogeneous, there was a significant difference in learning rates among the regions. Overall learning rate was highest in regions with more temporary employees working with heterogeneous products and when workload was not excessive.

More recently, researchers have suggested modeling organizational operational performance in a more longitudinal fashion, based upon the learning curve. McAfee [2002] examined the impact of technology adoption on operations before and after implementation of an ERP system. This quasi-experiment focused on the performance dip often precipitated by new system implementation. Operational performance improvements were realized several months

after system implementation. The implication is that improvements in performance take time, as revealed by the organizational learning curve.
In a similar study, Cotteleer and Bendoly [2006] examined lead-time improvement following implementation of an ERP system. The researchers noted continuous improvement over a 24-month period, as evidenced by the learning curve.

III. THE CASE OF EMS911

This is a single-case exploratory study of an EMS organization in a large southwestern municipality, termed EMS911. Case studies examine contemporary events in context where the boundaries of the phenomenon are not clear [Yin 1994]. As a research tool, the case study research strategy can contribute to knowledge of phenomena related to individuals, organizations, and societies. The case study methodology uses multiple sources of data to triangulate and validate research [Yin 2003]. These may include a variety of sources. For this study the focus was on operational performance data, interviews and anecdotal evidence used in the analysis of an interorganizational system.

The organization, which consists of more than 300 paramedics, responds to more than 100,000 emergency dispatches annually. Prior to 2000, patient charting (patient history, signs, symptoms, medications, etc.) was manually recorded by the paramedics, using a standard paper form. Copies of the form were made available to the hospital, a medical quality control center, and a contracted billing service. Another copy was maintained for EMS records. When the patient was transported, the paramedic completed patient charting and left a copy for hospital personnel. The paramedics retained the other three copies, and these were delivered to the EMS911 administrative offices each day.

Clerical personnel at the EMS911 administrative offices checked the forms for errors or missing information, retained one copy for their records, and forwarded the other copies to the medical quality control center and the contract billing service. Major problems with the manual system included lost form copies and erroneous transcription of recorded data. One notable problem was the quality of handwriting. If clerks at any of the organizations (EMS911, medical quality control center, or contract billing service) were unable to read the paramedic's handwriting the patient form was returned to the paramedic for handwriting interpretation. This delayed billing, reporting, and/or quality control services.

In the early 1990s, when the Department of Health began creating a trauma care database, they mandated all EMS agencies and hospitals to submit run level data in a prescribed data set to the trauma database. Previously, EMS agencies were only required to submit summary statistics on a quarterly basis. As a result, EMS agencies and hospitals were required to modify their information systems, making it possible to provide more detailed data on a per run basis.

Initially, none of the EMS agencies or hospitals was able to meet this unfunded legislative mandate. Because of the vast technical problems, the Department of Health waived compliance, and moved the deadline back several times, allowing the agencies and hospitals time to develop methods for meeting the requirements. After multiple trials, EMS911 decided on a wireless system with direct links to a central repository and 911 dispatch (Figure 2).

As ambulances respond to emergencies, a tablet PC in the dispatched ambulance receives a wireless transmission of the information. The call address, demographics, and other call information initiate a case for medical documentation upon receipt. During the call the paramedics press buttons which time-stamp segments of the call, such as responding, arrived, case completed, etc. Paramedics respond, treat, and transport patients to area hospitals and then complete the electronic patient form. This documentation is then transmitted back to the server and made available to affiliated agencies, including the Department of Health trauma database, medical quality control, and contract billing services.

Both manual and electronic systems required 107 fields of data entry or observation. The electronic medical record system split data entry over 12 tabbed screens. Although the navigation requirements appeared to increase the amount of time to complete a form, this was thought to be insignificant compared to the expected improvements in the back office and the ability to meet the Department of Health mandate.

The paramedics received an initial four-hour training session after which they were issued a new tablet PC for documentation purposes. The following shift they took part in a second four-hour training session where they could discuss problems they encountered during the initial shift of usage. A parallel rollout strategy ensured continued service during training. After six weeks, the majority of paramedics had completed training. The system, which satisfied the Department of Health mandate, was fully implemented in October 2000.

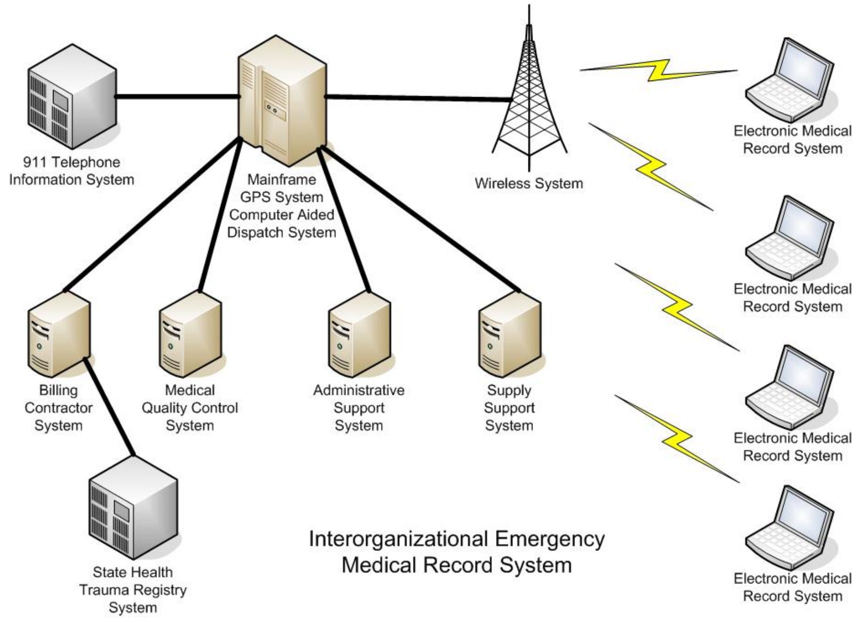

Figure 2. Interorganizational Information System

Post Implementation Benefits

As shown in Figure 3, EMS911 relied upon technology to interact with many organizations and deliver emergency healthcare services. The adoption of interorganizational information systems often provides benefits beyond the implementing organization [Williams 1997]. This was highly evident with the EMS911 system. At EMS911, clerical personnel were no longer required to check forms for errors or missing information, nor separate, collate, and store the forms for archival purposes. In addition, the system provided a search interface where records were retrieved and printable on demand, providing management improved access to data for evaluation and budgeting.

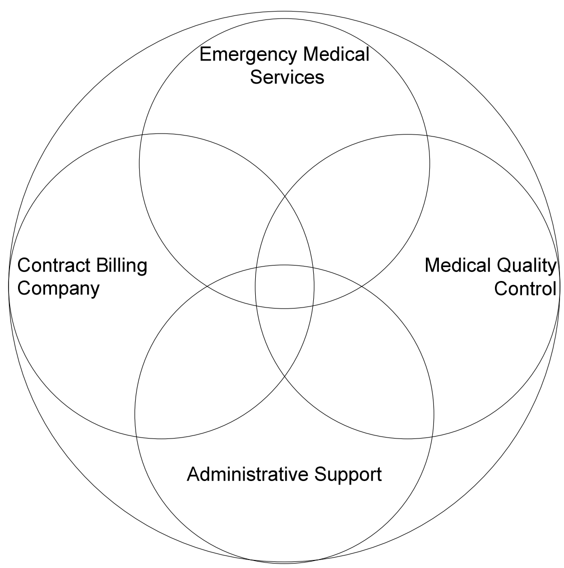

Figure 3. Interorganizational System Relationships

to reduce the number of forms requiring medical quality control review, specific triggers were built into the medical record database, thus empowering medical quality control to view specific cases for medical evaluation. As a result, time spent on exception reporting was greatly reduced.

The billing company benefited in many ways. Since the forms were wirelessly transmitted, they no longer had to physically pick up forms on a daily basis, Also, since clerks no longer had to transcribe hand-written forms, errors, billing time, and the number of required billing clerks decreased. In addition, electronic submittal of private insurance, Medicare and Medicaid claims was more efficient since there were no input lag or handwriting interpretation issues.

Since its initial mandate, the State Department of Health now requires all EMS agencies (more than 800 entities) and all hospitals (more than 400 entities) to report all cases (not just trauma) to the registry [Jones et al. 2004]. EMS911 is able to meet the new Department of Health mandate, and the electronic medical record system is still functional today.

Although all organizations impacted by the State Department of Health mandate experienced improved performance overall, operational performance at the paramedic level actually decreased. As expected, completion time (time to complete patient charting) increased when the electronic medical record was implemented. EMS911 increased the number of paramedics on active duty in order to avoid negatively impacting patient care as a result of technology implementation. As learning continued, completion time declined and again reached a performance equilibrium. However, once stable, electronic completion time still exceeded manual completion time. Following is a discussion of how performance was measured, based on the learning curve.

III. DATA COLLECTION AND METHODOLOGY

This research followed a quasi-experimental case study design to examine operational performance in the implementing organization. Case studies are generally acceptable when little is known concerning the phenomenon of interest. We sought to determine the technology's initial impact on operational performance as well as the long-term effects at operational, organizational, and interorganizational levels. Therefore, a longitudinal case study was deemed the method of choice. Implementation of the information technology represents the treatment, and the group learning curve was the tool for measuring the technology's effect on performance. Figure 4 shows the relationship between these variables.

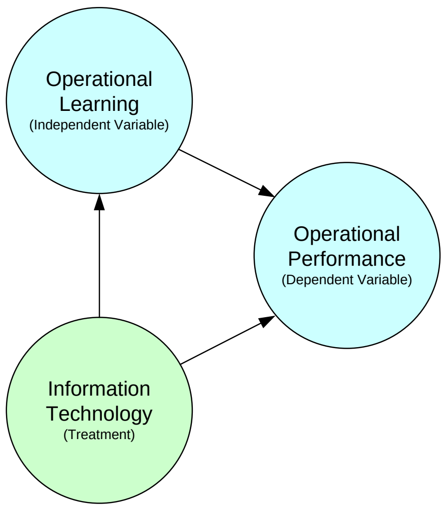

Figure 4. Research Model

Operational learning and performance are examined using an interrupted time-series design. Time series designs in quasi-experiment situations require many data points prior to and after the treatment to facilitate effect determination [Cook and Campbell 1979]. Figure 5 provides an example of the time series design, where O represents an observation in time and X represents the point of demarcation for the treatment or implementation.

$$O_1 \quad O_2 \quad O_3 \quad \ldots O_{50} \quad X_{51\text{-}56} \quad O_{58} \quad O_{59} \quad O_{60} \quad \ldots O_{118}$$

Figure 5. Time Series Analysis

This study focuses on the transition ($X_{51\text{-}56}$) from a paper patient form ($O_{1\text{-}50}$) to an electronic patient form ($O_{57\text{-}118}$). We began by analyzing baseline data from the initial period ($O_{1\text{-}50}$) when paramedics completed a paper medical record. Next, we studied the period post transition from the paper patient form to an electronic medical record ($O_{58\text{-}118}$). Table 1 details the period, range and number of weeks analyzed by segment. Data captured during the training period were not considered in this study because of parallel use of both paper and electronic systems.

While this research closely follows McAfee's [2002] design, we sought to extract additional information from this case such as when mastery occurs. In the ERP system examined by McAfee, a "cutover" rollout was used where production was stopped, all personnel were trained, and production was restarted using the new system. EMS 911 used a parallel rollout because 911 calls could not be stopped. We followed Cotteleer and Bendoly [2006] in excluding this time period from our analysis.

Table 1. Period, Range and Number of Weeks		
Period	Range	Weeks
Pre Implementation	1-50	50
Training Period	*51-56*	*6*
Post Implementation	57-118	62
Total	1-118	118

The raw data covers 118 weeks and involves emergency call data drawn from 244,416 records. Of these medical cases, not all patients were actually transported to a hospital. Since only the transported patient records contained the needed data, the number of cases decreased to 99,161. Transported cases are further broken down by medical severity into Code 2 and Code 3 cases. Code 2 cases are at a lower level of medical emergency, such as a broken arm with no complications. A Code 3 case might be a patient with multiple fractures, internal bleeding, and a head injury. Since Code 2 cases are much more prevalent and tend to have less variance in time required to document, we concentrated only on Code 2 cases. This reduced the data set to 82,097 Code 2 patient form completions in our analysis. Table 2 shows the number of cases occurring for each code type over 118 weeks.

Table 2. Cases by Code Type		
Type	Frequency	Percent
Code 2	82,097	83
Code 3	17,064	17
Total	99,161	100

It should be noted that Code 2 patient form completions comprised 83 percent of all calls for EMS911. Code 3 patient form completions only made up 17 percent of emergency transports.

IV. RESULTS

Patient documentation data for both paper and electronic systems were analyzed to model operational performance using the learning curve. Based on prior research, one would expect information technology to affect both baseline performance and operational learning. EMS911 expected that when the electronic medical record system was implemented, the paramedics would initially take more time to complete patient documentation. Although the goal of the implemented system was to meet a state mandate, it was hoped that once the new system was mastered, task completion time would be less than that of the paper patient form system.

The electronic medical record implementation produced significant changes in both daily operational performance and the performance trend over time. We observed these differences by plotting the organization’s primary performance metric, *completion time*, over both the pre and post implementation periods. Completion time is a critical benchmark for EMS911 because of its system wide effects related to ambulance availability and personnel costs. The *standard deviation* of completion time is also important as greater system variability leads to less effective resource planning. By plotting these variables over time we were able to contrast pre-implementation performance with post-implementation performance following the guidelines of Lucas [1991].

According to Lucas [1991], there are two criteria that must be met to demonstrate the impact of information technology on performance: 1) Performance changes must correlate with the implementation of a system; and 2) Performance changes must follow the implementation. Both of these conditions are met in the case of EMS911. Completion time increased significantly immediately following implementation of the electronic medical record. After this initial performance decrease, completion time gradually improved as paramedics became more familiar with the new system. There is an observable plateau to this learning curve effect, followed by more modest fluctuations in completion time well after system implementation. The post implementation period appears to have greater variability in completion times than the pre-implementation period. It is important to note that these changes in performance are strongly correlated with the system implementation.

Our initial findings are similar to the results of others using the learning curve to plot performance [McAfee 2002], with one notable difference. In the case of EMS911, operational performance in the post-implementation period never approached that observed in the pre-implementation period. As shown in Figure 6, the vertical line at 50 weeks indicates the end of the pre-implementation period.

The period from week 51 through week 56 is a training and rollout period when both the old and new systems were being used in parallel. Note the significant difference in task completion times at weeks 51 (prior to system implementation) and 57 (the completed changeover from paper patient forms to electronic medical record). Beginning at week 57 all medical documentation was electronic. The dependent variable in Figure 6 is *completion time*, as seen on the Y axis. Our time reference, Week, is plotted on the X axis. Time, in the form of days, serves as a proxy for the number of work units completed or cases. We followed Cotteleer and Bendoly [2006] in using time as a surrogate for units completed.

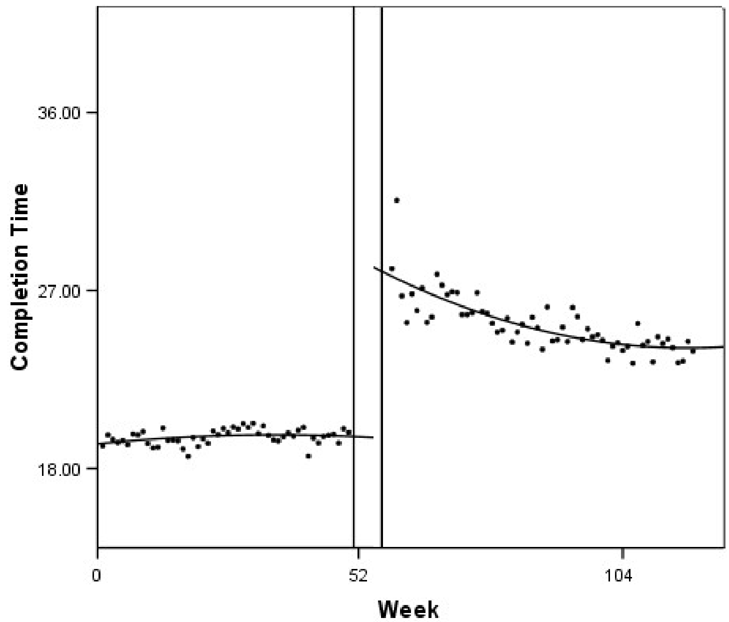

Figure 6. Completion Time Pre- and Post-Implementation

As shown, task completion time rose sharply immediately following system implementation and gradually decreased over time, but it never approached the completion time observed prior to system implementation. Task completion time eventually stabilized at week 118, which is 62 weeks after complete system changeover. The shape of the learning curve has important implications regarding post-implementation performance and thus labor costs. These implications are discussed later.

Table 3. Descriptive Statistics Pre- and Post-Implementation							
Variable	*Description*	Period	Weeks	Mean	SD	Min	Max
CT	*Average Time to Complete All Cases in a Week*						
	Pre-Implementation		50	19.59	0.39	18.62	20.29
	Post-Implementation		62	25.34	1.41	23.37	31.64
CTSD	*SD of Completion Time for All Cases Completed in a Week*						
	Pre-Implementation		50	8.76	0.35	7.94	9.28
	Post-Implementation		62	11.26	0.63	9.86	13.11
CASES	*Number of Cases Completed in a Week*						
	Pre-Implementation		50	713	56.73	604	885
	Post-Implementation		62	693	34.36	613	778

Where: CT = Completion Time
CTSD = Standard Deviation of Completion Time

Table 3 provides a comparison of the average weekly completion times before and after system implementation. The descriptive statistics reveal a significant change in completion time introduced by the adoption of the system. Prior to implementation of the electronic medical record system, average weekly completion in the pre-implementation period was less than 20 minutes, and the standard deviation of the completion time was relatively small (0.39). Weeks 51 to 56 are not considered in this analysis because both systems were used in parallel during this training and rollout period. Note the substantial change in operational performance during the post implementation period of 25.34 minutes. There was a significant difference between maximum and mean task completion times when comparing times prior to system implementation and times from system changeover to stabilization. The maximum task completion time rose from 20.29 minutes to 31.64 minutes, and mean value rose from 19.59 minutes to 25.34 minutes. Also note that the standard deviation of average completion time between these two time periods more than tripled (0.39 versus 1.41).

Overall, the statistics show that variance in completion time by paramedics was at its greatest during the first 62 weeks of the post-implementation period. During this period, the paramedics experienced the lowest minimum (23.37 minutes), highest maximum (31.64 minutes) and highest mean (25.36 minutes) for average completion time. This period also produced the greatest standard deviation (1.41 minutes) in mean completion time between weeks.

Standard deviation within a given week is also substantially higher in the post-implementation period than in the pre-implementation period at 11.26 versus 8.76 minutes. These results suggest that completion time costs attributable to the new system implementation are particularly high during the learning curve. Organizations must be aware of this potential outcome and be prepared to compensate for the impact of this variability in order to effectively allocate resources during the learning curve.

While the descriptive statistics in Table 3 provide an initial indication of the change in operational performance between the two periods, we were also interested in assessing the change in performance over time within each period. To determine if the post implementation period was significant, a regression analysis was performed and is displayed in Table 4.

Table 4. Regression Parameter Estimates

Code 2 Transports		
	Pre-Implementation	Post-Implementation
Independent Variable	Coefficient (SE)	Coefficient (SE)
Constant	19.252***	38.649***
	(.166)	(3.07)
week	.025	-.245***
	(.015)	(.072)
$week^2$	-0.00036	.001**
	(0.00029)	(0.0004)
Sample Size	50	62
R^2 (Adjusted)	.102 (.064)	.625 (.612)
DOF	48	60
F value	2.673	48.342
p value	.080	.000***
*** $p < .001$, **$p < .01$, *$p < .05$		

The curvature of the data in the scatter plot shown in Figure 6 suggested that a quadratic function of time was appropriate for the analysis. Based on this observation, we regressed average weekly completion time on a second order polynomial model representing the effect of time. As such, the analysis included two time predictor variables: week and $week^2$. In the pre-implementation period neither week nor $week^2$ was significant. However, when the electronic medical record system was fully implemented both week and $week^2$ became significant predictors of average weekly completion time and the amount of variance explained by the model increased substantially. The regression results indicate that the system was stable prior to system implementation and that operational performance is dependent upon the passage of time after implementation. This appears logical in that all paramedics were well-trained and experienced in using the paper form prior to the beginning of the case study. The pre-implementation data reflect this stability.

When transitioning from the paper based period to the electronic medical record, training consisted of only two four-hour classes per paramedic. Following this brief training period, paramedics immediately began using the new system in the operational environment. As a result, completion times were initially highly variable, yet stabilized over time.

We also performed a t-test to test the differences in completion time between the pre- and post-implementation periods. As reported in Table 5, the difference in average weekly completion time between the two periods is highly significant at t = - 27.973 (p < .001). The difference in the standard deviation of the completion times is also highly significant at t = -24.998 (p < .001). These results reinforce our previous findings by confirming a significant change in performance immediately following system implementation.

Table 5. Pre- and Post-Implementation t-test

Comparison of Performance over Two Time Periods

Measure	Pre-Implementation	Post-Implementation	% Difference	t value
Weekly Average Completion Time in Minutes				
Code 2 Cases	19.59	25.34	29.35	-27.973***
Weekly Standard Deviation of Completion Time				
Code 2 Cases	8.76	11.26	28.54	-24.998***
Average Number of Cases per Week				
Code 2 Cases	713	693		

*** p < 0.001, ** p < 0.01, * p < .05

V. DISCUSSION

As shown, EMS911 experienced a significant increase in the time required to document patient medical information following implementation of the electronic medical record. The new system implementation resulted in a 62-week learning period prior to stabilization. As noted, the primary purpose of this system was to meet the state mandate for patient reporting. However, like other healthcare systems [Ash et al. 2004; Campbell et al. 2004] several "unintended consequences" resulted. Although it was expected that it would take time for the paramedics to learn the new system, the actual time to stabilization was much longer than presumed. This extensive time can be partially attributed to post-interruption learning [Bailey and McIntyre 2003] or forgetting [Argote 1996]. On average, paramedics work once every four days. And, when they work, they do not always perform patient documentation. Therefore, they may have initially spent time relearning the system. It could also be associated with confusing electronic data representation or screen designs or the amount of required typing [Ash, Berg et al. 2004; Campbell, Sittig et al. 2004]. Even following this learning period, completion times never approached those observed prior to implementation. This is contrary to the findings of McAfee [2002] and Cotteleer and Bendoly [2006].

Although paramedic performance decreased, their effectiveness actually increased through creation of an electronic medical record that incorporated data validation routines. Thus, cost savings were realized by decreasing the need for external validation and review. Although the trade-off between these two functions cannot be accurately quantified, the decrease in errors and back-end support costs significantly diminished the impact on operational performance.

The success of the electronic medical record implementation must be gauged by looking beyond operational performance measures to other rational drivers of information technology adoption [Goldstein et al. 2002; Tsikriktsis et al. 2004]. Organizations may adopt technology to implement strategy [Barua, Kriebel et al. 1995], improve scientific management [Buhman et al. 2005] or to realize system benefits [Sanders 2005]. Understanding how these drivers impact operational performance and provide system benefits is a major goal of information systems case study research [Benbasat et al. 1987].

In the case of EMS911, the organization implemented the electronic medical record to meet a legislative mandate. On that basis, the new system was considered successful in meeting the mandated reporting requirement. EMS911 was able to efficiently collect and report all necessary patient trauma information using the electronic medical record system. The system also offered substantial interorganizational benefits between EMS911, medical quality control, and the billing service. As such, this was not a strategic alliance. Instead, it was an operational alliance with multiple organizations. Although operational performance among the paramedics decreased, it increased in other areas of EMS911, as well as the other organizations.

Reduced Operational Performance

There appear to be no obvious explanations for the changes in operational performance observed at EMS911 other than the electronic medical record implementation. Performance prior to the system rollout was remarkably stable. Both the pre-implementation and post-implementation periods covered approximately a year or more, making seasonal anomalies an unlikely factor in observed patterns. The number of cases processed showed slight annual growth due to annexation and a general pattern of urban growth. However, the number of paramedics on staff grew in proportion to the call volume, thus negating increased work load as a potential explanation for the observed phenomenon.

Because the electronic medical record system utilized the municipality's network infrastructure to transmit patient data to a central repository, we must consider the potential for network congestion or outages to impact performances measures. While the system was designed to provide automatic time stamps for the fields used to calculate completion time, paramedics can receive these times via radio and manually input them during infrastructure outages. Similarly, paramedics may mark the completion of a form, store it locally and transmit data to the repository at a later time. These features of the system preclude network congestion and outages as potential contributing factors. Thus it seems prudent to attribute the observed decreases in operational performance to the system implementation itself.

Summary of Interorganizational Improvements

Information technology often provides benefits beyond the original intent with indirect returns occurring unexpectedly [Lucas 1999]. EMS911 accrued benefits from other organizations indirectly using the electronic medical record system or its data. While operational performance declined within the emergency medical services organization, associated organizations realized direct benefits from the adoption of this technology.

EMS911 was able to significantly reduce their billing and storage costs. The electronic medical record system greatly reduced handwriting recognition problems for the billing contractor because of electronic data entry and data validation introduced by the system. This enabled the billing contractor to reduce the number of employees required to do data entry and further reduce the cost of their service to EMS911. An unforeseen gain in claim turnaround time from insurance companies and Medicaid due to quicker electronic submittal also reduced the number of clerks.

Another indirect benefit was realized in medical quality control, which was able to easily sort and evaluate medical forms in a timely manner. The new system provides exception reporting on medical issues, monitoring drug administration and at risk personnel. Nurses who previously spent hours collating and reviewing forms for exceptions are now able to review electronically generated exception reports. While the costs associated with medical quality control did not immediately change, impact on the quality of medical documentation was positive.

Chart audits are one method of ensuring quality control. It is standard practice for medical personnel to review the charts of others, checking to see if standard procedures were followed, searching for potential errors or omissions, and comparing patient charts for anomalies among patients. As a general rule, the number of chart audits increases when the number of patients and/or exception reports increases. As shown in Table 6, although the number of patients increased, the number of chart audits decreased significantly following implementation of the electronic system.

Table 6. Number of Medical Quality Control Audits to Average Completion Time per Year

Year	Chart Audits	Completion Time
1999	9266	19.58
2000	5412	25.32
2001	4993	24.6
2002	3614	25.06
2003	3171	24.81

The declining number of chart audits is highly correlated with the implementation of the electronic medical record. Exception reporting relieved quality control personnel of the responsibility for total chart audits. Rules for manual chart audits derived from the electronic medical record database allowed medical quality control personnel to focus on performance outside the standard operating procedures. Table 7 reports on the correlation between the number of chart audits and the average completion time.

Table 7. Pearson Correlation of Chart Audits to Completion Times

		Avg. Completion Time
Number of Chart Audits per Year	Pearson Correlation	-.906(*)
	Sig. (2-tailed)	.034
	N Years	5

* Correlation is significant at the 0.05 level (2-tailed).

Administrative Support System

EMS911 administration indirectly benefited from this implementation. Under the paper system, administration supplied hard copies of patient forms to the legal and judicial systems. This required clerical personnel to access the filed forms, pull and make copies, and send them via mail to the requesting agency. Under the new system, a clerk searches the database and emails a copy to the courts, saving processing time. Another benefit to the administration involved managerially monitoring of paramedic performance. Just as medical quality control gained by fewer exception reports, so did EMS911 administration. Better data capabilities also empowered administrative personnel to make better decision. As shown in Table 8, performance monitoring, budgeting and planning all improved upon implementation of the electronic medical record. Therefore, we strongly advise organizations implementing technology to consider both the direct and indirect benefits potentially available to them.

VII. CONCLUSION

This case examined an interorganizational system responsible for providing EMS service in a major metropolitan area. The case of EMS911 provided an interesting example of an interorganizational system in which multiple agencies interact to deliver healthcare services in a timely manner. We conclude that in order to adequately evaluate interorganizational adoption of technology, the entire system should be examined for both positive and negative effects. Although operational performance of the paramedics remained decreased, the effectiveness of the interorganizational system as a whole was greatly enhanced. Charting errors were significantly decreased, billing services received data in a more timely manner, and the trauma center received the mandated patient information within the required time period.

Overall, there were notable improvements in the efficiency and flexibility of all organizations within the system. As previously noted, patient care was not impacted by the decrease in operational performance of the paramedics.
While this work was an individual case study, it analyzed operational performance over a considerable period of time in a single organization, as well as the interaction with other organizations. The analysis of 62 weeks of post-implementation data provides a longitudinal view of performance, strengthening the evaluation. The experience of EMS911 in implementing an electronic medical record reveals several key issues. While operational performance declined for EMS911, the interorganizational system of systems improved functionality across affiliated organizations from the adoption of this technology. In this case, the implementation of an electronic medical record caused an increase in medical record completion time for EMS911, yet improved the pickup and submittal processes for the billing contractor, increased medical quality control and met the state mandate to submit trauma data.

Implications for Theory and Practice

As shown, operational performance of the paramedics (based on CT) was significantly reduced when the electronic medical record system was implemented. This affected the EMS 911 organization. However, this does not tell the full story of the success or failure of the electronic system for all organizations using the system. We suggest that affiliated organizations evaluate effects from an interorganizational perspective to determine the “true value” of adopting information technology. A system view fosters collaboration between partners, whereas a centric view leaves out important information about partner benefits. Examining overall effects might help to justify and/or allocate costs associated with interorganizational systems. This type of analysis would help determine the overall effects potentially improving interorganizational relationships and improving knowledge. Therefore, we suggest the following measures be taken when assessing the value of a new technology adoption:

Table 8. Qualitative and Quantitative Results			
Areas of Concern	Method Observed	Expected Results	Actual Results
Meet state mandate for delivering run-level data to trauma database	Switched from manual recording of patient charts to electronic, with direct link to central repository	Meet state mandate	EMS911 *As expected
Study operational performance of paramedics, based on time required to complete patient charting (completion time (CT))	Measure group learning curve prior to technology and post implementation to measure differences in time to complete patient charting	Stable baseline CT prior to implementation CT longer immediately post implementation Relatively short time to reach stabilization Once stable, mean CT post-implementation would be shorter than pre-implementation	EMS911 *As expected *As expected Long time to reach stabilization (62 weeks) Mean CT at post-implementation stabilization was longer (25.34 minutes) than pre-implementation stabilization (19.59 minutes)
Exploratory observation of performance changes within EMS911 as a result of state mandate	Discussion, interviews, historical data	No prior expectations established	EMS911 * Decrease in charting errors due to poor handwriting, lost copies, erroneous transcription of recorded data, etc. * Decreased billing and storage costs * Faster turn-around from Medicaid and insurance companies * Patient data in electronic form, facilitating improved data access and analysis
Exploratory observation of performance changes among the inter-organizational entities	Discussion, interviews, historical data	No prior expectations established	Billing contractor * Required fewer employees to handle billing * Received billing info electronically Medical Quality Control * Fewer required chart audits * Received charting reports electronically

- Determine the direct impact of the technology at both operational and organizational levels. What is the impact of both operational and organizational performance of all parties involved? What were the costs involved? Was there a subsequent cost savings—monetary, personnel time, decrease in errors, faster response to customers or suppliers, etc.? Have customer and/or supplier relations improved? Why, or why not? What is the total impact of the implementation?
- Determine the indirect impact of the technology on other organizations. Have they been able to benefit in time or cost? Are there benefits outside the normal cost and time parameters?

- Remember that not all alliances need to be strategic. Operational alliances can be just as beneficial. Remember that operational alliances may provide hidden benefits.
- Base overall benefits and costs upon the organization as a whole, as well as all other organizations involved. Can benefits achieved by partner organizations impact other entities?

Limitations

Case studies can involve either single or multiple cases [Yin 2003]. One of the issues related to single case studies is a lack of generalizability. This case was limited to a single organization and therefore conclusive inference is weak. Another limitation of this work was the use of anecdotal evidence from affiliated organizations. While this information supported the impact of interorganizational benefits associated with a "meaningful event" [Yin 1981], it lacked the scientific rigor necessary to draw conclusions.

Use of a single quantitative performance measure within one organization may not adequately explain interorganizational outcomes. Other measures may be important within and between affiliated organizations. Effectiveness measures may be more valuable than efficiency measures particularly when looking at multiple affiliated organizations. Cross-institutional linkages in systems are important considerations in the adoption of technology that are difficult to discern when looking a simple performance measures.

Directions for Future Study

Since a single case study was utilized future work might include additional organizations to overcome shortcomings. This would allow researchers to better understand the effects of interorganizational systems on affiliated organizations. Multiple cases might also better explain the effects of technology adoption by one agency on partners. Do associates participate in adoption decisions? If not, what might the impact be on other members?

This work used anecdotal evidence to support effectiveness measures. While this evidence "bolstered" findings, it did not allow for theory generation beyond providing description. Future research may survey affiliated organizations to determine their role in adoption of technology.

One of the goals of this study was to observe a municipal EMS agency using a system as a way of examining interorganizational linkages. The first step in understanding an interorganizational system such as this is to describe operational processes and linkages [Horan and Schooley 2005]. Comprehending how partnerships add to or subtract from the operational processes and linkages with other agencies would provide a better framework for analysis of such systems. Weighing individual affiliate's net outcomes might help organizations make better investment decisions in technology. Future research might model interorganizational relationships to assist in improving operational processes through organizational and technological improvements. Each organization should understand its own performance impacts. Aggregating and modeling these impacts would provide insight into total system performance.

Interorganizational trust and barriers to implementation might be another area for future research. Issues could include trust, funding, sharing, and control over technology. In order to understand how organizations function under an interorganizational information system requires examination and documentation. Exploratory research in additional cases might provide insight into interorganizational barriers and/or facilitators.

System performance is important, not only for the adopting organization but affiliated groups as well. Future research might examine perceptions of system performance across affiliates. Differences in perceived performance may also impact indirect benefits. A non-adopting organization which perceives a negative impact may withhold indirect benefits to the adopting agency. Research into this area might look at interorganizational perception management. Finally, studies of changes in interorganizational relationships and the impact of operational performance on those relationships might explain how organizations should view multi-agency systems and their output.

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