A Design Framework for Evaluating Changes in Clinical Communication Systems

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Abstract – **Poor communication in critical care settings has the potential to adversely impact patient outcomes and clinical team performance. Hence, improvements to clinical communication systems are continually sought. However, evaluating these modifications and assessing the risk of degraded performance are complex issues, which are typically addressed qualitatively. These approaches typically examine individual perceptions and can fail to capture the actual performance of the modified processes in the communication system. In order to avoid these issues and effectively analyze the changes in a given system, a Monte Carlo simulation methodology is proposed using data extracted from Electronic Medical Records (EMR) compiled by the Huron Consulting Group to precisely measure modified system performance. We couple a risk analysis, using control charts, with a temporal distribution analysis to determine whether to halt using a new system due to failures or determine if more observations are needed to make an adequate assessment. Specifically, we use EMR data to apply this methodology and show the tradeoff between sample size and the likelihood that the data converges to the current state of communication. This methodology will enable researchers to expedite the assessment of the impact of a technology, which is critical in a complex system such as the hospital.**

Index Terms - Healthcare simulation, risk analysis, temporal data analysis, transfer time, trauma team communication

INTRODUCTION

Hospitals are complex systems that require constant evaluation to ensure quality patient care and rely on a network of hierarchical communications between clinical roles. Poor communication between care providers, physicians and nurses increases length of stay (LOS), can lead to poor medical care and increases costs by $4 billion [1], [2]. The majority of clinical communication systems are comprised of inefficient and outdated paging networks, which cost the healthcare industry $5 billion a year [3]. Hence, time spent communicating takes away from time spent on actual patient care, which negatively impacts quality of care and increases health care costs [4].

Communication greatly impacts patient care and therefore must be highly effective and efficient. However, the complexity of the system makes isolating the impact of a change difficult. As a result, researchers typically rely on qualitative measures such as surveys and observations. With the advent of new technologies, electronic medical records can be used as an approach to capture quantitative metrics. The currently used qualitative measures have analytical limitations, which could be overcome with a more quantitative analysis using EMR data.

I. Data Collection Methods

Three common methods of medical data collection include surveys, on-site observations and abstraction from EMRs. Current research relies heavily on pre and post implementation surveys used to assess system performance, user feedback, attitudes towards system changes [5]–[17]. Survey responses are based on perceptions, which are biased due to the participant's role and many are reluctant to strongly agree or strongly disagree with statements [18]. A second method, on-site observations, can confirm findings from surveys, clarify the complexities of the system and focus on issues in detail and in depth [19]. However, observations are time intensive, not always feasible and depend significantly on the skills and beliefs of the researcher [19], [20]. In addition, on-site observations are not well accepted in the scientific community and can skew data due to the presence of the observer [19]. The third method, abstraction from EMRs, is an efficient and flexible data collection technology that allows records to be retrieved promptly when desired. Despite their efficiency, however, EMRs do not fully capture other tasks involved in data collection and habits for documentation vary across professionals leading to non-representative data [21]. Pairing quantitative EMR data with qualitative survey based interviews provides a more comprehensive, systematic analysis of trauma team communication.

II. Alternative Medical Communication System

The University of Virginia hospital trauma team currently relies on a system of pagers, wired telephones and cellular phones to coordinate the care of trauma patients and to contact other stakeholders in the patient care process. The current open-loop system lacks the feedback mechanisms necessary to alert team members when a critical message has been received and does not allow for messages to be sent to multiple staff members simultaneously. In order to improve

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the feedback mechanism, the hospital is experimenting with trunked radios in the Surgical and Trauma Intensive Care Unit (STICU) as a new closed-loop communication system. Trunked radios have the potential to improve the quality of care and decrease time to treat patients by promoting more direct communication between caregivers. Additionally, radios have the potential to reduce communication errors (broadcasting messages will allow others to hear messages and correct them), encourage a horizontal communication structure, eliminate unnecessary communications, and allow for more real-time updates. Most importantly, radios provide immediate feedback to all users as to whether or not a call has been received, thus closing the existing communication loop.

Methods

I. Data

The trauma team at UVa's tertiary care trauma center treated 1,811 trauma patients from July, 2013 to June, 2014. The Huron Consulting Group compiled patient records with information on patient LOS in the emergency department (ED). Patient LOS records time stamp critical events over the course of a visit to the emergency department. The data set also includes pertinent information such as initial patient condition, radiology count and number of medical consultants for each patient.

II. Communication Processes

We first identified the events most reliant on communication processes in order to analyze the impact that radios have on time spent communicating patient status in the hospital. The analysis focuses on two specific data points that radios heavily impact, *MD Seen to Disposition Decision* and *Disposition Decision to Departure* from the emergency department. *MD Seen to Disposition Decision* represents the time from when the patient sees the doctor to when the physicians have enough information to determine where the patient needs to go outside of the ED. Within this time, the MD evaluates the patient and communicates with the supervising physician. This step can also require communication with the trauma residents, consults, labs and the radiology department. *Disposition Decision to Departure* represents the time from when the disposition decision is made until the patient departs the ED. This step involves preparing a bed for the patient and requires communication between the MD, administrative staff and bed center.

III. Factors Impacting Patient Length of Stay

After identifying the most salient events in communication, the events are conditioned based on three different factors as represented by Figure 1. First, we condition data based on the three levels of severity (*Alpha, Beta, Gamma*) as they significantly impact the response from the trauma team. Patients in the most critical situation are given the *Alpha* designation, requiring the attending trauma surgeon to be present within 15 minutes of the patient arriving. Examples of *Alpha* alerts include but are not limited to airway obstruction, confirmed hypotension and gunshot wounds to the neck, chest and abdomen. *Beta* alerts require that the entire trauma team be present with the exception of the attending. Examples of *Beta* alerts include but are not limited to severe single system injury, cardiac arrests (blunt mechanism) and open or depressed skull fracture. *Gamma* alerts require treatment but time is not a critical factor. Examples of *Gamma* alerts include but are not limited to isolated injuries potentially requiring surgical repair. Second, we condition the data based on whether or not consults were required since they significantly impact patient transfer time.

Previous work shows that contacting consults is the biggest bottleneck in communication as it greatly increases patient LOS in the emergency department [5]. Third, the data is conditioned on the number of CT scans a patient receives in the emergency department since each scan increase a patient's LOS. For example, *Beta* and *Gamma* alerts are conditioned on the number of CT scans performed. A *Beta* trauma patient with no consults and 3 CT scans is denoted as "Beta No 3 CT." While all three variables are taken into consideration, there is insufficient data to model all combinations. For example, *Alpha* patients with consults are not included in the analysis since there were too few observations to develop a representative distribution. Similarly, *Alpha* patients without consults and *Beta* patients with consults are not conditioned on CT scans, as there is insufficient data available**.** Figure 1 below illustrates how *MD Seen to Disposition Decision* is conditioned. The same approach is used for *Disposition Decision to Depart*. Each node in Figure 1 indicates a subsample analyzed through simulation.

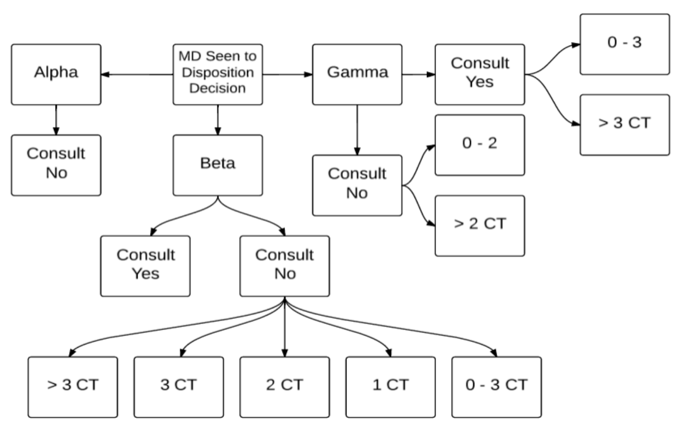

FIGURE 1
CONDITIONING *MD SEEN TO DISPOSITION DECISION DATA*

IV. Monte Carlo Simulation

This analysis uses Monte Carlo simulations to generate the proportion of convergence for subsamples of the different patient populations in Figure 1. Specifically, we randomly selected observations from various subpopulations for the Monte Carlo simulations. The samples are then smoothed using kernel estimations and tested against the original

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distribution to yield the outcome of the test. Monte Carlo simulations best suits this analysis as it develops probability distributions by using random numbers in equations that model events and repeating this process multiple times [22].

a. Kernel Estimation of Subpopulations

The analysis uses kernel smoothing function estimate (KSFE) in MATLAB R2014a on each subpopulation to distributions to test the consequences of an alternative communication system for the trauma team [23]. The default settings for KSFE in MATLAB utilize Gaussian kernels and an optimal bandwidth that is dependent on the estimated sample to create a density function.

The KSFE is a nonparametric technique that effectively represents multimodal data for future comparative analysis. Gaussian kernels estimate each observation in a sample as an individual normal distribution. The kernels run through a smoothing function, parameterized by bandwidth, to create a single density function from overlapping kernels. KSFE allows small data samples to form distributions more suitable for statistical testing than histograms. Figure 2 below illustrates the smoothing capabilities of KSFE compared to histogram values for *MD Seen to Disposition Decision* for all patients.

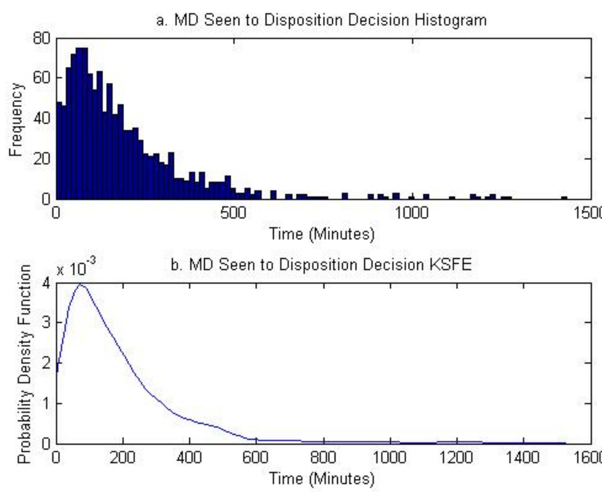

FIGURE 2
DATA DISPLAYED AS A HISTOGRAM IN PART A AND AS A DENSITY FUNCTION USING KSFE IN PART B

b. Calculating Proportion of Convergence

After developing distributions using the KSFE, the Kolmogorov-Smirnov (KS) test is employed to compare the original distributions to a subsample of random data points (without replacement) of pre-radio patient LOS times. The distribution of the patient data is non-parametric and non-paired, which requires analysis using either the KS test or Mann-Whitney (MW) test. The MW ranks the data to compare the medians and is better suited for ordering different probability [24]. The KS test calculates its statistic based on the maximum distance between two empirical distributions in order to determine if the test matches the known distribution [25]. As a result, this analysis utilizes the KS test to determine whether or not a subsample of the pre-radio data has the same distribution as the original sample.

After using the KS test, this analysis incrementally increases sample sizes to determine the minimum number of observations necessary to correctly estimate the original distribution. If a subsample is not significantly different from the parent distribution, then the sample converged to the true data set. Repeating the analysis for each sample size for 1,000 iterations produces a proportion of times a given sample size converges. A two proportion z-test determines the proportion of times a given sample size converges to the true distribution. The results include the minimum number of post-radio observations that will be needed to test the difference between the pre-radio and post-radio LOS. Next, the minimum number of observations is converted to the expected number of days needed for analysis. Risk analysis then uses the information to quantify whether or not there is a change in the post-radio scenario.

V. Risk Assessment

Finally, this analysis incorporates control charts in order to perform a risk analysis. While using the KSFE and KS test provides a method to determine the number of observations needed to analyze post radio communication, the state of communication must be continuously assessed. We use control charts to perform this constant assessment and evaluate risk by establishing a critical point at which the negative impact of a communication intervention such as radios is too great to merit further testing [26]. For example, if time between a doctor's disposition and patient departure from the emergency department increases significantly, medical experts must reevaluate the change in communication. In a hospital setting, risk analysis is vital due to the gravity of the consequences of failure.

RESULTS

I. Monte Carlo Simulation Results

We utilized Monte Carlo simulation with 1,000 trials to generate subsamples of varying sizes to determine the probability of convergence of the subpopulations. The probability of convergence is then determined by comparing the subsamples to the parent distributions using the KS test. This simulation generated the number of observations needed to develop a representative sample.

We then converted the number of observations to the expected number of days required based on the frequency of patient arrival for the specific subpopulation. Figure 3 demonstrates how a specific population subset compares to the overall patient patterns on both proportion of convergence and total number of days. The blue Y-axis labeled "Proportion of Converge" indicates the proportion of time a given sample size converges. The green Y-axis labeled "Days" indicates the estimated number of days needed for a given sample size. Figure 3 shows the results for *MD Seen to Disposition Decision* for both the whole

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population [smooth line] and *Beta* trauma alerts without consults and more than 3 CT scans [line marked with asterisks]. Figure 3 illustrates the need to analyze a variety of subpopulations since different populations converge at different rates. Subpopulations converge with a smaller sample size than the entire population. Smaller sample sizes do not imply shorter implementation times as patients in the specific subpopulations are less likely to enter the emergency department.

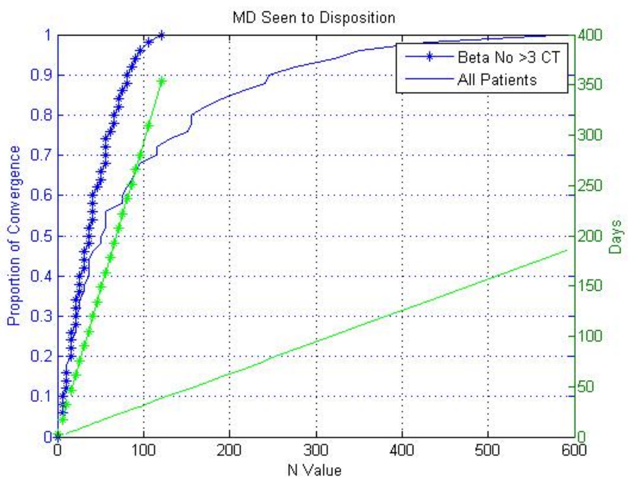

FIGURE 3
PROPORTION OF CONVERGENCE FOR "ALL PATIENTS" AND "*BETA*, NO, >3 CT" USING *MD SEEN TO DISPOSITION DECISION*

Tables I through IV formalize these results for 30 different subpopulations. The subpopulations are based on levels of severity (*Alpha,* α; *Beta,* β; *Gamma,* γ), presence of consults (yes, 1; no, 0), and number of CT scans (denoted by "CT" and the number of scans) The values in the tables represent the number of days (rounded up to the nearest whole number) needed for the data set to converge to the parent distribution at a given confidence level (C). For example, to assess a distribution for *MD Seen to Disposition Decision* of all patients in the emergency department, the analysis requires 105 days to converge with 95% confidence whereas 80% confidence only requires 49 days of observations. The decision to end testing at 80% confidence vs. 95% depends on the system at hand. The hospital is a critical system where the impact of a system change must be accurately captured and waiting the entire 105 days to be 95% confident might be necessary. If a less critical system is being tested, or if a situation requires timely analysis, it may be beneficial to stop testing at the 80% confidence level. In the case of *MD Seen to Disposition Decision* for all patients, reducing the confidence would cut implementation time by more than half, or 64 days.

Tables I through IV enable the user to assess the tradeoff between the proportion of convergence versus the number of days analysts are willing to wait for future analysis. Tables I and II contain the values for *MD Seen to Disposition Decision* and Tables III and IV contain values for *Disposition Decision to Departure*. All tables also show the significant difference in number of days need for more complex cases. In Table I, *Beta* patients with no consults and more than 3 CT scans (β, 0, CT > 3) requires 273 days to converge at a 95% confidence level while all patients requires 105 days to converge at the same confidence level. This pattern of more complex subpopulations requiring more days to converge is consistent between both *MD Seen to Disposition Decision* and *Disposition Decision to Departure*.

TABLE I
NUMBER OF DAYS FOR ALPHA AND BETA SUBPOPULATIONS TO CONVERGE AT VARIOUS CONFIDENCE LEVELS FOR *MD SEEN TO DISPOSITION DECISION*

C	Total	α	α, 0	β	β, 1	β, 0	β, 0 CT≤3	β, 0 CT >3
95%	105	181	190	213	191	264	271	273
80%	49	93	120	135	120	138	190	74
65%	28	71	74	75	63	85	140	57
50%	16	49	51	40	50	53	85	40

This pattern is largely a function of how frequently the event, such as *Beta* patients without consults and more than 3 CT scans, occurs. Infrequent events will require more days as they are not as likely to be present in the dataset. Stakeholders will analyze the graphs and tables of different populations to determine if the sample size is sufficiently large to accurately assess the state of communication in the emergency department. The results enable the users to understand the tradeoff between the length of the observation period and the probability of having a representative sample.

TABLE II
NUMBER OF DAYS FOR GAMMA SUBPOPULATIONS TO CONVERGE AT VARIOUS CONFIDENCE LEVELS FOR *MD SEEN TO DISPOSITION DECISION*

C	γ	γ, 1	γ, 1 CT≤ 3	γ, 1 CT >3	γ, 0	γ , 0 CT ≤ 2	γ , 0 CT > 2
95%	74	129	155	285	122	80	218
80%	36	64	82	200	53	41	155
65%	22	40	59	103	27	28	85
50%	15	25	36	78	21	16	41

II. Leveraging Control Charts for Risk Analysis

In emergency situations, any procedural changes must be closely monitored to ensure that they do not result in unintended negative consequences. Simulation outputs measure the long-term effectiveness of system changes in the hospital, but a risk analysis method must be implemented to determine if any alteration is negatively impacting the system. To quickly detect impact, two different control charts must be used simultaneously. A standard control chart will immediately determine if sequential observations are trending negatively after an intervention. Similarly, an $\bar{x}$ and R plot monitors change until a sufficient sample size is collected for full simulation analysis. An $\bar{x}$ plot analyzes the mean of small samples to track trends, while an R plot

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displays the range of the samples to monitor statistical dispersion. Combining these two control charts along with the simulation provides a detailed method for immediate, short term and long term risk analysis in order to determine the overall effect of a procedural change.

TABLE III
NUMBER OF DAYS FOR ALPHA AND BETA SUBPOPULATIONS TO CONVERGE AT VARIOUS CONFIDENCE LEVELS FOR *DISPOSITION DECISION TO DEPARTURE*

C	Total	α	α, 0	β	β, 1	β, 0	β, 0 CT≤3	β, 0 CT >3
95%	173	280	282	102	134	99	132	267
80%	49	203	190	61	77	57	79	189
65%	35	137	144	41	63	41	54	139
50%	23	93	109	29	35	29	35	89

TABLE IV
NUMBER OF DAYS FOR GAMMA SUBPOPULATIONS TO CONVERGE AT VARIOUS CONFIDENCE LEVELS FOR *DISPOSITION DECISION TO DEPARTURE*

C	γ	γ, 1	γ, 1 CT≤ 3	γ, 1 CT >3	γ, 0	γ , 0 CT ≤ 2	γ , 0 CT > 2
95%	173	269	269	163	217	213	270
80%	109	195	184	103	135	143	91
65%	79	137	139	78	87	105	53
50%	53	102	105	54	46	80	41

CONCLUSIONS

This paper presents a framework for evaluating the implementation of a new communication system at the UVa hospital. Radio implementation for the trauma team serves as a case study to demonstrate how many observations are needed to evaluate the impact a new technology. The case study proposes coupling control charts, used for risk analysis, with temporal distribution analysis. The temporal analysis utilizes the KS test applied to KSFEs to determine the number of observations needed to judge the effectiveness of radios in reducing patient transfer times with the corresponding number of days. The analysis was repeated using Monte Carlo simulations for 1,000 trials to determine the proportion of convergence for each sample size. Choosing the number of observations needed represents a critical tradeoff between speed of decision-making and confidence that there is sufficient data to make an informed decision. Although the analysis is performed on communication times in a hospital, the same methodology may be applied to analysis of other technological interventions. Specifically, providing information on distribution convergence and sampling times allow experts to make informed decisions specific to their own practice. Along with control charts, the outlined methodology provides a template for experts to analyze the short and long term effects of implementing system changes.

FUTURE WORK

Future work includes performing this analysis with post radio implementation observations. This presents an opportunity to both compare distributions pre and post radios and also confirm if the number of days required to converge is accurate. Future work also requires determining the ideal tradeoff between the proportion of convergence and number of days to obtain proper sample size. The results of this analysis can also be used to corroborate perception about the impact of the radios. Major limitations of this study revolve around using one year of data. Since a small sample size is used, seasonality could not be examined in the analysis. Additionally, certain subpopulations did have not enough observations to develop a representative distribution. While analysis of EMR data provides a systematic mechanism to monitor the impact of technology on clinical workflow, this analysis should be coupled with observations, interviews, and surveys to understand the full impact of interventions.

REFERENCES

[1] R. Agarwal, D. Z. Sands, and J. D. Schneider. July-August 2010. "Quantifying the economic impact of communication inefficiencies in U.S. hospitals.," *J. Healthc. Manag.*, 55(4), pp. 265–281.

[2] JCAHO. 2003. "Sentinel event statistics - May 7, 2003 (Sentinel events reviewed by JCAHO 1995 - 2003)," *Joint Commission on Accreditation of Healthcare Organizations*.

[3] Ponemon Institute. May 2013. "The Economic and Productivity Impact of IT Security on Healthcare Sponsored by Imprivata,"

[4] FEMA. October 2008. "Voice Radio Communications Guide for the Fire Service,"

[5] L. Ngo, K. Walker, A. Holowinsky, *et al*. May 2014. "Analysis of Communication Patterns in Critical Care Environments," in *Systems and Information Engineering Design Symposium*, Charlottesville, VA, pp. 129–134.

[6] F. Ighani, K. G. Kapoor, S. K. Gibran, *et al*. August 2010. "A comparison of two-way text versus conventional paging systems in an academic ophthalmology department," *J. Med. Syst.*, 34(4), pp. 677–684.

[7] A. F. Guerrero, L. B. Nuñez, J. C. Thompson, *et al*. January 2009. "Alphanumeric paging in an academic military hospital setting.," *Mil. Med.*, 174(1), pp. 82–85.

[8] T. C. Nguyen, A. Battat, C. Longhurst, *et al*. April 2006. "Alphanumeric paging in an academic hospital setting," *Am. J. Surg.*, 191(4), pp. 561–565.

[9] B. M. Wong, S. Quan, S. Shadowitz, *et al*. October 2009 "Implementation and evaluation of an alphanumeric paging system on a resident inpatient teaching service," *J. Hosp. Med.*, 4(8)

[10] P. S. Jacques, D. J. France, M. Pilla, E. Lai, *et al*. Febuary 2006. "Evaluation of a hands-free wireless communication device in the perioperative environment.," *Telemed. J. E. Health.*, 12(1), pp. 42–49,

[11] S. Breslin, W. Greskovich, and F. Turisco. October 2004. "Wireless technology improves nursing workflow and communications.," *Comput. Inform. Nurs.*, vol. 22(5), pp. 275–281.

[12] C. O'Connor, J. O. Friedrich, D. C. Scales, *et al*. October 2009. "The Use of Wireless E-Mail to Improve Healthcare Team Communication," *J. Am. Med. Informatics Assoc.*, vol. 16(5), pp. 705–713.

[13] R. C. Wu, D. Morra, S. Quan, *et al*. November/December 2010. "The use of smartphones for clinical communication on internal medicine wards," *J. Hosp. Med.*, 5(9), pp. 553–559.

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[14] O. Aziz, S. S. Panesar, G. Netuveli, *et al*. August 2005. “Handheld computers and the 21st century surgical team: a pilot study.,” *BMC Med. Inform. Decis. Mak.*, 5, p. 28.

[15] T. R. Hansen and J. E. Bardram. 2007. “Applying mobile and pervasive computer technology to enhance coordination of work in a surgical ward.,” *Stud. Health Technol. Inform.*, 129(1), pp. 107–111.

[16] K. A. Locke, B. Duffey-Rosenstein, G. De Lio, *et al*. January 2009. “Beyond paging: Building a web-based communication tool for nurses and physicians,” *Journal of General Internal Medicine*, 24(1). pp. 105–110.

[17] M. E. Seddon and D. Hay. October 2010. “Task Manager: An innovative approach to improving hospital communication after hours,” *N. Z. Med. J.*, 123(1324), pp. 57–66.

[18] N. J. Napoli, W. Barnhardt, J. Young, *et al*. June 2014. “Analysis and Evaluation of Clinical Communication in the Surgical Intensive Care Unit,” in *Human Factors and Ergonomics Society International Annual Meeting in Health Care 2014*, Chicago, IL, 3(1), pp. 142–147.

[19] C. Anderson. October 2011. “Presenting and evaluating qualitative research,” *Am. J. Pharm. Educ.*, 74(8).

[20] “Selecting Data Collection Methods,” CDC, Atlanta.

[21] C. Dimick. June 2008. “Documentation bad habits. Shortcuts in electronic records pose risk.,” *J. AHIMA*, 79(6), pp. 40–43.

[22] R. Carsel, R. Parrish. May 1988. "Developing Joint Probability Distributions of Soil Water Retention Characteristics". Water Resources Research, 24(5). pp. 745-769.

[23] “MATLAB.” 2003. The MathWorks Inc., Natick.

[24] H. Mann and D. Whitney. March 1947. “On a test of wether one of two random variables is stochastically larger than the other,” *Ann. Math. Stat.*, 18(1), pp. 50–60.

[25] R. Wilcox. July 2005. “Kolmogorov–Smirnov Test,” *Encycl. Biostat.*, pp. 83–90.

[26] K. Lee and C. McGreevey. Febuary 2002. “Using control charts to assess performance measurement data,” *Jt. Comm. J. Qual. Patient Saf.*, 101(12), pp. 90–101.

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