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Message from the Conference Program Chair

Utkarsh Shrivastava, Haworth College of Business, WMU

It has been an incredible journey for the Center for Health Information Technology Advancement (CHITA) at WMU to hold this biennial event since 2011. Like our previous events, this year as well, we have seen an increasing trend in the research contributions to our conference. Based on this year’s conference theme, “Transitioning to Smart Care: Challenges, Strategies, and Solutions,” we have accepted fifteen quality research papers, authored by forty-seven scholars, spread across multiple disciplines including nursing, health administration, computer science, management, and business information systems. The articles focused on a variety of topics, used diverse research methods, and have come up with interesting findings. To summarize the contributions, we have classified the accepted papers into five groups. A brief highlight is given below for each of these five categories.

A) HIT Applications for Healthcare. This category consists of three papers. An article authored by Valerie Pauli examines the factors that impact the adoption of interactive video technologies for online nursing courses. In the second paper, Singh and Varshney propose and analytically investigate three patient-level technology-based interventions to prevent the development of Opioid addiction. Lastly, Lee, Chagnon, and Marfa investigate the impact of IT investment by the hospitals on their financial performance and the quality of care.

B) Innovative Use of HIT. Three studies in this category focus on novel uses of IT in healthcare. The research by Fan-Osuala investigates the influence of message communication style in a medical crowdfunding campaign on funding performance and reception of emotional support. Maarup, Dohan, Zhao, and Wu, through qualitative research, study the perception of non-physician practitioners on technological innovations such as Chatbots. The third article by Lavariega-Jarquin, Schenker, Avila, and Gómez-Martinez describes the design and development of a mobile-based application for heat stress prevention.

C) HIT for Process Improvement. Three articles in this category focus on using HIT for improving hospital operations and workflow. The first paper, authored by Buxton, Knight, and Shrivastava, investigates the impact of integrating the vital sign monitoring device with the Electronic Medical Records on the efficiency of patient care services. In the second article, Ryan, Doster, Daily, and Lewis conduct a longitudinal study to understand the impact of business process redesign before the health IT integration on the hospital operations. Finally, Knight uses Lean and PDSA process improvement tools to understand the impact of automating the extraction of patient information on the efficiency and effectiveness of the audit process.

D) HIT and Patient Care. This category comprises of three research papers focusing various aspects of HIT and patient care. First paper by Spivak, Dohan, Wu and Zhao studied how patient trust influences their use of online portals for health related information. The second study by Oliver and Brown investigated the role of Practice Based Research Networks (PBRN) is encouraging pragmatic clinical trial research. The third study by Tusch, Higbea, Vanderkooi, Warkoczieski, Sankey, and Cole developed and tested a framework for understanding the unintended consequence from the adoption of an Electronic Health Record systems.

E) Health Analytics. Finally, the health analytics category also has three papers. The article by Tindol, Shrivastava, and Chen relates the disease progression patterns with online search information and healthcare costs. Alsaeid, Fong, Qader, Niaz, and Altaie use longitudinal patient data to build a computational model for early detection of the transition of a Mild Cognitive Impairment (MCI) to Alzheimer’s disease. Finally, the study by Siyu, Luo, and Fang uses a time series analysis with a generalized additive model to understand the association between air pollution and healthcare costs.

Having a collection of quality papers is not possible without the efforts of quality reviewers. Finally, sincere thanks must be directed to all paper reviewers (See Page 164). Without their tireless and professional critiques, it is impossible to have this volume of publication.
Message from the Transactions Editor

Huei Lee, Ph.D. Professor of CIS, Eastern Michigan University

It is my pleasure to present the Transactions of the International Conference on Health Information Technology Advancement, which is related to the ICHTA-2019 held in the Western Michigan University, Kalamazoo, Michigan on October 31 and November 1, 2019. I would like to express my appreciation to Bernard Han, Conference Co-chair of the ICHITA-2019 and co-director of Health Informatics and Information Management at WMU, for his outstanding leadership. Through his help, the editorial process became easier and smoother.

This was the fourth year to publish the Transactions. Since the last time, new information technologies have emerged as essential tools for healthcare systems. These technologies include Internet of Things (IOT), healthcare analytics, 3D printing, and virtual reality. Attending an academic/professional conference allows us to gain updated knowledge in both theories and practices. The purpose of this conference is not only to discuss the information systems of health care applications, but also to discuss academic curriculum trends and critical issues related to health care information systems. This year we received more submissions than we had expected. This volume contains about fifteen refereed papers in five categories, developed by more than forty authors and co-authors. These five categories are: A) HIT Applications for Healthcare, B) Innovative Use of HIT, C) HIT for Process Improvement, D) HIT and Patient Care, and E) Health Analytics. These papers have been gone through a rigorous double-blind review process. The Transactions publishes hard copy and online edition. The best papers will be considered for publication in the coming issues of International Journal of Healthcare Information Systems and Informatics. Secondly, I want to thank the authors, presenters, and reviewers for their persistent hard work for these papers/reviews for the Transactions of the ICHITA-2019 conference. I know that it was a lot of hard work, but it was well worth.

Finally, I would like to thank everyone again for their participation in the ICHITA-2019. It has been an honor and a privilege to serve as the transactions editor. Without your help and support, the Transactions would not have been possible. In addition, the committee will greatly appreciate it if you can provide them with ideas and issues so that they can improve the quality of the Transactions in the future. We wish you enjoy the conference in Western Michigan University and look forward to seeing you again in future ICHITA conferences.
Usefulness and Ease of Interactive Video Technology Integration among Faculty Members in Online Nursing Courses

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Abstract: A descriptive correlational design was used in this study to evaluate faculty perceptions of the usefulness and ease of interactive video technology integration in online nursing courses, in order to predict behavioral intention. This paper presents The Technology Acceptance Model (TAM) related hypotheses in the study which all showed positive correlations that were statistically significant. Using innovative technology to deliver course content that relates to healthcare technology, and supports student learning, is critical to clinical technology competency acquisition and implementation of best-practice in academia.

INTRODUCTION

According to Williamson and Muckle (2018), the Technology Informatics Guiding Education Reform (TIGER) initiative recommends that all nurses develop informatics competencies during their educational studies. The caveat is how nursing faculty are integrating technology in online courses to engage students in active and social learning in order to assist students in developing informatic competencies which will be needed in clinical practice. The significance is twofold: 1) nursing accrediting bodies call for integration of technology across nursing curriculums, and 2) the “millennial” generation expects faculty to implement technology to enhance the learning experience (May et al., 2013).

Technology not only plays an integral role in nursing practice, but it is essential in nursing education. While the concept of online course offerings has been realized through advances in technology such as learning management systems (LMSs), faculty struggle to implement the newest technologies in online courses which engage students, enable social learning, and enhance the learning experience. In addition, selecting practical multimedia materials for a class is a new challenge for educators (Weng, Yang, Ho, & Su, 2018). Posting static video lectures is one method of content delivery in online courses, but it does not afford the student an opportunity to interact with faculty or peers nor does it build informatic competencies. As noted by Zhang, Zhou, Briggs, and Nunamaker (2006), “interactive video technology increases learner-content interactivity, thus potentially motivating students and improving learning effectiveness” (p. 17). Interactive video technology refers to technology used by faculty that enables students to interact with video content itself through a variety of modalities such as clicking, dragging, scrolling, gaming, immediate response systems, videoconferencing, or gesturing. Telehealth is another example of interactive video technology that can be used in online nursing courses and relates directly to current technology use in the healthcare sector.

Barriers must be recognized in behavioral intention to integrate technology into nursing courses. Merrill (2015) highlighted how the integration of technology has the potential to be very stressful on nursing faculty who possess limited knowledge of the use of computers and technology. In addition, educators must be familiar with content of multimedia teaching as well as gathering teaching material which brings additional burdens (Weng et al., 2018). At the current time there are limited findings from research in regards to the integration of technology into nursing education settings (Williamson & Muckle, 2018). Integration of technology should not only enhance the delivery of content and increase student engagement, but it should also improve the teaching and learning process. May et al. (2013) highlighted how various technology is available to nurse educators, and when used appropriately can augment and enhance both the classroom and clinical experience. By understanding faculty’s behavioral intention to use interactive video technology, which therefore determines technology acceptance, this information can be used to guide processes of technology selection and implementation as well as recognizing external variables that impact behavioral intention and acceptance.
CONCEPTUAL FRAMEWORK

This study incorporated the Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bogozzi, & Warshaw, 1989) as the conceptual framework which is one of the most influential theories for examining new technology acceptance and adoption (Chen, Sivo, Seilhamer, & Sugar, 2013; Pavlou & Fygenson, 2006). The TAM has been validated as reliable for predicting the acceptance or adoption of new technologies by end-users and provides a causal relationship for explaining or predicting technology acceptance among users based off of their perceptions, attitudes, and intentions (Alharbi & Drew, 2014; Chuttur, 2009; Davis, Bogozzi, & Warshaw, 1989; Lai, 2017). Based on the TAM, there were four constructs that influence overall interactive video technology acceptance. Behavioral intention was the end construct and an important factor that determines whether faculty will actually utilize interactive video technology in online nursing courses to enhance the scholarship of teaching and learning. Perceived usefulness is the faculty’s internal belief that interactive video technology can enhance their teaching/job performance. Perceived ease of use is the faculty’s internal belief that integration of interactive video technology into online nursing courses can be done effortlessly. Feelings faculty possess in regards to using interactive video technology were measured by the attitudes construct. Furthermore, the TAM theorizes that perceived usefulness and perceived ease of use are affected by external variables (Davis, Bogozzi, & Warshaw, 1989). The two external variables of interest in this study were usage experience and job relevance. Therefore, perceived usefulness and perceived ease of use are affected by these variables and mediate the effect of users experience and job relevance on end user’s attitude and behavioral intention, therefore impacting actual interactive video technology use.

METHODOLOGY

Research Design and Sample

A descriptive correlational design was used in this study. The study sample consisted of nurse educators in the United States who had an active membership in Sigma Theta Tau International Honor Society of Nursing (Sigma). These faculty had given consent upon joining the organization to be involved in research. The response rate among the targeted 820 (N=820) members was 6.5%, or 53 members willing to participate voluntarily in this study. Among the 53 respondents to the study invitation, 7 (13%) failed to complete the survey, therefore were omitted from the study. All remaining 46 respondents completed the survey questions pertinent to the study in its entirety. Thus, the final sample size for the study was n = 46. This convenience sample of nurse faculty allowed for a diverse population to participate in the study. Participants completed an electronic survey. Research began after Institutional Review Board (IRB) approval.

Hypothesis

The following hypotheses (H) tested in the study aligned with the purpose of the study which was to evaluate faculty perceptions of the usefulness and ease of interactive video technology integration in online nursing courses, therefore defining the acceptance of this technology through behavioral intention. The five TAM-related hypotheses were as follows:

H1: Perceived ease of use positively affects perceived usefulness of interactive video technology.
H2: Perceived ease of use positively affects attitudes towards using interactive video technology.
H3: Perceived usefulness positively affects attitude towards using interactive video technology.
H4: Perceived usefulness positively affects intention to use interactive video technology.
H5: Attitude towards using positively affects intention to use interactive video technology.

Instrument

In this study, a questionnaire survey was disseminated to investigate the acceptance of interactive video technology in online nursing courses of nurse educators in the United States. The survey was based on the constructs validated by Davis (1989) and adapted to the context of this study. The scale uses a 5-point Likert Scale, ranging from 1-Stongly Disagree to 5-Stongly Agree. The original TAM is comprised of six questions that measure perceived
usefulness (PU) and six questions that measure perceived ease of use (PEOU). The two determinants for attitude are PU and PEOU, and according to the TAM, PU has an independent effect on behavioral intention while PEOU has an effect on PU (Davis, 1989). Cronbach’s alpha was used to address reliability concerns for internal consistency. Constructs are considered to have internal consistency reliability when the Cronbach’s alpha exceeds 0.70. In this study, the reliability assessment was done using Statistical Package for Social Sciences (SPSS) version 25. All measures in this study show a good to excellent level of reliability, ranging from 0.865 to 0.934, the results are as follows: perceived usefulness scale (Cronbach’s α = 0.887), indicating the internal consistency of the questionnaire was good; perceived ease of use scale (Cronbach’s α = 0.889), indicating good; attitude towards use scale (Cronbach’s α = 0.865), indicating good; behavioral intention scale (Cronbach’s α = 0.893), indicating good and behavioral intention scale-job relevance scale (Cronbach’s α = 0.934), indicating excellent. The pattern of internal consistency was consistent with published research and the overall instrument reliability had a Cronbach’s α of 0.950. Measurement criteria of this study was revised based on the related literature and discussed with invited experts. Dr. Davis granted permission to use the tool. The survey was disseminated via electronic format through the Sigma members only platform known as The Circle. The survey questions can be located in Appendix A.

DATA ANALYSIS AND RESULTS

Demographic data

Demographic information was analyzed with descriptive statistics generated by SPSS version 25. Of the surveys completed, 98% of the participants were female and 2% were male. The majority of participants were Caucasian (92%). The participants work setting showed that 47% worked in a private university, 38% in a public university, 11% in a community college, and 4% in a technical college. Academic rank of participants included 17% Professors, 20% Associate Professors, 33% Assistant Professors, 2% Lecturer, and 28% Instructor. The majority of participants were between 50 to 69 years, with 7% from 31 to 39, 20% from 40-49, 33% from 50-59, 35% from 60-69, and 7% above 70. Participants level of education ranged from Doctoral Degree 57%, Master’s Degree 41%, and Baccalaureate Degree 2%. Participants indicated they worked primarily in the following programs: Associate Degree Nursing (ASN) 13%, Bachelor of Science in Nursing Completion (RN-to-BSN) 11%, Pre-Licensure Bachelor of Science in Nursing (BSN) 44%, Masters of Science in Nursing (MSN)-Education, MSN- Leadership, and MSN-Advanced Practice 9% respectively, Doctorate of Nursing Practice (DNP) 4%, and other 1%. Usage experience ranged from over five years (32.6%), 3-5 years (8.7%), 1-3 years (19.6%), less than a year (21.7%), and concluded with no use (15.2%).

Hypotheses

Spearman’s Rho is commonly used in correlational research when variables are measured at the ordinal level and was the statistical approach in this study to examine the relationship between variables used within the study. Hypothesis testing on the relationship between TAM variables are presented next.

The first hypothesis was “Perceived ease of use positively affects perceived usefulness of interactive video technology.” Using Spearman’s Rho correlation, a statistically significant strong positive relationship can be observed between perceived ease of use and perceived usefulness ($r_s = .659, p< .05, N=46$), thus supporting hypothesis 1.

The second hypothesis was “Perceived ease of use positively affects attitudes towards using interactive video technology”. Using Spearman’s Rho correlation, a statistically significant moderate positive relationship can be observed between perceived ease of use and attitude towards usage ($r_s = .481, p< .05, N=46$), thus supporting hypothesis 2.

The third hypothesis was “Perceived usefulness positively affects attitude towards using interactive video technology”. Using Spearman’s Rho correlation, a statistically significant strong positive relationship can be observed between perceived usefulness and attitude towards usage ($r_s = .745, p< .05, N=46$), thus supporting hypothesis 3.

The fourth hypothesis was “Perceived usefulness positively affects intention to use interactive video technology.” Using Spearman’s Rho correlation, a statistically significant strong positive relationship can be observed between perceived usefulness and behavioral intention ($r_s = .768, p< .05, N=46$), thus supporting hypothesis 4.
The fifth hypothesis was “Attitude towards using positively affects intention to use interactive video technology.” Using Spearman’s Rho correlation, a statistically significant very strong positive relationship can be observed between attitude toward usage and behavioral intention to use ($r_s = .849$, $p< .05$, $N=46$), thus supporting hypothesis 5.

**DISCUSSION**

In this study, all five TAM-related hypotheses were proven to have positive correlations that were statistically significant. Overall, the findings from this study are consistent with the original TAM and published research. Nursing faculty who participated in this study showed positive attitudes towards using interactive video technology and intent to use this technology in their courses, which was the most dominant determinant of behavioral intention with a correlation coefficient of .849. These findings were similar to findings by Teo (2012) in that from the direct effects on behavioral intention, inferences can be made that when nursing faculty have positive attitudes and believe that technology will improve their work performance, they are likely to use that technology. Findings also indicate that when nursing faculty perceived interactive video technology as easy to use, they developed positive attitudes toward integrating it. Not surprisingly, perceived usefulness increased positivity toward use of interactive video technology which affected behavioral intention to use, these results were similar to results noted in a study conducted by Alharbi and Drew (2014). Technology with high perceived usefulness indicates that users believe in a positive use-to-performance relationship.

The two external variables studied included usage experience and job relevance. Surprisingly, the results show no significant correlation between usage experience and perceived usefulness, perceived ease of use, and behavioral intention to use. A very weak relationship can be observed between usage experience and perceived usefulness ($r_s = -.163$, $p=.285$, $N=46$), a weak relationship can be observed between usage experience and perceived ease of use ($r_s = -.372$, $p=.012$, $N=46$), and a very weak relationship can be observed between usage experience and intention to use ($r_s = -.198$, $p=.192$, $N=46$). The results of usage experience to the TAM constructs imply that these variables may not relate to one another and the direction cannot be deciphered. One reason for this may be due to the randomness affecting one or both variables, or perhaps other variables affect the two variables in question. Therefore, the moderator of usage experience did not have statistically significant effects on the TAM constructs and the direct relationship was not strong.

In terms of job relevance, a statistically significant strong positive relationship can be observed between job relevance and perceived usefulness ($r_s = .753$, $p< .05$, $N=46$) as well as a weak positive relationship between job relevance and perceived ease of use ($r_s = .434$, $p< .05$, $N=46$). Job relevance had statistically significant positive relationships with both perceived usefulness and perceived ease of use, which subsequently affects behavioral intention to use. Nursing faculty believe using interactive video technology is relevant to their job and is a useful resource. Age, academic rank, and highest earned degree did not correlate significantly with other variables. This was not a surprise as usage experience did not correlate with study constructs either. Furthermore, the study did not differentiate between voluntary use settings, mandatory use settings, or different types of technology used.

**Implication to Practice**

Academic freedom can allow for voluntary integration of resources in the delivery of course content. Therefore, it is important to explore the perceptions of nursing faculty toward new technologies whose use is voluntary and investigate which perceptions correlate with acceptance and use. This means that nursing faculty need more information and knowledge about interactive video technology as a product and evidence-based integration strategies which supports student learning outcomes and have job relevance. This knowledge could potentially offset the burdens and time constraints related to content development and integration of technology into course load. With that said, nursing educators and students may feel burdened or overwhelmed with this technology but students learn more when they are involved in both the academic and social aspects of the educational experience according to Astin's theory (1984) of involvement. Furthermore, administrators should devise implementation strategies and support structures that foster successful experiences in the use of technology for nursing faculty and students, which may lead to positive attitudes toward the use of interactive video technology and thus, strong intention to use (Teo, 2012). Lastly, interactive telehealth is a growing in popularity in the healthcare sector. According to McLendon (2017), telehealth may be an option for improving access to cost-effective quality care and reducing risks of chronic health complications. As noted by van Houwelingen, Moerman, Ettem, Kort, and Cate (2016), most nurses are insufficiently
trained to use these technologies effectively, thus the potential of telehealth fails to reach full utilization. Telehealth is a form of interactive video conferencing which as significant job relevance for nurses involved in clinical practice; therefore, students experienced with this technology through exposures in nursing coursework may have established positive attitudes regarding its use and ease of use, thus impacting behavioral intention to use this technology to improve patient care and impact patient outcomes.

Limitations

The limitations of this study include a small sample size based on g-power analysis and overall low survey response rate which impacts generalization. Another limitation was the self-report questionnaire and the fact that the majority of participants were female and Caucasian. Moreover, other statistical tests could be conducted on data as well as exploring the impacts and relationships of external factors such as technology availability and usage mandates. Lastly, the focus of the study was not on one specific interactive technology platform so no data was collected to explore what was being utilized and whether or not that was a factor in end system use or acceptance.

CONCLUSION

This study modified the original TAM in order to evaluate faculty perceptions of the usefulness and ease of interactive video technology integration in online nursing courses so that the research could measure behavioral intention to use said technology. The core constructs of the TAM were adopted for this study and used to develop the five hypotheses. Findings in this study were consistent with empirical evidence and prior findings from the utilization of the TAM and validates the relationship between perceived ease of use, perceived usefulness, attitude towards usage, and behavioral intention to use. The results of this study add to the body of knowledge related to nursing education as no other studies looked exclusively at the acceptance of interactive video technology in online nursing courses. The main contribution of this study is to predict behavioral intention based off of the TAM constructs. Further research will need to explore specific barriers to the integration of interactive video technology in online nursing courses so that technology can be used to provide learners an interactive learning experience and build upon informatic competencies. This study incorporated external variables such as usage experience and job relevance. Within the context of this study, job relevance had a positive relationship with the TAM constructs. One cannot assume usage experience to be an indicator of perceived usefulness, perceived ease of use, or predict behavior to use. Administrators in higher education may benefit from this study in their future plans to purchase or implement interactive video technology into online courses. Licensing agreements can be costly and limited, therefore fiscal responsibility is of importance while investing in technology to enhance the teaching and learning experience while also aligning technologies implemented with healthcare sector trends.

As noted by Weng et al. (2018), multimedia teaching has gradually substituted traditional teaching. Technology tools such as interactive video platforms offer an innovative method of content delivery and engage faculty and students in the use of technology as well as the teaching-learning process (Khan, Egbue, Palkie, & Madden, 2017). Interactive video that provides individual control over random access to content may lead to better learning outcomes and higher learner satisfaction (Zhang et al., 2006). Results from a study conducted by Hunga, Kinshukc, and Chen (2018) showed that learners who learned with embodied interactive video lectures performed better in comprehension and retention of learning content which provides needed evidence to nurse educators on best practices in education. LMSs tend to be focused, lack personal interaction, and have less capacity for networking than social media sites according to Brady, Holcomb, and Smith (2010); Chen and Bryer (2012), but that could change if interactive video technology was integrated and utilized in LMSs. Furthermore, Albayrak and Yildirim (2015) found that the use of social networking sites as a form of an LMS has the potential to increase out-of-class communication among instructors and expose students to the interactive capabilities that are similar to interactive video technology offerings in LMSs. Results of the current study has implications in nursing courses. The culture in nursing programs is shifting toward more technology. Advances in emerging technologies offer nurse educators a variety of current and future teaching applications (Foronda et al., 2017). The integration of interactive video technology must be used to maximize building interactions, communication, and relationships with students who are enrolled in online learning either through social networking sites or LMSs. Albiet, Bowman and Akcaoglu (2014) noted that students do not currently use LMSs to communicate with their instructor and peers which is a major concern in terms of soft skills necessary in the profession of nursing and for student retention, attrition, and informatic competency skills. Communication is an expected skill in the profession of nursing; therefore, nurses need to be prepared to use similar technology in patient-care areas.

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allowing one to communicate with the healthcare team, patients, and families. As noted by healthcare experts, the importance of being able to communicate clearly in videoconferencing and knowing what to do to enhance contact with patients is an essential technology skill required in nursing (van Houwelingen, Moerman, Ettem, Kort, & Cate, 2016). The use of interactive video technology allows nursing educators to transform the educational experience while meeting a call-to-action to integrate technology in nursing curriculums which prepare future nurses in the use of a wide range of healthcare technologies to improve patient outcomes and increase access to care.
APPENDIX A: MODIFIED TAM TOOL FOR STUDY

Perceived Usefulness (PU):

Q1. Using interactive video technology in online and/or hybrid nursing courses would enable me to control the pedagogy.

Q2. Using interactive video technology in online and/or hybrid nursing courses would enhance my teaching performance.

Q3. Using interactive video technology in online and/or hybrid nursing courses would increase my productivity.

Q4. Using interactive video technology in online and/or hybrid nursing courses would enhance my effectiveness on the job.

Q5. Using interactive video technology in online and/or hybrid nursing courses would make it easier to do my job.

Q6. I would find using interactive video technology in online and/or hybrid nursing courses useful in my job.

Perceived Ease of Use (PEOU):

Q7. Learning to operate interactive video technology would be easy for me.

Q8. I would find it easy to apply interactive video technology in my course.

Q9. My interaction with interactive video technology would be clear and understandable.

Q10. I would find interactive video technology flexible to interact with.

Q11. It would be easy for me to become skillful at using interactive video technology.

Q12. I would find interactive video technology easy to use.

Attitude Toward Using (ATU):

Q13. I believe it is good to use interactive video technology in online and/or hybrid nursing courses.

Q14. I like the idea of using interactive video technology in online and/or hybrid nursing courses.

Q15. It is a positive idea for me to use interactive video technology in online and/or hybrid nursing courses.

Q16. I think it is valuable to use interactive video technology in online and/or hybrid nursing courses.

Q17. I think it is a trend to use interactive video technology in online and/or hybrid nursing courses.

Intention to Use (BIU):

Q18. I intend to use interactive video technology in online and/or hybrid nursing courses in the future.

Q19. Assuming I have access to interactive video technology, I intend to use it.

Q20. Using interactive video technology in online and/or hybrid nursing courses enhance students’ learning interest.

Q21. In my job, the usage of interactive video technology is important (Job Relevance).
Q22. In my job, the usage of interactive video technology is relevant (Job Relevance).

REFERENCES


IT-based Patient Interventions for Opioid Abuse: Evaluation using Analytical Model

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Abstract: The number of people in the US with opioid abuse exceeds 2 million and the total cost is approximately $100B per year. In this study, we focus on patient-level interventions and present three IT-based interventions: (a) mobile reminders, (b) electronic monitoring, and (c) composite intervention. We have developed an analytical model for evaluating interventions using Return-on-Investment (ROI). The interventions are cost-effective for higher values of intervention effectiveness, hospital, and emergency room cost. However, with QoL improvement, cost-effectiveness improves significantly. We also explored the use of financial incentives for increasing the adoption of interventions. These results will help patients, healthcare professionals, decision-makers, and family members to choose the most suitable intervention to address opioid abuse.

Keywords: Opioid abuse, interventions, patient level, evaluation, analytical model

INTRODUCTION

Prescription opioid abuse is any intentional use of opioids outside of a physician’s prescription for a bonafide medical condition (Finley et al., 2017; Sinha, Jensen, Mullin, & Elkin, 2017). It can lead to addiction, higher healthcare costs, and serious harm to patients (Blendon & Benson, 2018). This abuse requires detoxification and hospitalization similar to a chronic condition. The number of people in the US with opioid abuse exceeds 2 million and the total cost is approximately $100B per year (NIH, 2019). According to NIH, about half of the drug overdose deaths in the US are due to opioids (NIH, 2019). The opioid abuse is a major challenge for patients and family members, healthcare professionals, employers, regulators, and the society. There is a need for interventions at multiple levels before patients develop opioid addiction and require major treatment.

Each patient has a certain chance of abusing opioids (single vs multiple prescriptions) based on their history, genetic makeup, current environment, medical condition and type of opioid prescribed. Some of the patients will have low, some moderate and some will have high level of opioid abuse. This is also time-dependent and patients can change from low to moderate to high or moderate to high. This has some chance to lead to addiction, which will require expensive inpatient treatment. This abuse should be considered a chronic disease and different patients will require outpatient treatment for different duration of time. A different set of actions will be needed (a) at the source (for healthcare professionals) managing the prescriptions, (b) patient-level during consumption of opioids and (c) after the patient has developed an addiction. In this paper, we focus on patient-level interventions, which are proactive and with some probabilities will be effective for some patients in preventing them from developing an opioid addiction. To design technological interventions, we present a design approach. Using multiple constraints and considering the environmental context, we have developed three technological interventions. The interventions are (a) mobile reminders (Voelker, 2019), (b) electronic monitoring of opioids (Jungquist et al., 2019), and (c) composite intervention (monitoring, reminders and support from other patients) (Schuman-Ölviétr et al., 2018; Varshney, 2015). The mobile
reminders will be sent to the patient to provide educational and motivational support to avoid overconsumption of opioids. The electronic monitoring will keep track of the prescribed opioids. This involves designing wireless monitoring systems for collecting and analyzing opioid consumption data. The composite intervention will include reminder, monitoring and motivational support from other patients. This intervention can reduce the consumption of prescription opioids by monitoring and reminding patients about taking and/or not taking certain doses within certain windows of time. The interventions can be implemented using both simple and sophisticated mobile apps, sensors, mobile devices, and smart medication boxes. This could proactively stop patients from becoming dependent on opioids or develop an addiction.

Using prescription opioid abuse and intervention data, we derive the healthcare cost of opioid abuse along with the cost of three interventions. Using an analytical model and ROI (Return on Investment) as a metric for cost-effectiveness of interventions, we derive several results for all three interventions and various levels of effectiveness. We found that ROI is lower than 1 for low and medium values of our parameters, while it is much more favorable when the values of the parameters are set to high. When the value due to a potential improvement in Quality of Life was included, the ROI significantly improved for all three interventions. Further, we wanted to explore if the use of financial incentives will be suitable to improve the adoption of three interventions. For this, we computed the maximum allowed financial incentives that can be offered to the patients while still meeting the cost-effectiveness goal for the interventions.

DESIGN APPROACH

The design of technological intervention starts with the identification of the environmental factors, patient’s condition and history followed by possible solutions. These include communication and notification with patients, observing consumption behavior, providing individual/group education and support, analyzing patterns of opioid consumption, and cognitive behavior therapy. These interventions can be single or composite (using two or more interventions). The interventions can be in the form of a mobile app implementing reminders, CBT, and monitoring functions. The composite intervention can include group support. All interventions can include analytics to study effectiveness of interventions. The interventions can be personalized to improve suitability to different patients and reduce the overall cost. If an intervention is not working as desired, it can be changed to the more desirable intervention. This entire process is shown in Figure 1.

INTERVENTIONS

In this study, we consider three interventions for managing opioid abuse. These interventions are based on (a) mobile reminders, (b) electronic monitoring and (c) combined reminders and group support from other patients. The interventions, termed INTV1, INTV2, and INTV3, are shown in Figure 2. INTV1 is based on reminders and can be supported by a mobile application or specialized software on a mobile device. INTV2 is based on communication with a smart medication box that keeps track of doses and timing. INTV3 can be supported by a website that allows patients to interact with one another and also receive educational information related to their specific conditions.
Figure 1: The Design Approach for Technological Interventions

Figure 2: Three Interventions for Preventing Prescription Opioid Abuse
The Figure 3 shows the operationalization of the intervention 1. This includes sending a reminder to patient at the prescribed time if the patient has not taken the dose already. As shown in Figure 3(a), the reminder app (Rem-App) sends a message to the patient to take the opioid dose within the time-window. The app also tells the patient to wait for the next dose until the next reminder. Finally, the Rem-App detects the patient’s mood for its context-aware operation. As shown in Figure 3(b), the CBT-OP helps patient on the potential side effects of the opioids, motivation for exercise, healthy eating habits, managing stress, and keeping doctor’s appointment. It asks healthcare professionals (HP) to intervene if doses taken too closely or more frequently or more doses at a time than prescribed (analysis of consumption patterns).

Figure 3: Operationalization of Intervention 1 (Context-aware Reminders)

The Figure 4 shows the operationalization of the intervention 2. The prescription opioid app (PO-App) retrieves dosing consumption data from the smart medication box. The consumption history is analyzed by the PO-App and if any abnormal patterns or behaviors are found then the healthcare professionals are contacted for a suitable intervention.
The proposed interventions are compared in Table 1, based on their functions, potential strengths, and limitations. INTV1 will collect opioid consumption information from the patient and send the reminder to avoid overconsumption. The potential problems include recall bias of the patient, user interface challenges, and any reliability and access problems. INTV2 will monitor and analyze opioid consumption information from a smart medication box. The potential problems include the operation of smart medication box and network access. INTV3 requires a sophisticated website and highly personalized support to the patient and can be fairly complex.

<table>
<thead>
<tr>
<th>Intervention</th>
<th>Functions</th>
<th>Operation</th>
<th>Potential Strengths</th>
<th>Potential Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTV1 (Mobile Reminders)</td>
<td>Simple Reminder</td>
<td>If taken do not take the next dose, else if not taken please take it now</td>
<td>Reduce overconsumption</td>
<td>Accuracy and Effectiveness</td>
</tr>
<tr>
<td></td>
<td>Context-aware Reminder</td>
<td>Will only come to maintain the prescribed opioid dose</td>
<td>Personalized</td>
<td>Complexity</td>
</tr>
<tr>
<td>INTV2 (Electronic Monitoring)</td>
<td>Electronic Monitoring</td>
<td>Monitoring and analyzing opioid consumption and necessary intervention</td>
<td>Works with Smart Medication Boxes and family members/healthcare professionals</td>
<td>Monitoring and analyzing overhead, trying to reach and use the time of family member and healthcare professionals</td>
</tr>
<tr>
<td>INTV3 (Composite)</td>
<td>Composite (group support, educational and reminders)</td>
<td>Integrating the operations of INTV1, INTV2, and technical/behavioral interventions</td>
<td>In addition to potential strengths of reminders and monitoring, effective due to interventions and support from patients</td>
<td>The complexity of group support and composite intervention</td>
</tr>
</tbody>
</table>

In this paper, we do not study the medical effectiveness of these three interventions, but rather focus on the cost of these interventions and when these interventions may be suitable. In the future, these interventions can be implemented and tested with real patients for improving the opioid consumption behavior.
ANALYTICAL MODEL

Analytical models are the representations of mechanisms that govern natural phenomena that are not fully recognized, controlled or understood (Tedeschi, 2006). They have become indispensable tools for policy and decision-makers and researchers (Tedeschi, 2006). However, certain techniques must be used to evaluate mathematical models for objectives, scope and assumptions, appropriateness or validation, and limitations. Essentially, the model should be appropriate for its intended purpose under the given conditions. The model is appropriate (Tedeschi, 2006) for studying opioids in chronic illnesses, where multiple opioids are used over an extended period. The interventions and their cost can be approximated by the model. Therefore, the model is valid and sound and does what it is supposed to do (Tedeschi, 2006). Further, the three steps of model validation (Hamilton, 1991): verification of the model, sensitivity analysis, and evaluation of the model, are performed below.

The verification involved step by step checking of the model and debugging where one or more changes in inputs could lead to unacceptable output (Hamilton, 1991; Tedeschi, 2006). Further, the model was calibrated using values from other studies (AHRQ, 2014; Aroke et al., 2018; Mallow, Belk, Topmiller, & Strassels, 2018; NYState, 2018; Schuchat, Houry, & Guy, 2017; Vivolo-Kantor et al., 2018). The model builds upon prior models, and the results obtained from the model are also supported by other studies. The model was validated by testing for many known cases to verify its functioning. Further, the causal relationships of Opioid with pharmacy cost, hospitalization cost, emergency room and outpatient cost, and the intervention cost for multiple chronic conditions were utilized (AHRQ, 2014; Aroke et al., 2018). All relationships in the model were verified and additional relationships were derived by utilizing known relationships.

The sensitivity analysis was performed to test the behavior of every equation in the model (Hamilton, 1991). There are several ways to perform sensitivity analysis for mathematical models (Christopher Frey & Patil, 2002). We focused on the nominal range sensitivity, which works well for models where there are no significant interactions among input values and the ranges of plausible values can be defined (using one’s judgment or from the literature). For our model, we broadly defined the ranges of all input values, obtained from other studies and expanded even further to cover more extreme cases. The analysis included combining several input values and measuring outputs for these combinations of inputs. The results of such analysis are presented in the next section. This also helps in answering “what-if” questions such as “what if patients lived in a city where hospital costs were lower” or “what if an intervention stopped working”.

The evaluation of the model was done to test the adequacy (or robustness) of the model based on the precision and accuracy of results (Hamilton, 1991; Tedeschi, 2006). The model is precise as it produces values that are close to one another in multiple iterations. The model accuracy is based on (a) known relationships and (b) calibration of results for decision making. To measure accuracy further, we tested our model on input data and results from (AHRQ, 2014; Aroke et al., 2018; Mallow et al., 2018; NYState, 2018; Schuchat et al., 2017; Vivolo-Kantor et al., 2018). We further evaluated our model by computing the ROI for all three interventions for low, medium, and high range of input parameters. These values are in close agreement, so our results on opioid abuse and healthcare cost are validated using published data, while other results on cost of interventions are extrapolated based on known relationships and available data from multiple studies.
Table 2: Input Parameters, Key Values and Sources

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Average for opioid abuse</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>The hospitalization rate</td>
<td>.08 per person/year (0.05 - 1)</td>
<td>(NYState, 2018; Schuchat et al., 2017)</td>
</tr>
<tr>
<td>The duration of hospital stays</td>
<td>4.35 days (2-10 days)</td>
<td>(Mallow et al., 2018)</td>
</tr>
<tr>
<td>The daily cost of hospital stays</td>
<td>$1884 per day ($1000 - $3000)</td>
<td>(Mallow et al., 2018)</td>
</tr>
<tr>
<td>The rate of emergency room visits</td>
<td>0.086 person/year (0.05 - 1)</td>
<td>(Vivolo-Kantor et al., 2018)</td>
</tr>
<tr>
<td>The cost of emergency room visits</td>
<td>$2150 ($1000 - $5000)</td>
<td>(AHRQ, 2014)</td>
</tr>
<tr>
<td>The outpatient visit rate</td>
<td>12 times a year</td>
<td>Assumption once a month</td>
</tr>
<tr>
<td>The cost of outpatient visits</td>
<td>$458 ($200 - $700)</td>
<td>(Mallow et al., 2018)</td>
</tr>
<tr>
<td>The annual cost of brand name medication/polypharmacy</td>
<td>$7078 ($4000 - $10000)</td>
<td>(Aroke et al., 2018)</td>
</tr>
<tr>
<td>The annual cost of generic medication</td>
<td>$692 ($120 - $1000)</td>
<td>(Aroke et al., 2018)</td>
</tr>
<tr>
<td>Probability of brand name prescription</td>
<td>6% (0-20%)</td>
<td>(Aroke et al., 2018)</td>
</tr>
<tr>
<td>Probability of generic prescription</td>
<td>94% (80-100%)</td>
<td>(Aroke et al., 2018)</td>
</tr>
</tbody>
</table>

Several assumptions were made to keep the analytical model tractable and reasonably accurate (Tedeschi, 2006). The assumptions are:
Assumption 1: The patients are adults and living independently.
Assumption 2: The patients can take opioids as prescribed.
Assumption 3: The patients are willing try one or more interventions.
Assumption 4: It is possible to amortize the cost over multiple patients.
These assumptions could be relaxed in future work. To improve the readability of the analytical model, the notations used are shown in Table 3.

To develop the model, we focused on healthcare savings which can be derived using the cost of healthcare without intervention and cost of healthcare with intervention as shown in equation 1:

\[
HC_{\text{Savings}} = HC_{\text{Cost without INTV}} - HC_{\text{Cost with INTV}}
\]  

As shown in equation 2, the cost of intervention per year can be given as the sum of two ratios: the ratio of fix cost to the number of patients amortized over the number of years intervention will be used and the ratio of variable cost to the number of patients.

\[
INTV_{\text{Cost per Year}} = \left(\frac{\text{Cost}_{\text{FIX}}}{NP - \text{NYR}_{\text{INTV}}}\right) + \left(\frac{\text{Cost}_{\text{VAR}}}{NP}\right)
\]  

The probability of prescription \(P_{\text{PRESC}}\) is derived as a function of finding a doctor to prescribe opioids \(\text{Doctor}_{\text{PrescOpioid}}\) and doctor willing to prescribe \(\text{Doctor}_{\text{WillingPresc}}\). Further, the probability that intervention is effective is a product of willingness of patient, suitability of intervention to a patient, and whether the intervention is accurate and reliable.

\[
P_{\text{Effective INTV}} = (\text{Patient}_{\text{Willingness}} \times \text{Patient}_{\text{Suitability}} \times \text{Accurate}_{\text{INTV}} \times \text{Reliable}_{\text{INTV}})
\]
<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accurate&lt;sub&gt;INTV&lt;/sub&gt;</td>
<td>Intervention is accurate</td>
</tr>
<tr>
<td>( C_{MIN} )</td>
<td>The cost per minute of cellphone calls</td>
</tr>
<tr>
<td>( CF_{HOUR-J} )</td>
<td>The cost of ( j )-th hour for a family member (salary and benefits)</td>
</tr>
<tr>
<td>( Cost_{FIX} )</td>
<td>The fixed cost of intervention</td>
</tr>
<tr>
<td>( Cost_{VAR} )</td>
<td>Variable cost of intervention per year</td>
</tr>
<tr>
<td>( CP_{HOUR-I} )</td>
<td>The cost of ( i )-th hour for healthcare professionals (salary and benefits)</td>
</tr>
<tr>
<td>( CS_{i \rightarrow i+1} )</td>
<td>The cost of switching from ( i )-th to ( i+1 )-th intervention</td>
</tr>
<tr>
<td>Doctor_PrescOpioid</td>
<td>Finding a doctor to prescribe opioids</td>
</tr>
<tr>
<td>Doctor_WillingPresc</td>
<td>Doctor willing to prescribe</td>
</tr>
<tr>
<td>( F_{MAX} )</td>
<td>Maximum allowed financial incentive for adoption of an intervention</td>
</tr>
<tr>
<td>( HC_{Savings} )</td>
<td>Healthcare Savings</td>
</tr>
<tr>
<td>( HC_{CostWithoutINTV} )</td>
<td>Cost of healthcare without intervention</td>
</tr>
<tr>
<td>( HC_{CostWithINTV} )</td>
<td>Cost of healthcare with intervention</td>
</tr>
<tr>
<td>( INTV_{CostperYear} )</td>
<td>Cost of intervention per year</td>
</tr>
<tr>
<td>( K )</td>
<td>The duration to study the benefits of reducing opioid abuse</td>
</tr>
<tr>
<td>( N_{MIN-K} )</td>
<td>The number of phone minutes used in the ( k )-th day</td>
</tr>
<tr>
<td>( NP )</td>
<td>Number of patients</td>
</tr>
<tr>
<td>( N_{YRINTV} )</td>
<td>Number of years intervention will be used</td>
</tr>
<tr>
<td>Patient_Willingness</td>
<td>Willingness of patient</td>
</tr>
<tr>
<td>Patient_Suitability</td>
<td>Suitability to a patient</td>
</tr>
<tr>
<td>( P_{Addiction} )</td>
<td>Probability of addiction</td>
</tr>
<tr>
<td>( P_{EffectiveINTV} )</td>
<td>Probability that intervention is effective</td>
</tr>
<tr>
<td>( P_{PRES} )</td>
<td>Probability of prescription</td>
</tr>
<tr>
<td>( QALY )</td>
<td>Quality adjusted life years</td>
</tr>
<tr>
<td>( QoL )</td>
<td>Quality of Life</td>
</tr>
<tr>
<td>Reliable&lt;sub&gt;INTV&lt;/sub&gt;</td>
<td>Intervention is reliable</td>
</tr>
<tr>
<td>( ROI )</td>
<td>Return of Investment</td>
</tr>
<tr>
<td>( TCI )</td>
<td>Total Cost of Intervention</td>
</tr>
<tr>
<td>( TF_{HOUR} )</td>
<td>Total time spent by a family member</td>
</tr>
<tr>
<td>( TP_{HOUR} )</td>
<td>Total time spent per year by healthcare professionals</td>
</tr>
<tr>
<td>( Total_{Value} )</td>
<td>The total value obtained due to intervention in 1 year</td>
</tr>
</tbody>
</table>
The cost of interventions includes the cost of training, the ongoing time cost of healthcare professionals or family members involved, and the cost of communications. The patient's time is not included as suggested by (Windsor et al., 1990). However, minutes used for cell phone calls are included in the total cost of the intervention. Thus, the general equation for the total cost of the intervention (TCI) can be given as:

$$ TCI = \sum_{i=1}^{TP HOUR} CP_{HOUR-i} + \sum_{j=1}^{TF HOUR} CP_{HOUR-j} + \sum_{K=1}^{D I Y} N_{MIN-K} \times C_{MIN} + INTV_{CostPerYear} $$

(4)

where, TP HOUR is the total time spent per year by healthcare professionals and CP HOUR-i is the cost of ith hour for healthcare professionals including salary and benefits. TF HOUR and CF HOUR-J represent the same factors for a family member. NMIN,K is the number of phone minutes used in the kth day and CMIN is the cost per minute of a phone call. DiY represents the number of days in a year. C_FIX is the fixed cost of intervention, such as the development cost, and is amortized over intervention duration and the number of patients covered. C_VAR is the variable cost and can include maintenance cost of the intervention (such as website/servers) amortized over the number of patients. Not all interventions will have every cost component, but the above equation can be used to derive total cost of interventions for all three interventions. If the selected intervention is not effective, then the total cost of intervention also includes the switching cost as follows:

$$ TCI = TCI_{\rightarrow I+1} + C_{FIX} $$

(5)

where, $C_{FIX}$ is the cost of switching from Ith to I+1st intervention.

For an intervention to be cost-effective, the savings have to be more than the total cost of interventions (or HC Savings >= TCI). To quantify savings to different costs of interventions, we define Return on Investment (ROI) as the ratio of the product of the probability of prescription, probability of addiction, healthcare savings for addicted patient, and probability that intervention is effective to the cost of intervention:

$$ ROI = (P_{Presc} \times P_{Addiction} \times HC_{Savings} \times P_{EffectiveINTV}) / TCI $$

(6)

Assuming non-negative quality of improvement values, the total QALY (Quality-adjusted Life Years) gained can be expressed as the sum of two improvements, one due to additional years obtained and another due to quality of life improvement in the existing years. However, we can focus on 1-year benefit, so the QALY gained is equal to the Quality of Life improvement when the patient does not have opioid abuse. Thus, the total value obtained in 1 year is the product of cost equivalent of one QALY and the number of QALY gained due to the intervention:

$$ Total_{Value} = C_{QALY} \times N_{QALY} $$

(7)

Now, we explore the use of financial incentive for the adoption of an intervention (not given as cash, but to meet insurance deductible/co-pay/out-of-pocket). The maximum value of this financial incentive over a year can be given as follows:

$$ FI_{MAX} = (P_{Presc} \times P_{Addiction} \times HC_{Savings} \times P_{EffectiveINTV}) - TCI $$

(8)

We are currently modeling a utility function involving personalized interventions for patients and patient’s desirability for the interventions and outcomes. We will also address the optimization of this utility function along with mathematical proofs of lemmas and theorems. This will allow our analytical model to be more generalizable. The QALY gained will be computed using both the utility and predicted life expectancy.

**RESULTS**

Although multiple interventions are medically suitable in preventing opioid abuse, we want to evaluate the cost of interventions and study when and where these interventions are cost-effective. Next, the cost components of various
interventions are shown in Table 4 along with the values used (BLS, 2018; Page, Horvath, Danilenko, & Williams, 2012; Varshney, 2013). The cost of electronic monitoring is a function of the dosing frequency as additional processing is required from the healthcare professional every time an opioid is consumed or scheduled. Mobile reminders are the simplest intervention while composite intervention is likely to be most effective. The cost of the mobile application is varied from zero to ten dollars a month to accommodate different versions (basic, premium, deluxe) of the app.

Table 4: The Cost Components of Various Interventions

<table>
<thead>
<tr>
<th>The Intervention</th>
<th>Included Components</th>
<th>Time (Total Cost)</th>
<th>Total Cost of Intervention (TCI) (Low, Medium, High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTV1: Mobile Reminders</td>
<td>Training of a nurse (one-time initial cost)</td>
<td>2, 3 and 4 hours ($40, $60, $80)</td>
<td>$1099, $1179, $1259</td>
</tr>
<tr>
<td></td>
<td>One phone call per day</td>
<td>5 minutes ($1.67)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rest two calls as recorded messages</td>
<td>2 minutes ($0.67)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mobile App cost per month</td>
<td>0, $5, $10</td>
<td></td>
</tr>
<tr>
<td>INTV2: Electronic Monitoring</td>
<td>Training and installation</td>
<td>2, 3 and 4 hours ($40, $60, $80)</td>
<td>$1199, $1419, $1639</td>
</tr>
<tr>
<td></td>
<td>Messages</td>
<td>2 minutes ($0.67)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Message Processing by a Nurse</td>
<td>5 minutes ($1.67)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cost of Monitoring System/Software</td>
<td>$100, $300, $500</td>
<td></td>
</tr>
<tr>
<td>INTV3: Composite</td>
<td>Informational Material Reminder</td>
<td>$500,000</td>
<td>$1080 (1000 patients), $1453 (600 patients), $3320 (200 patients)</td>
</tr>
<tr>
<td></td>
<td>Group Support</td>
<td>$5000/month maintenance cost</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Specialized Application</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Family/Healthcare professional</td>
<td>30 minutes ($20/hour cost=$10)</td>
<td></td>
</tr>
</tbody>
</table>

The ROI for different interventions is shown in Table 5. We included low, medium and high values of parameters, to cover many different scenarios, in deriving ROI. The ROI is <1 (shown in red) for low and medium values of our input parameters, while it is much more favorable when the values of the parameters are set to high. For the same level of effectiveness, INTV3 is cost-effective only for 100% medical effectiveness and high value of parameters.

Table 5: ROI for Various Types and Level of Intervention Effectiveness

<table>
<thead>
<tr>
<th>Effectiveness</th>
<th>INTV1</th>
<th>INTV2</th>
<th>INTV3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>25%</td>
<td>0.0005</td>
<td>0.04</td>
<td>0.66</td>
</tr>
<tr>
<td>50%</td>
<td>0.001</td>
<td>0.08</td>
<td>1.32</td>
</tr>
<tr>
<td>75%</td>
<td>0.0015</td>
<td>0.12</td>
<td>1.98</td>
</tr>
<tr>
<td>100%</td>
<td>0.002</td>
<td>0.16</td>
<td>2.64</td>
</tr>
</tbody>
</table>

Low, Medium, and High range for following input parameters: Hospitalization, Number of days, Cost/day, Emergency visit rate, Emergency cost/visit, Probability of addiction

Next, we decided to include the value due to a potential improvement in Quality of Life (QoL). The ROI for different interventions with QoL included is shown in Table 6. Now, the ROI is <1 (shown in red) only for low values of our parameters, while it is much more favorable (shown in green) when the values of the parameters are set to medium or high.
Table 6: ROI for Different Interventions with Quality of Life Improvement

<table>
<thead>
<tr>
<th>Effectiveness</th>
<th>INTV1</th>
<th>INTV2</th>
<th>INTV3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>25%</td>
<td>0.0232</td>
<td>0.57</td>
<td>2.646</td>
</tr>
<tr>
<td>50%</td>
<td>0.0464</td>
<td>1.14</td>
<td>5.292</td>
</tr>
<tr>
<td>75%</td>
<td>0.0697</td>
<td>1.71</td>
<td>7.938</td>
</tr>
<tr>
<td>100%</td>
<td>0.0928</td>
<td>2.28</td>
<td>10.584</td>
</tr>
</tbody>
</table>

Low, Medium, and High range for following input parameters:
Hospitalization, Number of days, Cost/day, Emergency visit rate, Emergency cost/visit, Probability of addiction, QoL

Next, we decided to add a financial incentive (not cash, but payment for insurance deductible, out-of-pocket expenses or co-pay for general healthcare and wellness) to improve the adoption of three interventions by patients. We wanted to compute the maximum allowed financial incentives that can be offered to the patients while still meeting the cost-effectiveness goal for the interventions. Based on the medical effectiveness level of intervention, the range of financial incentives varies from $165-$1509 for INTV1 for medium values and $2066-$12041 for high values. Similar numbers are $597-$1269 for INTV2 for medium values and $1686-$11661 for high values. The numbers and range for INTV3 for medium values are $563-$1235 and $5-$9980 for high values.

Table 7: Maximum Allowed Financial Incentives

<table>
<thead>
<tr>
<th>Effectiveness</th>
<th>INTV1</th>
<th>INTV2</th>
<th>INTV3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>25%</td>
<td>0</td>
<td>0</td>
<td>$2066</td>
</tr>
<tr>
<td>50%</td>
<td>0</td>
<td>$165</td>
<td>$5391</td>
</tr>
<tr>
<td>75%</td>
<td>0</td>
<td>$837</td>
<td>$7816</td>
</tr>
<tr>
<td>100%</td>
<td>0</td>
<td>$1509</td>
<td>$12041</td>
</tr>
</tbody>
</table>

Low, Medium, and High range for following input parameters:
Hospitalization, Number of days, Cost/day, Emergency visit rate, Emergency cost/visit, Probability of addiction, QoL

DISCUSSION, CONCLUSION AND FUTURE WORK

Prescription opioid abuse can lead to addiction, higher healthcare costs, and serious harm to patients. This abuse requires detoxification and hospitalization similar to a chronic condition. One of the major observations from the literature is that only 10% of people with opioid abuse get treatment or help. Therefore, the opioid abuse is a major challenge for patients and family members, healthcare professionals, employers, regulators, and the society. There is a need for interventions at multiple levels before patients develop opioid addiction and require major treatment. In this paper, we focused on patient-level interventions, which are proactive and with some probabilities will be effective for some patients in preventing them from developing an opioid addiction. The interventions are (a) mobile reminders, (b) electronic monitoring of opioids, and (c) composite intervention.

Using prescription opioid abuse and intervention data, we derived the healthcare cost of opioid abuse along with the cost of three interventions. Using an analytical model and ROI (Return on Investment) as a metric for cost-effectiveness of interventions, we derived several results for all three interventions and various levels of effectiveness. We found that ROI is lower than 1 for low and medium values of our parameters, while it is much more favorable when the values of the parameters are set to high. When the value due to a potential improvement in Quality of Life was included, the ROI significantly improved for all three interventions. Further, we wanted to explore if the use of financial incentives will be suitable to improve the adoption of three interventions. For this, we computed the maximum allowed financial incentives that can be offered to the patients while still meeting the cost-effectiveness goal for the interventions.
We are planning to conduct a meta-analysis/contextual analysis of data from multiple sources to further evaluate the model. We are comparing the IT-based interventions with the non-IT interventions for opioid abuse. The scope for future research includes a randomized controlled trial (RCT) to evaluate the medical effectiveness of three proposed interventions. The research can be further extended to field studies using Health Promotion Model, Theory of Addiction, Theory of Adaptation, and other theories on drug abuse.

REFERENCES


Does IT Spending Matter on Hospital Financial Performance and Quality?

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Abstract: This research explored impacts of IT spending on hospital financial performance and hospital quality. We developed two research hypotheses accordingly. The first hypothesis was that IT spending would be positively related to the hospital financial performance, and the second hypothesis was that hospitals with higher IT spending would have better quality metrics. We used the 2017 American Hospital Association Survey data and the HCAHPS dataset from Medicare website. We tested three hospital financials and three quality measures. We employed T-Tests and ANOVA models to test the hypotheses. Results were inconclusive for both hypotheses. Evidence showed statistical significance on two out of seven tests.

INTRODUCTION

IT expenses have ever been increasing in organizations. In compliance with Patient Protection and Affordable Care Act (2010), U.S. hospitals spent even more on IT. Much research was on the impact of IT spending in hospitals. It showed that there were financial benefits and a positive correlation between hospital financial performance and IT spending (Lee & Young, 2016). The literature also showed that higher IT use was related to high levels of expenses due to the associated costs of IT systems (Menachemi et al., 2006). However, no studies have done on the relationship between IT spending and hospital financial performance and quality using the 2017 American Hospital Association Annual Survey database and Medicare database. Therefore, this research filled the gap in the literature.

We used three variables to measure hospital financial performance: operating margin, total patient revenue and net income. We collected data on IT expenses and financials from the 2017 AHA Survey database. We also used three variables to measure hospital quality: hospital overall rating, patient experience rating, readmission rate, and serious complications. The quality data came from HCAHPS dataset from Medicare website. Our study grouped hospitals into two – high IT spending and low IT spending hospitals. Using T-Test and ANOVA models, we conducted hypothesis testing on the seven variables.
LITERATURE REVIEW

Lee & Young (2016) found that there was a significant and positive correlation between revenue and hospital information technology (HIT) expenses. It was concluded that an 8% increase in total revenue could be achieved by a 100% increase in HIT spending. Our hypothesis is aimed to test that research and see if it can be verified by the 2017 AHA data and financial metrics that we have. Numerous studies investigated the relationship between IT spending and hospital financial performance (Agha, 2014; Encinosa & Bae, 2012; Kohli et al., 2012; Li & Collier, 2000; Lee, McCullough & Town 2013; Menachemi et al., 2006; Walker, 2017; Wang et al., 2003; Williams et al., 2015; Zhivan & Diana, 2011). Therefore, we hypothesized a positive relationship between IT spending and financial performance.

\[ H_1: \text{If a hospital spends more on IT then the hospital will see increased financial performance.} \]

McCullough, Casey, Moscovice and Prasad (2010) collected data from 3,401 non-federal acute care U.S. hospitals from 2004-2007 to measure the quality of patient care following the adoption of EHR. Using this data they focused on six categories to measure quality and using multivariate regression they found that average quality was higher for hospitals with EHR by 1-2% in each category. Another big finding was that health IT value is context-dependent, with larger effects in academic hospitals. There have been numerous studies on the role of IT compared to the quality that it brings to the hospital (Agha, 2014; Kohli et al., 2012; Li & Collier, 2000; Meyer & Degoulet, 2008; Parente & McCullough, 2009). Therefore, we hypothesized a positive relationship between IT spending and hospital quality outcome.

\[ H_2: \text{If a hospital spends more on IT then the hospital will see increased quality metrics.} \]

METHODOLOGY

From the 2017 Annual AHA Survey data and HCAHPS database on the Medicare website, we collected our sample data. Variables were selected from the datasets. The variables were described below.

**IT Operating Expenses**

This variable was taken from IT Operating Expenses (ITEXP) in the 2017 Annual AHA Survey data. The variable represents total IT operating expenses at the end of the reporting period. We used this metric to calculate our primary grouping variable, IT Proportion.

**Total Operating Expenses**

This variable was taken from FY1 Total Operating Expenses (TOE) in the 2017 Annual AHA Survey data. The variable represents total operating expenses at the end of the reporting period. We used this metric to calculate our primary grouping variable, IT Proportion.

**Number of Beds**

This variable was taken from Number of Beds (BDTOT) in the 2017 Annual AHA Survey data. The variable represents total facility beds set up and staffed at the end of the reporting period. We used this metric to calculate the total patient revenue per bed and the net income per bed in order to help standardize the values between hospitals of different sizes.

**Total Patient Revenue**

This variable was taken from FY1 Total Patient Revenue (TPR) in the 2017 Annual AHA Survey data. The variable represents total patient revenue at the end of the latest reporting period (FY1).
Net Income (NI)

This variable was taken from FY1 Net Income from service to patients (NI) in the 2017 Annual AHA Survey data. The variable represents total hospital net income from service to patients at the end of the latest reporting period (FY1).

Operating Margin

This variable was taken from FY1 Operating Margin (TOM) in the 2017 Annual AHA Survey data. The variable represents total operating margin at the end of the latest reporting period (FY1).

Total Patient Revenue per bed (TPR_PB)

This variable was calculated with data from the 2017 Annual AHA Survey. We calculated this metric by dividing total patient revenue by number of beds. This variable represents standardized total patient revenues between hospitals of different sizes at the end of the reporting period.

Net Income per bed (NI_PB)

This variable was calculated with data from the 2017 Annual AHA Survey. We calculated this metric by dividing net income (NI) from services to patients by number of beds. This variable represents standardized hospital net income from services to patients between hospitals of different sizes at the end of the reporting period.

Hospital Overall Rating (HospOverall)

This variable was taken from the hospital overall rating (HospOverall) field in the HCAHPS database on the Medicare website. We adopted “Hospital overall rating” as a quality measure. The patient survey responses in the database had ratings of 1 thru 5. We re-coded 1 and 2 as “low quality” and 4 and 5 as “high quality.”

Patient Experience Rating (PatientExperienceRating)

This variable was taken from the patient experience rating (PatientExperienceRating) field in the HCAHPS database on the Medicare website. We adopted “Patient experience national comparison” as the quality measure. This variable was reported as: “Below the national average”, “Same as the national average” or “Above the national average.” We coded the values numerically as 1, 2 and 3 respectively.

Readmission Rate (30IPF)

This variable was taken from the 30IPF field in the HCAHPS database on the Medicare website. We adopted “READM-30-RPF Rate” as a readmission rate variable. The readmission measures are estimates of unplanned readmission to an acute care hospital in the 30 days after discharge from a hospitalization. Patients may have had an unplanned readmission for any reason.

Serious Complications (PSI90)

This variable was taken from the PSI90 in the HCAHPS database on the Medicare website. We adopted “PSI_90_SAFETY” as a quality measure. The measure name was “Serious Complications” and was compared to the national average. The variable was reported as “No Different than the National Value”, “Worse than the National Value” and “Better than the National Value.” We coded the values numerically as 1, 2 and 3 respectively.

IT Proportion (ITPROP)

This variable was calculated by dividing total operating expenses by IT operating expenses to generate what proportion of total expenses were spent on IT operations. The spending groups were derived from “ITPROP.” To get this variable
into a form that would make sense for our analysis, we had to clean up the data. Our original sample size was originally 6,282 hospitals but looking at the data more closely there were values that needed to be excluded. We removed 2,673 hospitals that had a value of “0%” and another 448 hospitals where data was not reported. Extreme values such as ITPROP over 100% were also removed as that did not make sense in this study and would skew our means.

Once those values were removed, we wanted to find which would represent the High Spend and which would represent the Low Spend. To figure this out, we ran descriptive statistics on our data set until we found a spot where the mean and the median of the sample were closest and easiest to analyze further without have outliers that would skew our results. Between 98% and 5% there were only about 600 hospitals of the 3100 that remained. We decided to exclude any hospitals with over 5% ITPROP and narrow our focus to hospitals 5% and below, which was represented as 82% of the data that was left after cleansing. We were left with 2541 hospitals for grouping.

The groups were represented as High IT Spend and Low IT Spend. The high spend group was made up of hospitals where the ITPROP was between 2.5% and 5%. The low spend group was made up of hospitals where the ITPROP was between 0.01% and 2.49%. Running descriptive statistics on this, we found the mean and median to be close as well as the standard deviation appropriate. High spend was made up of 1,249 hospitals and Low Spend was made up of 1,292 hospitals for further analysis.

Our research framework was presented in Figure 1.

Sample Data

The 2017 AHA Survey dataset had over 6,000 hospital responses. Among them, less than half reported IT expenses. We merged the hospital attribute data with financial data in the AHA dataset. We ended up 2,541 hospital cases. The descriptive statistics were presented in Table 1. In addition, we used about 2,000 hospital cases in HCAHPS database on the Medicare website.
Table 1: Descriptive Statistics of Sample Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>IT Operating Expenses</td>
<td>2541</td>
<td>$1,182.00</td>
<td>$175,781,646.00</td>
<td>$6,302,496.76</td>
<td>$13,066,309.09</td>
</tr>
<tr>
<td>Total operating expenses</td>
<td>2541</td>
<td>$1,925,624.00</td>
<td>$5,269,382,408.00</td>
<td>$210,736,035.43</td>
<td>$385,419,659.38</td>
</tr>
<tr>
<td>Number of Beds</td>
<td>2541</td>
<td>6</td>
<td>2877</td>
<td>167.74</td>
<td>216.662</td>
</tr>
<tr>
<td>Total patient revenues (TPR)</td>
<td>2541</td>
<td>$1,068,528.00</td>
<td>$16,863,431,079.00</td>
<td>$730,493,445.87</td>
<td>$1,334,424,944.06</td>
</tr>
<tr>
<td>Net income (NI)</td>
<td>2541</td>
<td>$(1,157,897,865.00)</td>
<td>$1,347,363,833.00</td>
<td>$(7,590,072.43)</td>
<td>$84,903,160.78</td>
</tr>
<tr>
<td>IT Spend Proportion</td>
<td>2541</td>
<td>0.01%</td>
<td>5.00%</td>
<td>2.46%</td>
<td>1.35%</td>
</tr>
<tr>
<td>Operating margin</td>
<td>2541</td>
<td>$(1,965.97)</td>
<td>$775.78</td>
<td>$(9.19)</td>
<td>$68.60</td>
</tr>
<tr>
<td>TPR per bed (TPR_PB)</td>
<td>2541</td>
<td>$28,761.56</td>
<td>$132,974,874.73</td>
<td>$3,645,022.46</td>
<td>$4,767,088.31</td>
</tr>
<tr>
<td>NI per bed (NI_PB)</td>
<td>2541</td>
<td>$(17,749,345.83)</td>
<td>$4,334,971.00</td>
<td>$(31,188.39)</td>
<td>$455,643.46</td>
</tr>
</tbody>
</table>

The descriptive statistics for Group 1 (hospitals with low IT spending proportion) were reported in Table 2:

Table 2: Descriptive Statistics of Group 1 (Low IT Spending Hospitals)

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>IT Operating Expenses</td>
<td>1292</td>
<td>$1,182.00</td>
<td>$79,700,000.00</td>
<td>$2,014,375.48</td>
<td>$5,333,977.59</td>
</tr>
<tr>
<td>Total operating expenses</td>
<td>1292</td>
<td>$1,925,624.00</td>
<td>$3,820,595,000.00</td>
<td>$130,280,495.47</td>
<td>$279,633,936.43</td>
</tr>
<tr>
<td>Number of Beds</td>
<td>1292</td>
<td>6</td>
<td>1379</td>
<td>122.01</td>
<td>152.278</td>
</tr>
<tr>
<td>Total patient revenues (TPR)</td>
<td>1292</td>
<td>$1,136,211.00</td>
<td>$13,584,179,971.00</td>
<td>$475,209,689.92</td>
<td>$995,112,876.32</td>
</tr>
<tr>
<td>Net income (NI)</td>
<td>1292</td>
<td>$(1,029,370,050.00)</td>
<td>$360,497,466.00</td>
<td>$(5,622,909.83)</td>
<td>$60,874,082.61</td>
</tr>
<tr>
<td>IT Spend Proportion</td>
<td>1292</td>
<td>0.01%</td>
<td>2.49%</td>
<td>1.34%</td>
<td>0.74%</td>
</tr>
<tr>
<td>Operating margin</td>
<td>1292</td>
<td>$(1,965.97)</td>
<td>$775.78</td>
<td>$(11.23)</td>
<td>$90.76</td>
</tr>
<tr>
<td>TPR per bed (TPR_PB)</td>
<td>1292</td>
<td>$35,506.59</td>
<td>$132,974,874.73</td>
<td>$3,645,022.46</td>
<td>$4,767,088.31</td>
</tr>
<tr>
<td>NI per bed (NI_PB)</td>
<td>1292</td>
<td>$(1,913,327.23)</td>
<td>$4,334,971.00</td>
<td>$(31,188.39)</td>
<td>$455,643.46</td>
</tr>
</tbody>
</table>

Descriptive statistics of Group 2 (hospitals with high IT spending proportion) were presented in Table 3.
Table 3: Descriptive Statistics of Group 2 (High IT Spending Hospitals)

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>IT Operating Expenses</td>
<td>1249</td>
<td>$114,923.00</td>
<td>$175,781,646.00</td>
<td>$10,738,247.52</td>
<td>$16,712,767.53</td>
</tr>
<tr>
<td>Total operating expenses</td>
<td>1249</td>
<td>$4,155,187.00</td>
<td>$5,269,382,408.00</td>
<td>$293,961,461.86</td>
<td>$455,863,150.98</td>
</tr>
<tr>
<td>Number of Beds</td>
<td>1249</td>
<td>6</td>
<td>2877</td>
<td>215.05</td>
<td>259.13</td>
</tr>
<tr>
<td>Total patient revenues (TPR)</td>
<td>1249</td>
<td>$1,068,528.00</td>
<td>$16,863,431,079.00</td>
<td>$994,565,994.06</td>
<td>$1,569,246,362.41</td>
</tr>
<tr>
<td>Net income (NI)</td>
<td>1249</td>
<td>$(1,157,897,865.00)</td>
<td>$1,347,363,833.00</td>
<td>$(9,624,959.60)</td>
<td>$104,066,122.92</td>
</tr>
<tr>
<td>IT Spend Proportion</td>
<td>1249</td>
<td>2.50%</td>
<td>5.00%</td>
<td>3.61%</td>
<td>0.71%</td>
</tr>
<tr>
<td>Operating margin</td>
<td>1249</td>
<td>$(563.23)</td>
<td>$64.03</td>
<td>$(7.08)</td>
<td>$32.35</td>
</tr>
<tr>
<td>TPR per bed (TPR_PB)</td>
<td>1249</td>
<td>$28,761.56</td>
<td>$110,979,851.43</td>
<td>$4,026,896.83</td>
<td>$4,212,952.02</td>
</tr>
<tr>
<td>NI per bed (NI_PB)</td>
<td>1249</td>
<td>$(17,749,345.83)</td>
<td>$1,983,904.46</td>
<td>$(47,540.44)</td>
<td>$557,526.79</td>
</tr>
</tbody>
</table>

RESULTS

We performed T-Test to test the first main hypothesis on the impacts of IT spending on hospital financial performance. T-Test models tested if there was a statistically significant difference in financial performance between hospitals with a lower spending on IT proportion compared to a hospital with a higher IT spend proportion. We used total operating margin, total patient revenue per bed (TPR_PB), and net income per bed as the test variables in T-Test models while IT spend proportion as the grouping variable.

High IT spending hospitals reported higher operating margin than the low IT spending hospitals, but the difference was not significant \( t = -1.55, p = .122 \). In contrast, total patient revenue per bed showed statistical significance on the difference between the two groups \( t = -4.00, p = .000 \). Evidence showed marginal significance on net income per bed \( t = 1.779, p = 0.075 \). While high IT spending hospitals reported higher operating margin and the standardized total patient revenue averages of high IT spending hospitals were higher than the low IT spending hospitals, the standardized net income from patient services showed the reverse. T-Test model results are shown in Table 4.

Table 4: T-Test Results on Financial Performance

<table>
<thead>
<tr>
<th>Test Variable</th>
<th>Group Spending</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>df</th>
<th>t statistics</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating Margin</td>
<td>Low IT Spend</td>
<td>1292</td>
<td>-11.2284</td>
<td>90.7613</td>
<td>1623.56</td>
<td>-1.55</td>
<td>.122</td>
</tr>
<tr>
<td></td>
<td>High IT Spend</td>
<td>1249</td>
<td>-7.0769</td>
<td>32.3476</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TPR_PB</td>
<td>Low IT Spend</td>
<td>1292</td>
<td>3275857.5</td>
<td>522612.7</td>
<td>2460.64</td>
<td>-4.00</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>High IT Spend</td>
<td>1249</td>
<td>4026896.8</td>
<td>4212952.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NI_PB</td>
<td>Low IT Spend</td>
<td>1292</td>
<td>-15380.57</td>
<td>327835.3</td>
<td>2539</td>
<td>1.779</td>
<td>.075</td>
</tr>
<tr>
<td></td>
<td>High IT Spend</td>
<td>1249</td>
<td>-47540.44</td>
<td>557526.8</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: TPR_PB indicates total patient revenue per bed. NI_PB indicates net income per bed.

For the second hypothesis testing, we ran four ANOVA models to see if there was a significant difference in quality metrics between hospitals with a lower spending on IT proportion and hospitals with a higher IT spend proportion. We used hospital overall rating (HospOverall), patient experience rating (PatientExpRating), patient 30 day readmission rate (30IPF), and safety/complications (PSI90) as the test variables, and IT spend proportion as the grouping variable.
ANOVA results showed no statistical significance on the HospOverall variable \( [F = 1.666, p = .198] \). Patient experience rating show no significance \([F = .224, p = .636]\). Readmission rate showed no significance \([F = .000, p = .986]\). In contrast, we found statistical significance on safety/complications \([F = 4.044, p = .045]\). A summary of the ANOVA results were presented in Table 5.

<table>
<thead>
<tr>
<th>Test Variable</th>
<th>df</th>
<th>F statistics</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>HospOverall</td>
<td>1, 1875</td>
<td>1.660</td>
<td>.198</td>
</tr>
<tr>
<td>PatientExpRating</td>
<td>1, 1722</td>
<td>.224</td>
<td>.636</td>
</tr>
<tr>
<td>30IPF</td>
<td>1, 643</td>
<td>.000</td>
<td>.986</td>
</tr>
<tr>
<td>PSI90</td>
<td>1, 1562</td>
<td>4.044</td>
<td>.045</td>
</tr>
</tbody>
</table>

Note: HospOverall=hospital overall rating, PatientExpRating = patient experience rating, 30IPF = patient 30 day readmission rate, and PSI90 = safety/complications (PSI90)

### DISCUSSION

#### IT Spending and Financial Performance

Operating margin of the hospitals was not different whether the hospital was high or low spending on IT \((p = .122)\). The results were consistent with Kohli et al. (2012) who found that that IT’s influence on hospital value might not be evident if solely profitability measures such as operating income were deployed. Therefore, employing a market value based measure combined with traditional accounting performance measures can provide valuable insights for hospital managers.

Standardized total patient revenue of the hospitals is different whether the hospital was a high or low spending on IT \((p = .000)\). The results were fairly consistent with Lee & Young (2016) who found that there was a significant and positive correlation between revenue and HIT expenses, reporting that an 8% increase in total revenue could be achieved by a 100% increase in HIT spending. Our results were also in line with Agha (2014), which reported that HIT was associated with a 1.3% increase in billed charges.

Standardized net income from services to patients of the hospitals was marginally significant \((p = 0.075)\). Contrary to operating margin and total patient revenue, low IT spending hospitals reported higher net income on average than high IT spending hospitals. Our findings here are consistent with Menachemi et al. (2006) who found that even though higher IT use had a positive relationship with higher values of hospital finances, it was shown that it is also related to high levels of expenses due to the associated costs with IT systems.

#### IT Spending and Quality

Hospital overall rating was not different whether the hospital had a high or low IT spending proportion \((p = .198)\). Patient experience rating also showed no significant difference \((p = .636)\). Readmission showed no significance \((p = .986)\). In contrast, safety/complications variable was different whether the hospital had a high or low IT spending proportion \((p = .045)\). Therefore, 1 out of 4 quality variables tested showed significance between the IT spending groups. Since we weren't able to prove our hypothesis correct across all of the quality variables that we used, we found that our results were consistent with Agha (2014) who analyzed the impact of HIT on the quality and intensity of medical care. HIT is associated with a 1.3% increase in billed charges \((p = 0.056)\), and there was no evidence of cost savings even five years after adoption of HIT. Additionally, it was found that HIT adoption appears to have little impact on the quality of care, measured by patient mortality, adverse drug events, and readmission rates.
Figure 2: Summary of Results

Managerial Implications

We were able to make some key findings that the community should take into account, but with further research and more data we could prove more of our hypothesis correct and help hospitals and hospital administrators. Our research was intended to help hospitals and also help the patients that received care at these hospitals. Patient care was of utmost importance, even though the executives at hospitals seemed to only care about the profitability. We feel that given our research, hospitals could have it all and the implementation of a strong IT department could help them get where they wanted to be.

CONCLUSION

In our study, we hoped that we could show that hospitals have increased financial performance if they have higher amounts of IT spending while also improving the quality of care that patients receive. We felt that the results from comparing IT spending groups and financial performance yielded good results showing that standardized total patient revenue was higher when IT spending was higher. Differences in complications were also found between the high and low IT spending groups, as related to quality.

In the future study, tweaking the IT spend proportion could be explored, as we used 5% as our cut-off on the high end. In addition, we could investigate any control effects of hospital attributes such as teaching hospital, ownership control, location. We felt this quality study could also be improved by finding more measures of quality.

REFERENCES


Communication Style in Medical Crowdfunding: Effect of Emotional Framing and Updates Frequency on Funding and Emotional Support

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fanosuaoo@uww.edu

Abstract: Despite the rise of medical crowdfunding and its benefits to patients including reducing financial hardships and providing emotional social support, limited attention has been paid to how a campaign organizer can drive performance. In this study, we investigate how the communication style used in a medical crowdfunding campaign can affect both the funding performance and emotional support received. We find that emotional framing and frequent updates have a positive effect on funding and emotional support and discuss the implications.

INTRODUCTION

More recently, online medical crowdfunding – soliciting for funds from the internet crowd - has become an increasingly common response to healthcare costs. Medical crowdfunding has been helping individuals finance medical expenses and reduce medical bankruptcy (Burtch & Chan, 2018). In addition, it has become a resource for emotional social support for patients (Gonzales, Kwon, Lynch, & Fritz, 2018; Kim, Vaccaro, Karahalios, & Hong, 2017), a positive spillover effect where the crowd also show concern, provide warmth and encouragement to the patient.

While prior crowdfunding research has explored the different drivers of crowdfunding performance (e.g. Cordova, Dolci, & Gianfrate, 2015; Mollick, 2014), and have demonstrated the importance of communication in attracting donations to crowdfunding campaigns (e.g. Wang, Li, Liang, Ye, & Ge, 2018), they have mostly focused on communication in the entrepreneurial financing context with little to no attention paid to non-entrepreneurial contexts including medical crowdfunding. However, we know that different communication styles matter in different crowdfunding contexts. For instance, Parhankangas and Renko (2017) show that the communication style that matters when crowdfunding for social projects is different from the communication style that matters when crowdfunding for commercial projects. As such, we expect that communication style may play a significant role in the performance of medical crowdfunding campaigns.

Against this backdrop, we investigate how the communication style used in a medical crowdfunding campaign relates to its performance in terms of funding level and emotional social support. Particularly, we ask the following question: how does the emotional framing of the medical crowdfunding campaign and the frequency of interaction with the crowd affect the level of funding and emotional social support received? We investigate the aforementioned question because the willingness to donate may still be limited due to the relative newness of medical crowdfunding and because of the limited amount of studies exploring factors that drive the dual outcomes of funding and emotional support in medical crowdfunding.

Given the altruistic nature of giving in medical crowdfunding and the fact that scholars have shown that emotions can sometimes motivate people to action more than cognition (Bagozzi & Moore, 1994; Sudhir, Roy, & Cherian, 2016), we argue that emotional framing will play a positive role in the performance of medical crowdfunding campaigns. Further, we argue that a medical crowdfunding campaign whose organizer interacts frequently with the crowd will receive more funding and emotional support because the crowd will feel better informed and connected with the campaign.

To test our hypotheses, we use a sample of 306 medical crowdfunding campaigns extracted from the YouCaring (now GoFundMe) platform. In line with our prediction, we find that communication that makes the campaign more emotional, informs and builds a connection with the crowd is associated with higher funding and emotional support.
Our study contributes to the growing literature on medical crowdfunding. While prior literature on medical crowdfunding has mostly focused on understanding some of its impact (e.g. Burtch & Chan, 2018) and potential consequences (e.g. Snyder, 2016; Snyder, Mathers, & Crooks, 2016), we take the perspective of the campaign organizer to understand how the communication style might impact the funding level and emotional support.

Beyond contributing to the literature, our findings have important implications to organizers of medical crowdfunding campaigns especially now that medical crowdfunding platforms are exploring campaign-coaching services (e.g. Giveforward.com). The subtle nuances of the organizer’s communications in terms of emotional framing and frequency of updates are important to the funding performance and emotional support.

**BACKGROUND AND HYPOTHESES**

**Medical Crowdfunding**

Whereas online crowdfunding has been adapted into fundraising for medical expenses, it initially gained prominence as a mechanism through which individuals could raise funds from the internet crowd for projects and business ventures. With the growing cost of health care, medical crowdfunding, has become commonplace. Medical crowdfunding differs from crowdfunding activities targeted at entrepreneurial funding for projects and business ventures. For instance, while individuals organizing projects and business venture crowdfunding can offer different tangible incentives (e.g. rewards, equity, or interests) to motivate donors, organizers of medical crowdfunding campaigns do not offer tangible incentives and therefore may rely on donors altruism and empathy for funds.

Research on medical crowdfunding has been on the rise with studies seeking to understand its usage (Berliner & Kenworthy, 2017), impacts (Burtch & Chan, 2018), and potential consequences (Snyder, 2016; Snyder et al., 2016). For instance, while Berliner and Kenworthy (2017) documents that medical crowdfunding is utilized by financially constrained individuals, Burtch and Chan (2018) show that it can reduce financial hardship and medical bankruptcy, and Snyder et al. (2016) highlights the potential for loss of privacy for patients and fraud to donors (Snyder et al., 2016). Studies have also investigated how campaign organizers demonstrate trust and motivate the crowd to donate (e.g. Kim, Kong, Karahalios, Fu, & Hong, 2016; Snyder, Crooks, Mathers, & Chow-White, 2017). They find that organizers typically rely on close–connections, collective endorsements, and a demonstration of the patient’s depth of need in order to motivate the crowd to donate. In sum, the extant literature on medical crowdfunding still has not explored how communication style drives funding and emotional support.

**Communication and Medical Crowdfunding Performance**

Research suggests that an individual’s communication style can influence others (e.g. Charlton, Dearing, Berry, & Johnson, 2008). In order to identify the communication styles that attract funding and emotional support in medical crowdfunding, it is important to consider how organizers can attract and develop a relation with the crowd. Unlike donors in entrepreneurial crowdfunding who are mostly driven by incentives, donors in the medical crowdfunding are often driven by altruism, empathy, social participation, and interaction (Gerber, Hui, & Kuo, 2012; Liu, Suh, & Wagner, 2017). Hence, communication styles that draws on the crowd’s empathy, provokes altruism, informs them and allows for the development of a relation are expected to boost the funding and emotional support levels of a medical crowdfunding campaign.

According to psychologists, communication styles that have the potential to evoke empathy and build rapport in individuals are often emotional (Dickert, Sagara, & Slovic, 2011; Dickert & Slovic, 2013). Empathy, an emotional response triggered by another person’s misfortune has been shown to lead to prosocial behavior (Bagozzi & Moore, 1994; Batson et al., 1997). Emotional communication can trigger empathy through different mechanism like identified victim effect or in-group effect (Sudhir et al., 2016). Once triggered, prosocial behavior resulting from empathy can be an instrumental support like financial donation and/or emotional support. Hence, we expect that medical crowdfunding campaigns with more emotional framing will receive higher funding and emotional support.
**DATA AND METHODOLOGY**

To test our hypotheses, we extracted data from YouCaring (now GoFundMe). YouCaring was a crowdfunding platform that allowed individuals to organize medical crowdfunding campaigns. Medical crowdfunding campaigns on YouCaring typically included information about the purpose of the campaign, including for whom, the financial goal, and the organizer. YouCaring campaigns are typically not time-bound and the organizer can withdraw funds from the campaign at any time during the campaign to help the patient. Our data consist of 306 ongoing medical crowdfunding campaigns launched for breast cancer patients in 2016. The measures are presented in Table 1 and the descriptive statistics is available upon request.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>FundingLevel</td>
<td>Percentage of the funding goal raised</td>
<td>Dependent</td>
</tr>
<tr>
<td>EmoSupport</td>
<td>The number of encouraging wishes and prayers received</td>
<td>Dependent</td>
</tr>
<tr>
<td>Emotional</td>
<td>Binary indicator of whether the campaign has a high emotional framing or not. Coded by graduate students who read the campaign pitches</td>
<td>Independent</td>
</tr>
<tr>
<td>Updates</td>
<td>The number of updates in a campaign provided by the organizer</td>
<td>Independent</td>
</tr>
<tr>
<td>Shares</td>
<td>Number of social media shares of the campaign</td>
<td>Control</td>
</tr>
<tr>
<td>FundingGoal</td>
<td>The amount of money the campaign intends to raise</td>
<td>Control</td>
</tr>
<tr>
<td>Image</td>
<td>Number of images in the campaign</td>
<td>Control</td>
</tr>
</tbody>
</table>

**Estimation Approach**

We estimate a linear regression (OLS) model for the funding level outcome and a Tobit model for the emotional support outcome. We use Tobit model because of the censored nature of the EmoSupport variable. Equations (1) and (2) show the model specifications for the funding level and emotional support outcomes respectively. We report the results of our analyses in Table 2.

\[
\begin{align*}
\text{FundingLevel} &= \beta_0 + \beta_1\text{Emotional} + \beta_2\text{Updates} + \text{Controls} + \epsilon \quad (1) \\
\text{EmoSupport} &= \beta_0 + \beta_1\text{Emotional} + \beta_2\text{Updates} + \text{Controls} + \epsilon \quad (2)
\end{align*}
\]

**PRELIMINARY RESULTS AND CONCLUSION**

Results from our preliminary results in Table 2 show support for all our hypotheses. Model 1 shows evidence supporting H1(a) and H2(a), while Model 2 shows evidence supporting H1(b) and H2(b). We observe that Emotional has a positive and significant effect on funding (FundingLevel) and emotional support (EmoSupport). In the same line,
we observe that Updates has a positive and significant effect on funding ($FundingLevel$) and emotional support ($EmoSupport$). Interestingly, we observe that the control variable $FundingGoal$ has contrasting effects on funding and emotional support. While it has a negative and significant effect on funding, it has a positive and significant effect on emotional support. The positive effect on emotional support may be because large funding goals signal dire situations the crowd is further moved to offer words of encouragement.

Table 2: Results of Preliminary Analysis

<table>
<thead>
<tr>
<th></th>
<th>Model 1 (OLS)</th>
<th>Model 2 (Tobit)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DV= $FundingLevel$</td>
<td>DV= $EmoSupport$</td>
</tr>
<tr>
<td><strong>Emotional</strong></td>
<td>0.5935*** (0.1633)</td>
<td>10.820** (4.354)</td>
</tr>
<tr>
<td><strong>Updates</strong></td>
<td>0.0319** (0.0145)</td>
<td>0.7844** (0.384)</td>
</tr>
<tr>
<td><strong>Shares</strong></td>
<td>-0.2265 (0.2306)</td>
<td>-0.0483 (0.1041)</td>
</tr>
<tr>
<td><strong>FundingGoal</strong></td>
<td>-0.000001*** (0.00000)</td>
<td>0.0005*** (0.0000)</td>
</tr>
<tr>
<td><strong>Image</strong></td>
<td>0.0046 (0.0114)</td>
<td>0.3943 (0.3038)</td>
</tr>
<tr>
<td>Observations</td>
<td>306</td>
<td>306</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-1467.5</td>
<td>2951.1</td>
</tr>
</tbody>
</table>

Note: ***p<0.01; **p<0.05; *p<0.1, Standard errors in bracket

As medical crowdfunding continues to become commonplace due to rising healthcare costs, understanding factors that help drive funding performance and emotional support becomes important. This work-in-progress offers some insights by showing that communication style plays a significant role. Particularly, it shows that more emotionally framed medical crowdfunding campaigns evoke empathic responses from the crowd and can lead to higher funding and emotional support. Further, it shows that frequent updates can inform the crowd, create connections and show transparency, which can trigger donations and emotional support. The study adds to the growing literature on medical crowdfunding while providing practical guidelines to campaign organizers.

REFERENCES


Radical Technological Innovation and Perception: A Non-Physician Practitioners’ Perspective

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msdohan@lakeheadu.ca

Abstract: Radical technological innovations, such as chatbots, fundamentally alter many aspects of healthcare organizations. For example, they transform how clinicians care for their patients. Despite the potential benefits, they cannot be integrated into practice without the support of the clinicians whose jobs are affected. While previous research shed important light on physicians’ perceptions, little is known on non-physician practitioners view said innovations. This paper reports on a qualitative study, involving 10 non-physician clinicians from Ontario, Canada, conducted to determine the perceptions and cognitions of clinicians regarding radical innovation and their previous experiences with technological change. Results indicate that clinicians as semi-autonomous agents can interpret and act upon their environment with regard to determining how innovations such as chatbots are implemented.

INTRODUCTION

There has been an influx of digital innovations within the healthcare industry that have created opportunities to improve many aspects of healthcare. Despite the availability of these innovations, the important question as to how a technological innovation achieves widespread adoption remains. Many studies of healthcare innovations focus solely on the factors that would be important for a single actor to use the technology, but this approach ignores much of a complex context that characterizes healthcare. One aspect of this context would be the healthcare institutions, which contain many diverse professions, competing interests and other forces that may influence the adoption and use of these technologies. One must consider as well that these technological innovations may bring about a fundamental change to healthcare processes, and not merely consist of an additional task that users must perform. Artificial Intelligence (AI) can be considered one of these technologies. AI seeks to mimic human cognitive functions, enabling physicians to make clinical decisions based on the health information gained from the patient (Jiang, Jiang, Zhi, Dong, et al., 2017). Chatbot agents are one implementation of AI capabilities in an interface that is familiar to patients. Chatbots have been implemented to provide support for independent elderly people (Fadhil, 2018), psychiatric counselling for mental healthcare (Oh, Lee, Ko, & Choi, 2017), and others. These and other technologies have the potential to fundamentally change how healthcare providers and patients manage their relationship and perform their respective activities, within the context of healthcare institutions. Despite this, research on chatbots in healthcare has largely focused on patients. Therefore, this research seeks to address this gap and answer the following question: What are the cognitions and perceptions of clinicians regarding radical technological innovation in healthcare organizations? To fulfill this purpose a qualitative study was conducted to determine the influence of institutional and contextual factors affect the clinicians’ intent to implement the technology.

LITERATURE REVIEW

Technology in healthcare provides many opportunities for patients, clinicians, and many more actors. Among these are the ability for patients to have health related interactions online, and the sharing of big health data from institution-to-institution broadening the scope of available information (Eysenbach, 2001). Artificial Intelligence (AI) is one of these technologies that is increasingly implemented in healthcare. The purpose of AI is to mimic human cognitive functions, enabling physicians to make clinical decisions based on the health information gained from the patient (Jiang et al., 2017). Chatbots in particular encompass a multitude of AI components, such as machine learning, natural language processing, image and voice processing, in a way that engages with patients in a
familiar manner (AHIMA, 2017). They can help track symptoms (Alescanco et al., 2017) and facilitate adherence to a medical regimen (Marciel et al., 2010) for chronic disease patients, connect with an electronic medical record (Ni et al., 2017), or provide wellness-related education (Crutzen et al., 2011).

Although the potential for chatbots to provide benefits to both patients and healthcare systems are clear, the difficulty arises in adoption and embedding these systems successfully into practice, so that they have sustained benefits. Research has determined that there have been reportedly more failures than successes with regards to technological implementations in the healthcare field; the glaring issue, appearing to be the scale of the technological innovation, the broader the scope of implementation the more daunting the task, which affects the potential to achieve a successful implementation (Berg, 2001). According to previous research, the success of information systems can be largely based on the level of acceptance the healthcare professionals have regarding the technology, thus necessitating the acceptance of the technology by the healthcare professionals in order for the technology to be adopted and implemented successfully (Oroviogoicoechea, Elliott, & Watson, 2008).

A technological innovation is considered radical when the innovation fundamentally alters the work processes, the means of communication, or the work environment as whole (Ringberg et al., 2019). The decision-makers engage in divergent thinking when considering implementing a radical innovation as this form of technological implementation necessitates a fundamental shift from the previous methods (Ringberg et al., 2019). Chatbots are considered a radical technological innovation as it has the ability to alter the means by which patients, and healthcare professionals interact within the healthcare field. The implementation of chatbots and many other healthcare technologies would fundamentally shift the means by which patients are able to receive health related information tailored to their specific health issues. As well, the radical innovation would fundamentally shift the means by which healthcare professionals disseminate information, and are able to collect real time statistics based on the wireless monitoring of their patients.

Research Gaps

This research seeks to address two research gaps. First, despite the potential benefits of chatbots, their adoption and use in healthcare have not been extensively studied. Several focused applications of chatbots have been studied, specifically in the contexts of cystic fibrosis (Marciel, et al., 2010), substance abuse for adolescents (Crutzen et al., 2011) and a few others. This study seeks to add to the literature on chatbot adoption. Second, the existing studies focus on patients (Yu, Beam, & Kohane, 2018) and physicians’ perception (Sarwar et al., 2019) of artificial intelligence. For instance, we know that among physicians, AI is generally perceived as a diagnostic tool to facilitate improvements in workflow efficiency and quality assurance in pathology. However, little is known on the the perspective of non-physician healthcare practitioners. As healthcare practices involve multiple parties in a more complex context, our extant silence on non-physicians is regrettable. Therefore, it is important to grasp the clinician’s perceptions with a consideration of their institutional context if chatbots and other radical technological innovations are to be adopted effectively and widely. Therefore, this research seeks to answer the following question: What are the cognitions and perceptions of non-physician clinicians regarding radical technological innovation in healthcare organizations?

MICRO-INSTITUTIONALISM

The theoretical foundation for this research is micro-institutionalism. Institutions are “structured social practices that have a broad spatial and temporal extension: that are structured over long periods of time, and which are followed or acknowledged by the majority of members in society” (Giddens, 1981). Institutional theory has recently begun a fundamental shift from a solely macro-level approach toward a multilevel paradigm explicitly incorporating individuals and on the ground dynamics (Schilke, 2018; Bechky, 2011; Fine & Hallett, 2014: Thornton et al., 2012).

For this research, we turn to micro-institutionalism for building our analytical framework on non-physician clinicians’ perceptions. To begin, a micro-institution is considered to be an organization that has shared values and vested interests, and is comprised of formal structures and procedures developed to assist in the achievement of organizational objectives (Bhattacharya, & Elsbach, 2002). Micro-institutionalism focuses on individual agents as the basic unit of analysis, in some instances referred to as actors interchangeably (Schilke, 2018). Micro-
institutionalism seeks to extend the literature on institutionalism and acknowledge the interplay of decision-makers in the environment and their cognition. For institutional inquiry to be extended it is crucial to focus on how local conditions shape the way decision-makers perceive, interpret, and act within the environment (Schilke, 2018; Bechky, 2011; Creed et al., 2014; Hallett, 2010; Powell & Bromley, 2013).

Micro-institutionalism provides an opportunity to explain variations in resistance to adopting organizational practices (Schilke, 2018), thus illuminating the role decision-makers’ cognitions play in organizational practice adoption. Therefore, conveying the organizational decision-makers are the institutional mediators as they mediate the interface between the organizational environment and organizational action (Barley, 2008); from this conceptualization it is apparent the need to understand the cognitive processes of the mediators as their actions are reflections of the effects of the external institutions (Barley, 2008). It is pertinent to identify the local contexts of the environment and explore the individual actors’ cognitive processes in order to understand the enabling conditions of actorhood (Schilke, 2018). A main facet for micro-level inquiry is cognition, specifying two cognitive mechanisms—certainties, and attention, which explain decision-makers’ variation in resistance to institutional pressures (Schilke, 2018).

**METHODOLOGY**

The research design for the study encompasses primary data collection and analysis of the data. A qualitative research design is necessary as the facets being explored are emergent. Clinicians in Ontario, Canada, were sought individually through an online advertisement. The advertisement contained the qualifier dictating only clinicians who have encountered technological change in the workplace are eligible to participate in the research; this ensured that the participants were able to provide relevant information for the study. The clinicians as individuals are the unit of analysis.

The interview guide was developed in accordance with facets of micro-institutionalism, and radical technological innovation. The key themes for this are: previous technological experiences, perceptions of chatbots, and potential resistance and issues. The questions were derived from the literature and the theory to gain insights regarding the clinicians’ experiences and perceptions. To ensure that the participants understood chatbot technology, the interview process commenced with two videos to debrief the participants regarding chatbot and its capabilities.

After the interviews were completed, the audio files were transcribed by the researcher, and uploaded to nVivo 12 for thematic analysis. Data was analyzed using a thematic analysis (Braun et al., 2018) approach, involving six phases: 1) familiarization with the data, 2) creating a set of initial codes, 3) identifying the themes, 4) reviewing the themes, 5) naming and defining the themes, and 6) developing the final report (Braun, et al., 2018). Lakehead University Research Ethics Board has provided ethics clearance to this protocol.

**KEY FINDINGS**

Data collection took place between May and June 2019. Interviews took place in person, and over the phone. The researcher found that 10 interviews were validated, as saturation point was reached purporting that newer participants were not contributing additional knowledge to the results (Lee, 1999). All participants explicitly stated that they consented to having the interview audio recorded; as well consent forms were signed. There was no personally identifiable information collected to protect the anonymity of the participants. The semi-structured interviews were conducted with a Clinical Nurse Manager, Registered Nurses, Medical Students, and a Registered Practical Nurse, with a female representation rate of 90%. The primary professions being represented are registered nurses with 60% representation rate, and medical residents with 20% representation rate. Table 1 (below) summarizes this information.
Table 1: Description of the Participants

<table>
<thead>
<tr>
<th>Profession</th>
<th>Age</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>Registered Nurse</td>
<td>53</td>
<td>Female</td>
</tr>
<tr>
<td>Registered Nurse</td>
<td>52</td>
<td>Female</td>
</tr>
<tr>
<td>Medical Student</td>
<td>27</td>
<td>Female</td>
</tr>
<tr>
<td>Clinical Nurse Manager</td>
<td>34</td>
<td>Female</td>
</tr>
<tr>
<td>Registered Nurse</td>
<td>25</td>
<td>Female</td>
</tr>
<tr>
<td>Registered Nurse</td>
<td>22</td>
<td>Female</td>
</tr>
<tr>
<td>Registered Practical Nurse</td>
<td>29</td>
<td>Female</td>
</tr>
<tr>
<td>Medical Student</td>
<td>24</td>
<td>Male</td>
</tr>
<tr>
<td>Registered Nurse</td>
<td>24</td>
<td>Female</td>
</tr>
<tr>
<td>Registered Nurse</td>
<td>54</td>
<td>Female</td>
</tr>
</tbody>
</table>

Analysis of the interviews yielded 4 overarching themes related to the impact of technology, local conditions, resistance, and implementing chatbots. A concise version of the findings is presented here, and an expanded version will be presented at the conference and made available on request.

**Impacts of Technology**

The benefits of technological innovation range from enhanced organizational workflow to improved patient outcomes. The organizational processes have been improved, as clinicians are now able to more efficiently dictate patient reports and review empirical information. Furthermore, technology provides additional accountability, as uploaded information can be time stamped:

“And there is always proof that things were sent and received versus just getting a piece of paper where there’s not actually a time stamp. So online it has exactly what time it came in so that we knew a report was late” (Interviewee 5).

Technology requires accountability from the patients as well, much like an additional technology for the Telehomecare program:

“Required patients to every morning or however many times a day they are instructed to get on their scale, take their blood pressure through the electronic blood pressure cuff, and then those results are sent to the telehome nurse which was an advantage as a lot of people like the patients in the community, you know you can teach them so much but whether they are doing it or not like you have no idea this way you are getting the actual numbers because everything is hooked up to that iPad which automatically transfers to the nurses” (Interviewee 5).

The interviewees communicated the pitfalls of current technology, as well as mentioned the work processes that would benefit from technology. A detriment of technology mentioned was an over reliance on the information at hand:

“A main drawback is that we need to make sure that we are not just relying on those electronic medical records. For example we had a lady going in for gastric bypass surgery. [...] The surgeon looked at the electronic record and thought everything was fine, anaesthetists looked over the record everything was fine. I looked over the record and this is online and everything looked fine. So when I saw the patient I’m flipping through her chart and I find a tucked in sheet of paper for a sleep apnoea clinic [...] so she has a statistically significant increased risk” (Interviewee 1).

It became apparent that for widespread changes to the technology the majority of clinicians encountered similar training experiences. Training sessions and support were important:

“We had courses and different sessions that the technology team would introduce the technology, and that was pretty good, they took the time with us” (Interviewee 9).
“With the Meditech system there is the IT team that we can call at anytime that helps us through issues” (Interviewee 4).

Local Conditions

It is apparent that local conditions shape the way these agents as decision-makers act within their environment. The local conditions vary from organization to organization as the work processes and the organizational divisions are unique. For instance, in a remote community they may experience variations in methods of care:

“We do it currently in the ICU we were having issues we weren’t able to, as we are a small rural hospital, we didn’t have arterial line monitoring. So the nurses like we talked to our manager and said that we should probably really get that since it’s an ICU, and we were able to convince them to bring it in” (Interviewee 6).

A couple of clinicians expressed that they felt that they did not have the opportunity to act on behalf of themselves to promote technological advances nor were presented with opportunities to voice their concerns regarding issues with their work processes:

“No, not really, it’s kind of just more like organizationally driven. It’s not driven by us, I would say, it’s unfortunate we don’t get our opinions asked on many things” (Interviewee 4).

While, other organizations encourage open interdivisional communication by providing specific communicative tools to the staff:

“So at least specifically on our floor they’ve just started, we're one of the pilot projects and it's a whiteboard communication tool on a daily basis that we have to do and it's to say okay what's working what's not working. How can we improve it. We're one of the pilot floors and management is behind it. Right now we're getting things done and through quickly. Now once everybody's on board and management is now going to be a little bit more scarce about supporting things but that would be one of the platforms that we could bring it forward to and say hey you know what. [...] This is an idea we can put it forward and at any point we can send an email to our CEO of the hospital” (Interviewee 10).

Resistance

Resistance with regards to technological innovations within the micro-institutionalism scope were explored based on previous experiences with technological implementations. To begin the perceptions of clinicians who experienced no resistance in their healthcare establishments will be reviewed:

“If there is a need more physicians are willing to pick things up or they’ll at least try and see is this easier, does this make my practice easier” (Interviewee 1).

While, another clinician explained the resistance to be a fear associated with altering the work processes to be more technologically advanced:

“Everybody was scared to go from writing in a paper chart to go to using a computer” (Interviewee 9).

To combat this resistance the organizations generally remedied the matters with similar methods:

“A lot of the senior nurses were given additional time” (Interviewee 3).

While another clinician mentioned that:

“The educators kept reinforcing and educating on how to use it, and how it is a good thing for us” (Interviewee 5).
The repetition aids in the reinforcement of the information allowing for more opportunities for the clinicians to learn the components of the new technologies:

“The older nurses watched the videos a few more times and paid more attention” (Interviewee 6).

Implementing a Chatbot

Affirming that a large portion of patients have access to a smartphone device that would be capable of accessing chatbots. Focussing on accessibility there is a need for access to relevant health information as there may be a lack of access to routine healthcare in some instances. Many applications exist, such as health coaching, treatment adherence, education. Chatbots have potential to assist a broad range of illnesses by helping patients to track their symptoms and issues and providing them with relevant medical advice:

“The ones (patients) with hypertension just to be able to monitor that much like the fellow from the video, they're having the remote blood pressure and they were able to see that. [...] But I could certainly see it that the patients would be better managed at home before they came into have surgery and then to be followed after” (Interviewee 10).

Potential exists to divert unnecessary trips to the emergency department:

“I think some of the advantages would be like lots of people when they come in and they're like newly diagnosed with stuff and then they don’t really have any resources in the community and they end up going to emerge a lot for things like that and that's like a big burden on healthcare people going to emerge because they like don't know what meds they should have taken and stuff like that, and they don't have a family doctor” (Interviewee 4).

The optimal implementation strategy may differ from organization to organization based on the environment’s work processes, and dispersion of resources. The clinicians shared their personal cognitions regarding potential implementation strategies. It may be ideal for certain subsets of the patient population to have the clinician further elaborate on the pamphlet, and in that scenario it may be best executed in a family medical practice where there are allotted times for each patient. An opportunity akin to the previously mentioned pilot projects a clinician recommended to:

“Pick one group at a time to do it with a common condition and I would probably communicate the information to patients as they wait for appointments, sometimes there's information in the waiting rooms and try to pitch it that way. So that sounds like an option but it can cause you to keep more organized with their health information..... if it's done to a limited extent and might focus more on mental health care. But if more of that if it also had that connection to linked to existing telehealth networks so that that is the same way they also talk to their doctor so that the technology is associated with. The medical professionals communication as well if it's all happening in one place and it doesn't seem like two systems going at once” (Interviewee 7).

The healthcare professionals may be more resistant if they are uncomfortable using the technology themselves, or advocating the technology to patients. Therefore, it would be important to educate the healthcare professionals to ensure that they are comfortable promoting the tool, and are able to facilitate the provisioning of the app. Another prominent focus would be on selecting the appropriate level of healthcare professional that would be responsible for initiating the conversation with the patients if the advocacy were to be one-on-one as there are levels of healthcare professionals that lack the time necessary to educate their patients on the benefits of chatbots itself.

Another potential issue is users become embedded in their ways and would potentially be uncomfortable using the technology or would be uncertain as to how secure their information would be. Therefore, from the patient perspective there may be some resistance as people are more likely to resist a radical innovation if it disrupts their embedded approaches to life in this case their healthcare:

“There are a lot of resistive people like when you get used to something for so many years you don’t want to change obviously I think change for some people is scary (Interviewee 5).
“We have a lot of the older population who don't have cell phones it's not really a great technology for them” (Interviewee 3).

DISCUSSION

This research seeks to explore the cognitions and perceptions of clinicians regarding radical technological innovation in healthcare organizations. This research employed a micro-institutional lens focussing on the conditions under which actors perceive technology. This research sheds light on the enduring agency debate—questioning whether the clinicians are merely institutional carriers or active agents who perceive, interpret, and act upon their environment (Schilke, 2018). The research determined that indeed in most instances clinicians were actively participating within their environments, advocating for changes, and successfully changing their local conditions. The clinicians’ perceptions of radical technological implementation varied based on their previous technological experiences and their personal preferences, and espoused a need for such a technology to be instituted into healthcare organizations. The participants provided insights as to how to optimally implement the tool, concerns regarding resistance, potential problems and outcomes. In a couple of instances, the clinicians considered themselves mere institutional carriers succumbing to the environmental pressures they considered to be administration’s guiding policies. Therefore there is evidence that supports the agency debate, proving that agents are able to interpret and act upon their environment if the local conditions are conducive to such actions.

The theoretical contributions provide the potential to expand upon the micro-institutionalism framework. Information Systems research is generally conducted with the Unified Theory of Acceptance and Use of Technology (eg. Kijjanayotin, Pannarunothai, & Speedie, 2009), and the Technology Acceptance Model (eg. Yarbrough, & Smith, 2007); this research sought to be transformational, reticulating radical innovation with micro-institutionalism to discover whether different facets of micro-institutionalism may affect the clinicians’ perceptions of radical technological innovations. As posited by Schilke (2018), there are limited studies focussing on decision-makers’ experiences and reactions to environmental pressures. This research provides an extension to the theoretical foundations as the majority of clinicians that were interviewed communicated that they were able to act as agents within their organizational contexts, and were able to advocate for change. The majority of the clinicians explained their personal experiences with technological innovations in the workplace, communicating the environmental pressures and the local conditions that were present, which triggered in most cases the resistance from other clinicians in those environments. These findings generally indicate the viability of this new approach for information systems research in healthcare.

The managerial implications associated with this research are as follows. The clinicians have varying perceptions of their abilities to act as agents within their organization, this signifies the differences in organizational policies. A managerial consideration would be to encourage interdivisional transparency to ensure that clinicians have the opportunity to participate in organizational decision-making. The clinicians are the frontline employees that work directly with the patients that would be using chatbots; therefore, they are the optimal source of information when it comes to the applicability and viability of the technology for their patients. As well, their perceptions regarding the optimal implementation strategy are invaluable as they are able to gauge the optimal form that will translate to the best reception of the technology from the patients as well as the other medical staff affected. If clinicians are involved in the decision-making process they are less likely to be resistant to new policies and procedures.

LIMITATIONS

Although this is a small scale study, it has several other limitations. First, the study would have been more effective if the clinicians had the opportunity to engage in an interactive demonstration of the system to gain a better understanding of the capabilities of chatbots. Therefore, this study used chatbots as a reference technology for ideation purposes only, which is not a very robust approach. An additional limitation was the access to clinicians as the representation of nurses is exorbitant in comparison to other healthcare related positions. It would have been beneficial to gain insights from primary care physicians that would be able to advocate for chatbots and their implementation. As well, the opinions of those interviewed may be biased based on their past experiences with
technology; therefore, their perceptions may be considered biased. Regarding the data analysis, reliability could be improved with interrater reliability measures, which would involve another researcher confirming the themes through a parallel coding process. Future research therefore could focus on more rigorous data analysis, ensuring a wider representation of participants, or improving the focal artifact.

CONCLUSION

The purpose of this research is to determine the cognitions and perceptions of clinicians regarding radical technological innovation. A qualitative research design was employed, involving 10 Ontario clinicians. Overall, the results of this study are generalizable to other healthcare establishments as the contexts and experiences are generally similar throughout the healthcare organizations represented. The perceptions and cognitions gathered are reflective of the research question and present the experiences of clinicians, which shape their perceptions of the viability of chatbots. Future directions for research include the integration of chatbots into practice, and the analysis of the effects the implementation has within the micro-institution.

REFERENCES


HSP: A Tool for Heat Stress Prevention for Farm Workers

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Abstract: We present the initial development of an integrated application for heat stress and heat related illness prevention in farm workers. In developing the application we have follow the OSHA guidelines and an extended project includes the social, cultural and economic factors of farm workers. Even though, our development focus is on workers in the California fields, we believe our project will be useful in multiple situations where individuals are exposed to extreme heat working conditions. This paper describes the motivation for our development, the overall approach we are following, and the first version of our application.

INTRODUCTION

In 2013, Courville, Wadsworth and Schenker (Courville, M.D., Wadsworth, G., and Schenker 2015) conducted a research about heat illness in farm workers in the Northern California fields. As a result, they found that heat stress and heat related illness results in multiple deaths in California farm fields every year, regardless of campaigns to reduce Heat Related Illness (HRI). Factors causing HRI are more complex than just a consideration of environmental, work intensity and/or physiological components (CDC, 2008). For an integral solution to HRI, we need to consider additionally the cultural and socio-economic factors unique to the largely immigrant pool of farm workers. A more complex study to reduce and prevent HRI (Schecker, 2016), includes: a socio-economic analysis with agricultural stakeholders from farm organizations and labor to develop appropriate and effective strategies to reduce the risk of HRI. Such study also includes a proposal for determine the economic cost and predict the benefits of reducing HRI in California agriculture; and a set of mobile and smart applications (or apps for short) to implement primary and secondary HRI prevention approaches.

The project presented in this paper derives from (Schecker, 2016) and focuses on the specification and development of technology solutions using smartphones and body sensors to prevent HRI.

In the following sections, we describe the overall solution we are proposing, and then we address the system specification of our project and the status, and characteristics of the first application we developed. Finally, we conclude with the follow up actions defined in our approach.
SMARTPHONE INNOVATION

Instructing agricultural workers (especially Latino workers) to rest in the shade and drink more water has proven to have a limited effect as a strategy to reduce HRI, largely because of the other forces at play; such as economic, cultural and harvest production realities. For example, workers do not want to look weak if they take a break, or they do not want to slow down others, sometimes they mistrust employer’s water cleanliness or prefer other liquid than water. Some other times workers simply do not recognize HRI symptoms or the training materials are not adapted properly for low literacy or cultural needs.

We propose to use a novel engineering solution involving the development of a new smartphone application (app) that will be oriented to the specifics of their workforce, crop, location and real-time weather conditions and forecasts. This will be a major enhancement over the basic California Occupational Safety and Health Administration (Cal-OSHA, 2015) app currently available that uses the National Weather Service network and the mobile instrument’s GPS to provide the current heat index, level of alert and very general suggestions for work, rest, shade and drink schedules.

Study Design:

Electronic Health or “eHealth” is the application of information technology to support, complement or provide health related services to the people (CITRIS 2014; Jennett 2005; Latifi R 2007; Macleod 2012). In particular wireless systems provide vast opportunities to deploy new services to cope with needs in underserved communities (Nadal 2007). The power of eHealth systems to prevent health problems may be augmented by the capabilities currently available in smartphones and other mobile devices. eHealth systems have been developed in urban settings where cell phone coverage is reliable (Chu 2004; Macleod 2012; Van der Velden 2008). In the case of rural areas, the use and availability of wireless and mobile technology has been increasing during the last few years (Jennett 2005; Macleod 2012; Nadal 2007; OpenSignal 2015). Creation of new applications, especially in public health and health care services is increasing exponentially worldwide. Studies of immigrant farmworkers in the US have found that over 80% of these individuals own cell phones and a large percentage of these are smart phones (Price et al. 2013). Further, the majority (81%) of farmworkers expressed a willingness to receive health related messages via their phones. Mobile messaging has been used among California farmworkers to reduce risk of pesticide illness (Versel 2013). Technologies have already been developed to integrate individual sensors and wireless networks in secure transmission systems (Challa 2008; Villarel 2013).

A set of Information Technology apps for Heat Stress Prevention (HSP), HSP-1 and HSP-2, will be described next. They will be designed to work independently but also in conjunction with each other.

HSP-1 will be used to send Informative and Periodic Recommendations Reminders to supervisors and on-site work leaders of field workers.

Concett:HSP-1 is a multipplatform application that presents information about current weather conditions and farm specific work types and computes/predicts the heat risk factor and outputs recommendations for preventing heat related illness. The application is accessible through a web portal in different devices: personal computers, tablets, basic mobile or smartphones. Additionally, HSP-1 can send text messages to mobile phones with specific preventative actions to do during the working day. HSP-1, can be viewed as an improved development to the Cal-OSHA app [Cal-OSHA] which only computes the heat risk factor and present a useful but lengthy recommendation text for actions.

Plan: Our inputs will include:

- Current time, location local temperature and humidity which will be taken directly from the device, its GPS and public available web services or may be introduced manually.
- Workload categorized (low, medium, high) will be included similar to the Cal-OSHA app.
- Other site specific information: task, crop and demographic data such as age, gender, language (English, Spanish, other) and mobile phone number.
Values taken from web services or sensors may be updated automatically during the working session and the corresponding outputs will be recalculated.

The output information will be:

- **HRI Risk Index** We will categorize an index of HRI risk into 3 levels similar to the current Cal-OSHA Heat Index, and include additional information to individualize the risk estimation for the particular site, crop and work task(s). The index would be based on an algorithm of the input values developed from our current study. The maximal HRI index for the work day may be predicted using temperature and humidity forecasts.

- **Scheduling recommendations for current and predicted conditions and work/task types**
  - List of Breaks. Timing and duration of break, and frequency of liquid intake suggestions.
  - Reminders. Supervisors may be sent short text reminders to alert their teams to rest or drink.
  - General Alerts. Considering the input information some general alerts may be issued, for example “Work should be shortened to half day”, etc.

*High Risk Alerts.* If for example, a heat wave is expected or weather conditions suddenly change during the day negatively affecting work conditions. If there are more vulnerable sub-groups of workers present, the app may be used to provide them with specialized instruction.

**HSP-2,** will be used to monitor local and Individual HRI in real-time.

Concept: HSP-2 builds on HSP-1 functionality and adds assessment of HRI evaluation of individual farmworkers using biological input data. The real time monitoring in the fields will allow the detection of signs of potential HRI in workers, and alert their supervisors. The detection of early stage HRI directly addresses requirements in the most recent heat stress standards for California, which states: “if a supervisor observes, or any employee reports, any signs or symptoms of heat illness in any employee, the supervisor shall take immediate action commensurate with the severity of the illness.” The standard, however, does not provide easily understood guidance as to what constitutes “signs and symptoms of possible heat illness”. Our HSP-2 app will provide a specific tool to assist supervisors in evaluating workers with potential heat illness. The physiologic measurements, collected by a Body Sensor Network or BSN, may include one or more of the following: heart rate, body temperature, and hydration level. In addition, simple clinical signs or symptoms can be inputted into the program such as nausea, sweating, weakness, and orthostatic symptoms. This information notify the supervisor of the probability of heat stress illness and its severity. The app will further spell out the appropriate emergency response procedures, as required by the state regulations.

Plan: Our inputs will build on HSP-1, the additional inputs will include the acceptance range of values for vital signs, individual farm worker skin or tympanic membrane temperature, heart rate, from the BSN, farm emergency contacts from the Illness and Injury Prevention Plan (IIPP).

Regarding outputs, the acceptable ranges of vital signs for farmworkers determined using data collected in the current study will be included in HSP-2. HSP-2 will also send notification to the supervisor whether a farmworker’s symptoms suggest HRI, and if so, the severity of the HRI, the appropriate and mandated follow-up procedures including monitoring and immediate action commensurate with the severity of the illness. The data gathered by local sensors (weather stations at airports and irrigation districts) and BSN may be stored in a data repository (removing personal identifiers) for further data analysis and research.

Developmental Process: For both applications, we will utilize mobile devices (smart phones or basic cell phones with text messaging capabilities) and a web portal base application accessible by smartphones. We will use short text message service (SMS), and cellular communication networks (3G, 4G) or WiFi if available. Otherwise Bluetooth Communication Protocol or Civil Band Radio will be used to communicate HRI related information to the supervisor. We will develop the HSP-1 and HSP-2 technologies using a mixed approach of software development methodologies. Initially, a traditional Waterfall model will be used for the first set of requirements elicitation and specification activities. Once we have specified and prioritized the first set of functional and other requirements for both applications, we will proceed with an Incremental Model to build our HSP-1 and HSP-2 apps. The Incremental Model will iterate over the phases of Design, Codification, Testing, Integration and Delivery.
CURRENT STATUS OF THE APP AND FUTURE RESEARCH

Currently we have finished our first version of the HSP 1 application that has the following characteristics. Basic functionality includes:

- Based on geolocation
- Shows temperature and user location
- Shows humidity percentage at user location (or to specific location input by user)
- Computes heat risk index for user location
- Provides a list of actions to follow considering heat risk index, user location, and OSHA recommendations
- Generates notifications with periodic recommendations based on the previous list
- Allows making 911 calls directly from app.

The system is design considers the following users characterization (personas)

Field Worker
- Works in the open
- Works for long periods (sunrise to sunset)
- She/he has access to a smartphone, we already conducted and study including a focus group to verify that most of the workers already have a smartphone.
- Speak English, or Spanish, or both

The following images illustrate some of the functionality available in the current version of our application. At this time, we have versions for the two most popular operating systems in smartphones Android and iOS.

In the following months, we will start adding body sensors for detection of humidity and temperature. This part has become difficult due to cultural aspects such as workers do not want to wear anything else besides their own clothes, and to the nature of the sensors which most of them are designed to take body measures in a controlled environment, i.e., a room with controlled temperature with people seated and not moving.
Compared with the current OSHA applications our HSP-1 adds some few features not available at OSHA app.

First, our version includes a more intuitive and visual interface, heat risk indicators are present at all times, also the locator indicator and hourly heat index information are always available and updated. Currently we are using the OSHA recommendations and forms to calculate heat risk index.

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Implications of Vital Sign Monitor and Electronic Medical Record Integration on Identification of Patients in Deteriorating Condition

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Abstract: The manual transcription of patients’ vital signs often delays entry of critical information to Electronic Medical Record (EMR) systems. This documentation delay within inpatient settings results in a lack of recent information on patient condition, decreased ability for providers to make clinical decisions, and an increased risk of data error. To alleviate these concerns, hospitals are adopting device interface systems which digitally integrate medical devices and EMRs. Prior studies have found that this type of system integration can potentially reduce the time spent on manual entry of information in the EMR and support other value-added activities in the hospital. However, these studies suffered from intervention bias from direct monitoring of clinicians using time-motion methodologies, which are resource restrictive and can affect patient care. In this study, we utilize a natural experiment setting to understand how the implementation of a device interface system between vitals monitors used on medical/surgical units and the EMR has impacted hospital workflows and patient care in a regional hospital. Our investigation focuses on two areas. First, we examine if the new system influenced documentation delays, and whether the impact was similar for different employee roles. Since vitals on medical/surgical units are typically taken by Patient Care Assistants (PCA’s) or other ancillary staff, we hypothesize that a greater average decrease in documentation delay will be found in their role. Second, we study the effect of interface system implementation on downstream patient care activities, such as models designed to identify patients in deteriorating condition. We analyze data on documentation delays across more than 5,000 patients and 330,000 documentation events for one week before and after system implementation. Additionally, we intend to utilize hierarchical models to distinguish the impact of systems for various roles (including PCA’s and nurses) across the hospital. Preliminary findings suggest that the interface system results in a statistically significant decrease in time between when vital signs are taken and documented, as well as The findings from this research would inform hospitals of the benefits and the requirements for a successful integration of medical devices and EMR systems, as well as the impact on activities dependent on accurate and timely vital signs documentation.

INTRODUCTION

Vital signs are routinely obtained measurements of a patient’s hemodynamic status in both ambulatory and inpatient settings. The ability to closely monitor vital signs has been identified as an advantageous practice for recognizing both deteriorating patients and those that may no longer require acute care (Ludikhuize, Smorenburg, de Rooij, & de Jonge,
2012). Despite this, significant issues have been discovered in analysis of the workflow for obtaining and documenting patient vital signs on medical-surgical floors where continuous monitoring systems are not commonly employed (Weenk et al., 2018). Clinicians have been found to regularly enter data incorrectly into the electronic medical record (EMR), delay entry of data until long after it has been obtained from the patient, and even omit entries until shift-end (Fieler, Jaglowski, & Richards, 2013). This has encouraged the adoption of both fixed and mobile EMR-integrated vital signs documentation devices which are designed to reduce error in data entry, increase value-added patient care time, and shorten documentation delay. Implications of such systems have been studied, and dramatic decreases in both error and delay have been noted. However, the effects of a vital sign integration system on scoring models which identify patients in declining condition, and are commonly calculated automatically by the EMR, have not been studied.

This research examines the effects of integration of a vital sign capture device and EMR on both the delay of documentation of vital signs by staff and the timeliness of warnings that allow patients who are exhibiting unstable vital signs to be recognized, and intervention to be taken, sooner. We particularly examine the effect of the implementation on the timeliness of warnings based on the Modified Early Warning Score (MEWS), a widely used algorithm for identifying patients in need of immediate assessment or intervention. We find that the implementation of such a system will significantly impact the timeliness of warnings created by the EMR, providing a substantial benefit to both the hospital and hemodynamically unstable patients affected.

The positive clinical applications of EMR usage have been well documented. EMR’s have been noted to reduce errors as compared to paper charting (Hogan & Wagner, 1997). EMR usage has been strongly encouraged through the HITECH Act of 2009, which provided incentives for EMR adoption and penalties if hospitals failed to implement them. However, the time efficiency of EMR documentation has been questioned. Anecdotal experience from the authors reveals that nurses and clinical staff frequently comment that EMR documentation detracts from time spent on direct-patient care activities. Despite the anecdotal comments of clinicians, literature has identified that EMR utilization does not affect documentation time vs. paper charting (Hakes & Whittington, 2008). Due to the current ubiquity of adoption of EMR’s, research has shifted from implementation to optimization. Utilization of systems that optimize workflow inefficiencies, especially those related to patient complexity, has been suggested as a “next step” in developing more effective EMR’s at both the vendor and hospital level.

Reduction in the amount of times a clinician is required to document in an EMR during a shift offers the opportunity to reduce both frequency of data error entry and the outright time spent documenting. One of the most obvious targets for such an intervention is the documentation of vital signs, which reflect a patient’s hemodynamic status. Typically obtained using a machine, these values must then be transferred to the EMR, creating an opportunity for error and delay, particularly when paper “workarounds” like notes are used (Stevenson, Isrealsson, Nilsson, Petersson, & Bath, 2018). Previous literature has noted the effects of poor data quality on predictive acuity scoring models, including the Modified Early Warning Score (MEWS) (Keene, Kong, Clarke, & Brysiewicz, 2017). Communicating this data from the machine to the EMR eliminates the risk of human error in documentation, as well as greatly reducing delay (Meccariello, Perkins, Quigley, & Rock, 2010; Smith, Banner, Olney, Friedman, & Eng, 2009).

The effect of the implementation of such a system on nursing workflows has been examined; however, it has mainly consisted of time-motion studies with direct observation of employees by researchers (Fieler et al., 2013). These studies are possibly subject to both the Hawthorne effect and observation bias, which could skew findings (Eckmanns et al., 2006). They additionally require extensive workhours to directly observe employees while timing workflows. We conduct this study using an entirely retrospective method, utilizing EMR documentation from before and after the intervention to evaluate efficiency improvements on thousands of patients.

Most critically, the impact of automatic documentation of vital signs on predictive scoring models, such as MEWS, has not been examined in non-critical care settings. We predict that implementation of the vital signs interface system has a significant effect on timeliness of warning alerts, which can expedite patient assessment and intervention, thereby reducing the detrimental effects of further patient decline.
BACKGROUND

Preparation

Information Technology staff at a 404-bed regional hospital were approached regarding the possibility of implementing a vital sign interface system by Operations staff at the institution. Following examination of multiple vendors, a third-party integrated EMR interface and device vendor was selected for implementation. This system offered compatibility with the EMR used by the hospital.

Workflow for documentation of patient vital signs prior to system implementation was frequently prolonged due to clinicians delaying entry of data until after all vital signs sets for assigned patients had been obtained. This was especially frequent when clinicians (particularly Patient Care Assistants, the main non-nursing ancillary staff at the hospital) had a sequence of patients with vital signs documentation required at the same time. Workflow analysis revealed that they frequently documented vital signs on paper notes carried on their person, then inputting the data later. This time difference between the time vital signs were taken, “Time Taken” and the time vital signs were documented, “Time Recorded”, is obtainable from the EMR, and was the main variable of interest in this study. The vital signs monitors sought to reduce this delay by automatically uploading data to the EMR following measurement acquisition by the machine.

To accomplish this, the system utilizes three main parts. First, the monitor used to obtain patient vital signs was enabled, via radio card installation, to speak to the interface. Since the model of device selected was already in use at the hospital prior to the interface system installation, some devices required hardware upgrades to accomplish this. The device then had to be appropriately configured via files provided by the vendor to create messages that are understood by the interface. Next, the data obtained by the device was transmitted over an internal wireless connection to the Connex interface. This interface, installed on a hospital server, both converts and stores data received from the devices into a Health Level 7 (HL7) message that can be interpreted by the EMR. Data from the interface is then transmitted to the EMR, where it is read and recorded within Documentation Flowsheets, the location vital signs data is stored. The entire process takes about thirty seconds from the time the clinician selects “Send” on the device to when the data is visible within the chart.

From a clinician’s perspective, the workflow for utilizing the integrated monitor adds few new tasks. First, the clinician scans their ID badge. The clinician’s badge is linked to the system, allowing for identification of the clinician on the device and within the EMR. They then scan the patient’s wristband, which links an encounter-specific identifier in the EMR and the device. Following visual verification of both identifiers, the clinician proceeds to take vital measurements. These measurements typically consist of blood pressure, heart rate, temperature, pulse oximetry, and respiratory rate. However, the devices were also configured to offer the ability to document weight, scale used, oxygen flow type, and oxygen flow rate. These options are present on a different screen and are used much less frequently by clinicians. Once the data has been obtained, the clinician presses “Send”, initializing the aforementioned data flow between the device to the EMR. Logs of the messages sent are kept on the device, the server, and within the EMR. Clinicians can validate the transmission of data by looking at the sent messages on the device, as well as validating within the EMR. Clinicians were advised to validate data regularly to ensure they are consistently crossing over throughout the shift.

Implementation

Implementation took place over a four-month period in 2019. Input was needed from Server, Interface, Clinical Documentation, Nursing, and Biomedical Technologies teams. Two hospital units were originally selected as pilot groups for the go-live; however, this was later changed to all non-ICU medical surgical units at the hospital. The project was not planned to replace all devices in use at the hospital. Instead, 71 devices were either upgraded or purchased to enable connectivity. Clinicians were expected to continue to manually document vital signs if an integrated device is not available.

Integrated testing took place two weeks prior to go-live. All known problems were resolved to the satisfaction of users prior to go-live. Go-live took place over a two-day window in late June, with 13 medical/surgical units receiving integrated devices. Intensive care units were purposefully excluded from implementation, since all ICU’s had fixed
hemodynamic monitoring systems that obtain readings at more frequent intervals. A technical and clinical specialist from the vendor came on site and trained end-users at all units which received devices. An issue involving clinician identification within the EMR was identified on the second day, but was able to be quickly resolved through the intervention of IT leadership. No other potential safety issues were noted during go-live, potentially due to prior clinician experience with the device. Since the device had been used for manual data entry prior to integration, clinicians were familiar with the device design.

**Evaluation**

Following implementation, the IT team primarily responsible for the system was requested by IT and Operations leadership to determine the efficacy of the intervention. This request, in line with the “Check” stage of the Plan-Do-Check-Act model, provided an opportunity to evaluate the system and clinicians’ opinions of it. Anecdotal and informal surveys were conducted by Clinical Informatics Nurses who regularly round on inpatient units to identify and help resolve documentation questions posed by clinicians. Feedback from clinical staff was positive, with most remarking about the time savings the new system brought to their workflow.

One unexpected comment from a nurse involved downstream patient care activities seemingly unrelated to the device integration. Nurses are advised in hospital policy to have recent vital signs recorded before administering a high-risk medication. This leads to delays when vital signs have already been taken by ancillary care staff but have not been documented in the EMR. It is inadvisable from a patient satisfaction perspective to repeatedly take vital signs in a short period for non-acuity related reasons, so nursing staff would then try to reach the PCA or other ancillary staff that obtained the measurements prior to administering the medication. Depending on the workload and availability of staff, this could delay medication administration. This comment led to the consideration of other downstream patient care activities that utilize hemodynamic status data and the impact of the integration on those workflows.

The first, and primary, downstream activity identified was the Modified Early Warning Score (MEWS) model, which utilizes six data points (Table 1) to identify patients who may require immediate evaluation and intervention. The model is automatically scored by the EMR based on the values input by clinicians. When the patient’s score exceeds a threshold of five points, a warning banner appears when opening the patient’s chart, alerting the clinician and advising them to contact the provider or rapid response team to evaluate and intervene to avoid further decline. Since the model is dependent on accurate vital signs to identify declining patients, it was identified as something that could be affected by the system implementation. More important was the evaluation of the impact of improved documentation timeliness on when the alert occurs relative to the most recently taken vital signs. Reduction in this time allows for clinicians to intervene sooner, especially when they are unaware that the patient has declined from a previous state and still may appear to have otherwise acceptable vital signs (Keene et al., 2017).

**Table 1: MEWS Criteria**

<table>
<thead>
<tr>
<th>Variable</th>
<th>MEWS Criteria</th>
<th>Points contributed to MEWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respiration Rate</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Heart Rate</td>
<td>&lt;= 7</td>
<td>&lt;= 9</td>
</tr>
<tr>
<td>Systolic Blood Pressure</td>
<td>&lt;= 100</td>
<td>&lt;= 100</td>
</tr>
<tr>
<td>Oxygen Saturation %</td>
<td>&lt;= 88%</td>
<td>-</td>
</tr>
<tr>
<td>Temperature</td>
<td>&lt;= 100.6</td>
<td>&gt;= 100.6</td>
</tr>
<tr>
<td>Level of Consciousness</td>
<td>Lethargic,</td>
<td>Sedated</td>
</tr>
<tr>
<td></td>
<td>Comatose,</td>
<td>Drowsy</td>
</tr>
<tr>
<td></td>
<td>Obtunded</td>
<td>Alert</td>
</tr>
</tbody>
</table>

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METHODOLOGY

Cohort Identification

The first task in evaluating efficacy of the intervention was to identify patients who should be considered in the data set. While previous studies had closely examined one to two units (Fuller, Fox, Lake, & Crawford, 2018), we decided to evaluate all patients admitted to the hospital that may have been affected by the change. This large sample base both preserves patient anonymity and helps protect against unrelated, unit-specific factors that may influence results. Patients within non-interfaced departments were also excluded from the analysis when they could be identified. This primarily was accomplished by excluding data taken via fixed devices, typically utilized in ICU, ED, and surgical departments.

To obtain the relevant vital signs data, one week before and after the intervention was queried from the EMR. All of the documentation of interest is completed within Documentation Flowsheets, a spreadsheet-style functionality for recording data that changes over time. All Flowsheet documentation for one patient is stored within the same record for a 24 hour period, necessitating the extraction of all Flowsheet documentation, including that unrelated to the study, in patients that met criteria. This resulted in daily extracts of approximately 200,000 rows.

Prior to extracting Flowsheet documentation, identification of employees of an employee cohort was required. To accomplish this, the employee user file was queried for nine employee types. These nine employee types includes: registered nurse, licensed practical nurse, medical assistant, patient care assistant, patient care technician, vascular access specialist nurse, medical assistant intern, certified nurse assistant, and nursing student. This provided ~10,000 employees who were associated with one of the nine employee types, including all such employees since the EMR had been implemented. Employees were further refined to include only those that had a last login department of one of the interfaced units. This served to limit employees to those who conceivably could have taken vital signs on a patient within the cohort. Since float staff are instructed to log into the department of the unit where they are currently working, their exclusion was not a concern. This resulted in a set of approximately ~3,000 employees, which was acceptable for the large granularity filtering desired.

Once employees who may have taken vital signs on a cohort patient were identified, the record containing Flowsheet data was queried for documentation that met all of the following criteria in Table 2. For pre-intervention data, this resulted in a cohort of 2576 inpatient encounters. For post intervention data, this resulted in a cohort of 2462 inpatient encounters.

<table>
<thead>
<tr>
<th>Table 2: Flowsheet Data Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Criteria</strong></td>
</tr>
<tr>
<td>User who took the vital signs (or any flowsheet row that day) is contained within the previously established employee cohort</td>
</tr>
<tr>
<td>Documentation is limited to one 24-hour period from 0000 to 2359</td>
</tr>
<tr>
<td>Flowsheet documentation contains at least one blood pressure recording that day</td>
</tr>
</tbody>
</table>

Alert Identification

Following establishment of patient cohorts, alerts based on vital signs were then identified. Alerts due to a MEWS score of five or greater from the weeks evaluated were extracted and linked with Flowsheet data. To establish a relevant link between the alert and the time vital signs were recorded, the criteria in Table 4 were established.
Table 3: Alert Criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Alert Criteria</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vital signs taken and alert occurred with identical patients.</td>
<td>Ensures patient is the same in both instances</td>
<td></td>
</tr>
<tr>
<td>Flowsheet row matches rows used in MEWS model.</td>
<td>Limits data to that which can affect MEWS</td>
<td></td>
</tr>
<tr>
<td>The vital sign/MEWS row time taken and time recorded pre-date the alert instant</td>
<td>Excludes data that is generated after the alert</td>
<td></td>
</tr>
<tr>
<td>Time recorded is the greatest time recorded prior to the alert instant</td>
<td>Selects the latest value that is recorded prior to the alert</td>
<td></td>
</tr>
<tr>
<td>Only one row per alert is selected</td>
<td>Even when multiple rows are documented at the same time, only one is selected</td>
<td></td>
</tr>
</tbody>
</table>

RESULTS

Table 4 below describes pre and post intervention variables. We analyzed the time to enter vital signs into the EMR for 2576 patients before and 2462 patients after the implementation of the integrated system. During the post-intervention period there is a sharp increase in the total vital signs documented. About 36% of the documentation during the post-intervention period was done using the integrated device. We conduct one tail and two tailed t-test to test to discern if the mean time taken between when vital signs were obtained to the firing of MEWS alert is the same for both pre and post intervention scenarios or not. In this study, the intervention is the implementation of the device integration in the hospital. However, it should be noted that post intervention about 36.885% of the vital signs documentation events utilized the integrated system.

Table 4: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre- Intervention</th>
<th>Post-Intervention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients in cohort</td>
<td>2,576</td>
<td>2,462</td>
</tr>
<tr>
<td>Total vital sign documented</td>
<td>160,207</td>
<td>179,150</td>
</tr>
<tr>
<td>% Taken by RN/PCA</td>
<td>80.61%</td>
<td>81.74%</td>
</tr>
<tr>
<td>% Recorded by integrated device</td>
<td>0%</td>
<td>36.88%</td>
</tr>
<tr>
<td>Total MEWS documented</td>
<td>83,478</td>
<td>83,727</td>
</tr>
</tbody>
</table>

Table 5 below shows the outcome of three two sample t-tests. In the first test we investigate if there is a significant difference in the time taken to fire MEWS when the vitals were entered using integrated device versus not using the integrated device. During our two week observation period there were only 303 instance when the patient’s vitals were so critical that the warning based on the MEWS was triggered. However, during only 45 of those warning was the integrated system used to record the vitals data to the EMR system by the hospital employee. The results show that the time taken to fire the warning was significantly smaller (by ~30 minutes) when the integrated system was used. This significant improvement can prove to be life saving for the patients who arrive at the hospital in a critical condition or decline while admitted.

Next, we conduct the test of difference in mean for time taken to enter vitals by the hospital employees with or without the integrated device for all vitals entry observations (including in the pre and post intervention period). Again, we find that vitals entry using the integrated device is significantly faster (by 17.1 minutes). Another, t-test (Test 3 in table 5) only considers observations during the post intervention period, when about 38.88 % to the overall vitals were entered using the integrated device. This test also shows that the average time to enter vitals is significantly reduced from 19.5 mins to 1.382 mins when the integrated device is used.
Table 5: Two Sample T-Test

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Test 1</th>
<th>Test 2</th>
<th>Test 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>46.9003</td>
<td>16.9948</td>
<td>18.4873</td>
</tr>
<tr>
<td>Variance</td>
<td>6038.8861</td>
<td>508.5038</td>
<td>5860.1429</td>
</tr>
<tr>
<td>Observations</td>
<td>258</td>
<td>45</td>
<td>273293</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>t-Statistic</td>
<td>5.0762</td>
<td>107.3140</td>
<td>93.6375</td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>3.8708E-07</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>t Critical two-tail</td>
<td>7.7416E-07</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Alpha value</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**DISCUSSION & CONCLUSION**

The implementation of the integration system had a significant impact on both the documentation delay for all vital signs taken and on the delay between vital signs being taken and the alert regarding the declining hemodynamic status of the patient. The clinical implications of such an improvement are notable. Delay in rapid response team activation results in a significantly higher risk of mortality and longer hospitalizations (Gupta et al., 2017). Though not all rapid response team activations are predicated by warnings within the EMR, such warnings provide the ability to alert clinicians that may not be aware of a patient’s deterioration. In cases where rapid response activation is due to a decision-support system-based warning, presentation of the warning as soon as the patient’s decline is recognizable is paramount. Delay in entry of vital sign documentation due to clinician workload, fatigue, or other factors is suspected to be significantly improved due to this intervention. Faster response once a patient is declining may result in lower morbidity and mortality.

Two-sample T Tests assuming unequal variances found a statistically significant difference in the time between when vital signs are taken and when they are recorded when an integrated device was used and the time between when vital signs are taken and the instant of the MEWS Alert. Further research to be completed in this study includes the analysis of documentation and alert delay due to vital sign entry for various departments and employee types in the hospital. We would also like to account for the heterogeneity the response to integrated system for different types of employees, vital types and hospital units. Additional relevant outcomes may be established by looking at the time between when vital signs are taken and rapid response team arrival at the bedside, in cases where activations were preceded by an alert.

Limitations of this study are evident in the implementation of the integration system. Since device integration was not implemented for all vital sign measurement devices in the hospital, many vital sign documentation events were not completed using the integrated devices. This reduces the effect of the intervention and dilutes data. This is partially avoided through the identification of vital sign documentation events that utilize the integrated system. Additional factors include the training of employees using the device. Initially, only Nurses and Patient Care Assistants were trained to use the integration system. Other users (such as respiratory or physical therapists) had to learn from another user who had been trained to use the device or learn via trial and error. In future study we plan to account for this endogeneity arising due to selection bias.

Since data analyzed in this study were entirely based on user-entered values, there exists a possibility for inaccuracy. The primary variable analyzed, documentation delay, is reliant on users accurately reporting when they actually
obtained the vital signs from the patient. It is expected that users may frequently round to the nearest easily rememberable time (such as five or ten minute intervals) or may fail to record the actual time they obtained the vital signs, instead documenting the time vital signs were taken as the time that they entered them in the EMR. The assumption of the study is that clinicians accurately and consistently record the time that vital signs were obtained from the patient.

Finally, one variable used in calculation of MEWS, Level of Consciousness, was not interfaced using the device. Alerts that were prompted due to a change in that value would not be affected by the integration. However, since that variable alone does not possess a point-value great enough to trigger an alert, an integrated device would have some effect on the time between when vital signs are obtained from the patient and the alert.

This study highlights how hospitals can reap the benefits of a meticulously integrated system. Though the costs of such an integration are significant, the subsequent reduction in documentation delay and expedition of care for critically ill patients may offset the cost of the investment. Future studies can further investigate the monetary incentives of such an integration strategy. The findings of this study may encourage the adoption of such a system for institutions which are considering cost-reduction strategies through technological investment. Additional opportunities for further commercial development include other technologies focused on reducing clinician documentation time, optimizing hospital workflows, and minimizing the opportunity for human error.

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Abstract: This case study investigates business process redesign within the perioperative process as a method to achieve digital transformation. Specific perioperative sub-processes are targeted for re-design and digitalization, which yield improvement. Based on a 184-month longitudinal study of a large 1,157 registered-bed academic medical center, the observed effects are viewed through a lens of information technology (IT) impact on core capabilities and core strategy to yield a digital transformation framework that supports patient-centric improvement across perioperative sub-processes. This research identifies existing limitations, potential capabilities, and subsequent contextual understanding to minimize perioperative process complexity, target opportunity for improvement, and ultimately yield improved capabilities. Dynamic technological activities of analysis, evaluation, and synthesis applied to specific perioperative patient-centric data collected within integrated hospital information systems yield the organizational resource for process management and control. Conclusions include theoretical and practical implications as well as study limitations.

INTRODUCTION

Within the hospital environment, the perioperative process yields patient end-state goals: (1) a correct diagnosis for surgical intervention is identified with noted co-morbidities and patient consent; (2) a patient undergoes the surgical procedure; (3) a patient exhibits minimal exacerbation of existing disorders; (4) a patient avoids new morbidities; and (5) a patient experiences prompt procedure recovery (Silverman & Rosenbaum, 2009). To these end-state goals, the perioperative process provides surgical care for inpatients and outpatients during pre-operative, intra-operative, and immediate post-operative periods. Consequently, perioperative workflow tightly couples patient flow, patient safety, patient quality of care, and hospital stakeholders’ satisfaction (i.e. patient, physician/surgeon, nurse, perioperative staff, and hospital administration). Accordingly, the perioperative sub-processes (e.g. pre-assessment, pre-operative, intra-operative, and immediate post-operative) are sequential where each activity sequence paces the efficiency and effectiveness of subsequent activities. Furthermore, perioperative sub-processes require continuous parallel replenishment of centralized sterile supplies along with the removal and sanitation of soiled materials, instruments, and devices. Hence, implementing improvements or digitalization is both a challenge and an opportunity for hospital stakeholders, who often have a variety of opinions and perceptions as to where efforts should focus.

Integrated hospital information systems (IS) and information technology (IT) provide measurement and subsequent accountability for healthcare quality and cost that represent the foundation for healthcare improvement (Dougherty & Conway, 2008). Similarly, the Centers for Medicare & Medicaid Services’ (CMS) Electronic Health Record Incentive Program (CMSEHRIP) has quickened the digital transformation of healthcare delivery across the U.S. healthcare ecosystem, in order to exploit the consensus that IT value propositions will improve healthcare quality and reduce costs (Agarwal et al., 2010). Furthermore, the Joint Commission on Accreditation of Healthcare Organizations (TJC),
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and CMS require periodic performance and clinical outcome reporting as evidence of organizational quality, efficiency, and effectiveness. Consequently, administrators and medical professionals alike must leverage IS and IT to yield quality patient care and safety, coupled with increased efficiency and cost effectiveness (PwC, 2012). The widespread healthcare IS/IT adoption from CMSEHRIP necessitates the need for realized value (Jones et al., 2014). However, successful digital transformation requires strategy on change management and application as well as technology implementation (Hess et al., 2016). Hence, this research study focuses on understanding business process redesign prior to health IT integration and use, as the perioperative digitalization will have little impact on performance if not well integrated into daily healthcare providers’ workflows (Agarwal, et al., 2010; Wears & Berg, 2005).

A hospital’s perioperative process is complex (Fowler et al., 2008) and the complexity challenges multidisciplinary teams to maneuver within fast-paced and critical situations. Compounding factors of complexity and urgency affect patient quality of care, patient flow, patient safety, operational efficiency, as well as stakeholders’ satisfaction (i.e., patient, physician, nurse, perioperative staff, and hospital administration). Financially, the perioperative process is typically the primary source of hospital admissions, averaging between 55 to 65 percent of overall hospital margins (Peters & Blasco, 2004). Other research shows 49 percent of total hospital costs are variable, with the largest cost category (i.e., 33%) being the perioperative process (Macario et al., 1995). Hence, IT value propositions via digital transformation offer perioperative quality, efficiency, and effectiveness improvement to ultimately yield hospital financial performance.

This research investigates complexity and change dynamics observed during a hospital’s digital transformation of perioperative sub-processes. The observed effects span a longitudinal study of an integrated clinical scheduling IS (CSIS) implementation, integration, and use. The systematic analysis and subsequent contextual understanding associated with intra-operative, pre-operative, and post-operative digital transformation prescribed opportunity for measured improvement. Specifically, this study investigates the research question as to how business process redesign within the digital transformation of a hospital’s perioperative sub-processes can yield operational excellence and enable improved patient flow, integrated hospital IS to workflow coupling, and stakeholder satisfaction.

The following sections review previous literature with respect to digital transformation, business process redesign (BPR), business process management (BPM), and key performance indicators (KPIs). Following the literature review, we present our methodology, case study background, observed effects, and discussion. By identifying a holistic framework via digital transformation, this study prescribes an a priori strategy for operationalization and replication. The conclusion also addresses study contributions, limitations, and implications.

LITERATURE REVIEW

A digital business strategy identifies how an organization aligns IT to create a fusion between IT strategy and business strategy (Bharadway et al., 2013). Likewise, the digital business strategy distinguishes how healthcare providers leverage healthcare IT capabilities and differentiates the success level of digital transformation. To this end, Applegate, McFarland, and Austin (2009) noted how organizations can view their core capabilities and core strategy through an IT lens to delineate IT impact. The resulting IT Impact Map, illustrated in Figure 1, depicts the four quadrants and modes an organization can exhibit by varying IT impact levels on core capabilities versus core strategy.

Digital Transformation

Schadler (2017) suggests digital transformation strategies focus on internal operational excellence (i.e., defensive IT impact) and external customer experience (i.e., offensive IT impact). Digital transformation is similar to the IT Impact Map’s representation of defensive and offensive IT in Figure 1. Digital transformation is evolutionary and leverages...
digital capabilities with emerging IT to create value via business models, operational processes, and customer experiences (Morakayane et al., 2017). Re-phrased, digital transformation reflects the changes new IT makes in an organization to change products or services, organizational structures, and/or the automation of business processes (Hess et al., 2016). Moreover, simply implementing or using IT is not enough to achieve digital transformation (Andai-Ancion et al., 2003; Bharadway et al., 2013; Hess et al., 2016; IDG, 2018; Kane et al., 2015; Matt et al., 2015; Morakayane et al., 2017; Schadler et al., 2017; Sebastian et al., 2017). A key driver of digital transformation is the level of organizational digital maturity (e.g., higher is desired) found among organizational strategy, culture, and talent (Kane et al., 2015). Organizational culture, talent, and strategy develop over time, so digital transformation is evolutionary. Likewise, higher digital maturity yields more innovative IT success (Kane et al., 2015).

At the organizational level, digital transformation strategies must consider financial aspects that balance IT use, value creation, and structural changes (Matt et al., 2015). At the patient level, digital transformation strategies have cross-functional characteristics, which require operational alignment for complex coordination efforts due to multiple strategy interaction (Matt et al., 2015). An example of multiple strategy interaction is illustrated in the clinical use of IS and IT integration within acute critical care settings (Rothschild, 2004) to improve patient monitoring, bedside charting, and artificial support devices.

**Business Process Redesign (BPR)**

Continuous process improvement (CPI) is a systematic approach toward understanding process capability, customers’ needs, and sources of observed variation. Tenner & DeToro (1997) views CPI as an organizational response to an acute crisis, a chronic problem, or an internal driver. CPI encourages bottom-up communication in day-to-day operations (i.e., patient level) and requires process data comparisons to control metrics. Incremental improvement (e.g., Figure 1) gains occur via iterative cycles of analysis, evaluation, and synthesis (i.e., plan-do-study-act; Walton, 1986) to minimize observed variation. Doubt can exist as to whether: (1) the incremental improvement addresses symptoms versus causes; (2) the improvement effort is sustainable year after year; or (3) management is in control of the process (Jeston & Nelis, 2008). The IT Impact Map’s incremental improvement mode (i.e., CPI) is invisible to external stakeholders over the short term.

Business process redesign (e.g., Figure 1) offers the most radical change when compared to CPI. IT impact capabilities from BPR do not digitally replicate manual processes. BPR offers radical redesign when compared to CPI, with greater reward of upwards to 1,000 percent, while assuming higher risk, durations, costs, and difficulty (Tenner & DeToro, 1997). BPR is rethinking and redesigning to achieve dramatic improvements in performance (e.g. cost, quality, service, and speed) by questioning activity relevance and reinventing innovative ways to accomplish work. With respect to the IT Impact Map, the BPR mode has core business processes online in real-time, yet IT impact provides little strategic differentiation.

**Business Process Management (BPM)**

Incremental improvement and BPR are tenants of BPM. This study uses the BPM definition provided by Jeston and Nelis (2008, p. 10) as “the achievement of an organization’s objectives through the improvement, management, and control of essential business processes.” The authors further elaborate that process management and analysis is integral to BPM, where there is no finish line for improvement. Hence, this study views BPM as an organizational commitment to consistent and iterative business process performance improvement that meets organizational objectives. To this end, BPM embraces the concepts of incremental improvement and BPR aligned to hospital strategy. Specifically, this study uses BPM techniques to measure improvement.

Business analytics is the body of knowledge identified with technology solutions that incorporate performance management, definition and delivery of business metrics, as well as data visualization and data mining (Turban et al., 2008). Business analytics within BPM focus on the effective use of organizational data and information to drive positive business action (Turbin et al., 2008). The effective use of business analytics demands knowledge and skills from subject matter experts and knowledge workers. Similarly, Wears and Berg (2005) concur that IS and/or IT only yield high-quality healthcare when the use patterns are tailored to knowledge workers and their environment. Therefore, BPM success has a strong dependence on contextual understanding of end-to-end core business processes (Jensen & Nelis, 2008).
Key Performance Indicators (KPIs)

Performance measurement is essential for purposeful BPM, as information before and after the intervention is an integral part of process improvement. Early in the IT literature, Ackoff (1967) proposed embedding control feedback in IS design to avoid management misinformation. Similarly, organizations define data metrics as KPIs to monitor critical success factors (CSFs) (Munroe & Wheeler, 1980) within business processes (i.e., organizational action). The perioperative process is information intensive (Catalano & Fickenscher, 2007), due to its complexity (Fowler et al., 2008). BPM of perioperative sub-process KPIs reduce complexity and information intensity (Ryan, et al., 2017).

Operational and tactical KPIs in perioperative sub-processes are numerous, but intra-operative KPIs for operational excellence should include: (1) monitoring the percentage of surgical cases that start on-time (OTS) or first-of-the-day surgical case on-time starts (FCOTS), (2) OR turn-around time (TAT) between cases, (3) OR utilization (UTIL), and (4) labor hours expended per patient care hour as units-of-service (UOS), [49, 13, 19, 29] (Herzer et al., 2008; Kanich & Byrd, 1996; Peters & Blasco, 2004; Wright et al., 2010). Customer experience KPIs should include Consumer Assessment of Healthcare Providers and Systems surveys (HCAPHS, 2017) for patient perspectives of hospital care (i.e., HCAHPS) or clinician group care (i.e., CGCAPHS), as well as employee satisfaction surveys. Tarantino (2003) noted how OR TAT and a flexible work environment are CSFs for physician satisfaction, which in turn is a CSF for hospital margin. Poor KPIs on operational and tactical metrics (e.g., OTS, TAT, UTIL, UOS, or HCAHPS) affect strategic CSFs of patient safety, patient quality of care, surgeon/staff/patient satisfaction, and hospital margin (HCAPHS, 2017; Marjamaa et al., 2008; Peters & Blasco, 2004). With respect to the IT Impact Map, KPIs are applicable to measure performance in either defensive or offensive healthcare IT applications.

RESEARCH METHOD

This research investigates the digital transformation of a hospital’s perioperative sub-processes and questions how business process redesign can yield operational excellence and enable improved patient flow, integrated hospital IS to workflow coupling, and stakeholder satisfaction. To this end, case research is particularly appropriate (Eisenhardt, 1989; Yin, 2003). Another advantage of the positivist approach (Weber, 2004) to case research allows concentrating on a specific hospital service in a natural setting to analyze the associated qualitative problems and environmental complexity. Hence, our study took an in-depth case research approach.

Our research site (i.e., University Hospital) is an academic medical center, licensed for 1,157 beds and located in the southeastern region of the United States. University Hospital is a Level 1 Trauma Center, with a robotics program over eight surgical service specialties (SSS) as well as a Women’s/Infant facility. University Hospital’s recognition includes Magnet since 2002 and a Top 100 Hospital by U.S. News and World Report since 2005. Concentrating on one research site facilitated the research investigation and allowed collection of longitudinal data. This research spans activities from August 2003 through December 2018, with particular historical data since 1993. During the 184-month study, we conducted field research and collected data via multiple sources including interviews, field surveys, site observations, field notes, archival records, and document reviews.
CASE BACKGROUND

Perioperative Services (UHPS) is the University Hospital department designated to coordinate and manage perioperative patient care across Pre-admissions, Admissions, Surgical Preparations (PreOP), Central Sterile Supply (CSS), Intra-operative and Endoscopy (OR), and Post Anesthesia Care Units (PACU). The workflow through CSS reprocesses all reusable surgical instruments/devices and transports supplies to and from PreOP, OR, and PACU areas.

UHPS replaced its prior CSIS of 10 years in 2003. The new CSIS supports OLAP tools, a proprietary structured query language, and both operational and managerial data stores (i.e., an operational database and separate data mart). Flexible routing templates as surgical preference cards (SPCs) allow standardization of surgical care data (i.e., particular supplies and instruments) or SPC customization for specific surgeons and/or procedures.

Since the new CSIS implementation, over 7,750 generic and custom SPC configurations facilitate the surgical specialty services (SSS) represented in Table 1. Similarly, the CSIS data mart serves as the central repository for perioperative process data used to support improvement initiatives as well as report KPIs via a business intelligence layer for data visualization. The following sections highlight tools, events, and outcomes that have shaped UHPS’ BPM approach.

Perioperative Process Improvement

University Hospital opened a new diagnostic and surgical facility (i.e., North Pavilion) in November 2004, expanding capacity by 33% with state-of-the-art OR suites having standardized as well as surgical specific equipment. In six weeks of occupancy, a scheduling KPI reflected chaos. Surgical OTS plunged to 18% during December 2004. Having only 18% OTS is unacceptable, as 82% of scheduled surgeries experience delays and risk patient care and safety.

In January 2005, UHPS expressed concerns before a quickly convened meeting of c-level, nursing, and physician representatives. The meeting yielded a hybrid matrix-style management structure and governance in the formation of a multidisciplinary, executive team empowered to evoke change. The executive team consisted of perioperative stakeholders (e.g., surgeons, anesthesiologists, nurses, and UHPS), chartered to focus on patient care and safety, attack difficult questions, and remove inefficiencies.

The resulting CPI effort addressed the perioperative crisis via numerous task forces employing data-driven evaluation of specific opportunities, which founded UHPS’ current BPM approach. Table 2 details a complete listing and timeline of UHPS’ perioperative improvements.

Since 2005, UHPS has expanded its management beyond the initial general (GENOR) and cardio-vascular (CVOR) ORs of the North Pavilion campus. UHPS management includes other campuses of the University Hospital Health System (UHHS) including OR suites at the Highland campus (HHOR) and Endoscopy (ENDO) labs at the TK Clinic campus. UHPS also developed a preoperative assessment, consultation, and treatment (PACT) clinic to manage all PreOP patient flow into UHPS. The PACT Clinic exists virtually in the CSIS, so the TK Clinic and HHOR allocated physical space for patient evaluations. Overall, UHHS has experienced a 10.9% increase in surgical cases since 2007 with 59% of the average case volume being in-patient and 41% being out-patient. Emergency surgeries account for 5.3% of the average case volume. Surgical case volume during FY2018 was 44,287 cases over the 58 ORs and 11 endoscopy labs.

<table>
<thead>
<tr>
<th>Surgical Service Specialty (SSS)</th>
<th>SPCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>BURN – Trauma burns</td>
<td>26</td>
</tr>
<tr>
<td>CARDIO – Cardiovascular &amp; Thoracic</td>
<td>946</td>
</tr>
<tr>
<td>ENT – Ear, Nose, &amp; Throat</td>
<td>1,030</td>
</tr>
<tr>
<td>GI – Gastro-intestinal</td>
<td>460</td>
</tr>
<tr>
<td>GYN – Obstetrics, oncology, incontinence</td>
<td>611</td>
</tr>
<tr>
<td>NEURO – Neurological</td>
<td>763</td>
</tr>
<tr>
<td>ORAL – Oral Maxil Facial</td>
<td>236</td>
</tr>
<tr>
<td>ORTHO – Orthopedic, joint/device</td>
<td>1,208</td>
</tr>
<tr>
<td>PLAS – Plastic surgery</td>
<td>681</td>
</tr>
<tr>
<td>SURG ONC – Surgical oncology</td>
<td>329</td>
</tr>
<tr>
<td>TX – Transplants (liver, renal)</td>
<td>194</td>
</tr>
<tr>
<td>TRAUMA – Trauma, MASH</td>
<td>203</td>
</tr>
<tr>
<td>URO – Urology</td>
<td>533</td>
</tr>
<tr>
<td>VASCULAR – arteries &amp; blood vessels</td>
<td>558</td>
</tr>
</tbody>
</table>

Table 1: University Hospital SSS
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<table>
<thead>
<tr>
<th>Area</th>
<th>Improvement</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>Implemented the current CSIS</td>
<td>2003</td>
</tr>
<tr>
<td>All</td>
<td>Relocated CSS and ORs</td>
<td>2004</td>
</tr>
<tr>
<td><strong>All</strong></td>
<td>Governance change—initiated CPI</td>
<td>2005</td>
</tr>
<tr>
<td>OR</td>
<td>Initiated OR heuristic scheduling</td>
<td>2006</td>
</tr>
<tr>
<td>All</td>
<td>Addressed hospital-wide patient flow (EMR, patient tracking, CPoE, etc.)</td>
<td>2007</td>
</tr>
<tr>
<td>All</td>
<td>Established KPI reporting (strategic, tactical, and operational)</td>
<td>2008</td>
</tr>
<tr>
<td>All</td>
<td>AMC21 Balanced Scorecards</td>
<td>2010</td>
</tr>
<tr>
<td><strong>PreOP</strong></td>
<td>Developed PACT Clinic</td>
<td>2011</td>
</tr>
<tr>
<td>OR</td>
<td>RFID phased implementation</td>
<td>2012</td>
</tr>
<tr>
<td>CSS &amp; OR</td>
<td>Redesigned supply workflow (CSS-to-OR-to-CSS)</td>
<td>2013</td>
</tr>
<tr>
<td><strong>PACU</strong></td>
<td>Phase II and ICU Overnight EMRs</td>
<td>2014</td>
</tr>
<tr>
<td>All</td>
<td>Automated charges via EMRs</td>
<td>2014</td>
</tr>
<tr>
<td>CSS &amp; OR</td>
<td>Instrument reprocessing &amp; tracking (CSS-to-OR-to-CSS)</td>
<td>2015</td>
</tr>
<tr>
<td><strong>All</strong></td>
<td>Real-time perioperative KPIs &amp; dashboards</td>
<td>2016</td>
</tr>
<tr>
<td><strong>All</strong></td>
<td>Automated EMR Reconciliation</td>
<td>2017</td>
</tr>
</tbody>
</table>

**Table 2: Perioperative Improvements**

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![Figure 2: UHHS Integrated IS](image-url)
Patient Flow and Integrated IS

Surgical patient admissions occur via the PACT Clinic, with referrals via three venues: 1) diagnostic office visits to physicians within the TK Clinic, 2) non-UHHS physicians, or 3) the Emergency Department. Figure 2 depicts the integrated hospital IS used to facilitate and document perioperative patient care across UHHS. UHHS patients' (i.e., in-patient or outpatient) medical records, admissions, diagnostics, clinical data and observations, as well as discharges are processed and recorded via the same integrated hospital IS. All IS depicted in Figure 2 are integrated with either uni-directional constraints for limited data exchange or bi-directional data exchange. The seven IS clustered around the CSIS are modules that directly support and extend the CSIS suite, where the Clinical Charting IS houses CPoE and EMRs. The HIPPA compliant Web services and BMDIB (i.e., biomedical device interface bus) integrate ancillary IS, clinical data sensors, and bio-medical equipment. The institutional intranet serves as single entry portal access to extend each IS according to particular user-IS rights and privileges negotiated via user authentication.

OBSERVED EFFECTS

Surgical UHHS patients move through perioperative workflows via events: (1) A clinic visit resulting in a surgery diagnosis, (2) surgical patient scheduling, (3) PACT Clinic evaluation, (4) day of surgery admission, (5) PreOP, (6) intra-operative procedure, (7) PACU, (8) PACU Phase-II, and (9) discharge or movement to a medical bed. However, the current perioperative workflow and resulting patient flow are the product of BPM efforts, where numerous BPM task forces have targeted multiple perioperative sub-processes for improved patient workflow.

All of the BPM efforts in Table 2 leveraged specific defensive healthcare IT applications (i.e., Figure 1) to improve perioperative capabilities. The four BPR examples highlighted in Table 2 and discussed in this study are: (1) OR scheduling; (2) hospital-wide electronic medical record (EMRs) integration; (3) preoperative patient evaluations; and (4) PACU EMR documentation. The following subsections explain the BPM efforts to redesign these sub-processes and workflows to enable digital transformation and gains toward operational excellence.

OR Scheduling

The initial CPI efforts during 2005 identified that traditional block scheduling (e.g., assigning a 7 a.m. to 4:30 p.m. block of time for a particular OR suite to a particular SSS) yielded inefficiency and failed to reflect actual SSS patient volume. SSS with low patient volume had surplus ORs assigned, while SSS with high patient volume had deficit ORs assigned, yielding further delays in perioperative scheduling. The inefficient OR utilization associated with block scheduling also concealed other perioperative sub-process inefficiencies upstream and downstream of intra-operative procedures.

The actual OR hours used by SSS patients (i.e. SSS cases) stored in the CSIS data mart were analyzed against OR block assignment hours allocated to each SSS (i.e., Table 1). The data analysis identified BPR opportunity in the OR scheduling process. Straight SSS specific OR block schedules were discontinued, excluding one OR retained to meet Level I Trauma Center requirements. As physician satisfaction is linked to SSS specific OR

<table>
<thead>
<tr>
<th>SSS</th>
<th>FY05 Days</th>
<th>FY07 Days</th>
<th>FY18 Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>BURN</td>
<td>2.929</td>
<td>1.964</td>
<td>0.559</td>
</tr>
<tr>
<td>CARDIO</td>
<td>4.570</td>
<td>0.926</td>
<td>3.446</td>
</tr>
<tr>
<td>ENT</td>
<td>12.128</td>
<td>11.959</td>
<td>3.770</td>
</tr>
<tr>
<td>GI</td>
<td>8.615</td>
<td>10.784</td>
<td>3.360</td>
</tr>
<tr>
<td>GYN</td>
<td>12.051</td>
<td>15.123</td>
<td>9.660</td>
</tr>
<tr>
<td>NEURO</td>
<td>2.525</td>
<td>1.840</td>
<td>4.080</td>
</tr>
<tr>
<td>ORAL</td>
<td>5.746</td>
<td>4.138</td>
<td>7.704</td>
</tr>
<tr>
<td>ORTHO</td>
<td>6.549</td>
<td>3.599</td>
<td>4.034</td>
</tr>
<tr>
<td>PLAS</td>
<td>11.375</td>
<td>9.235</td>
<td>13.280</td>
</tr>
<tr>
<td>SURG ONC</td>
<td>11,784</td>
<td>9.516</td>
<td>21.611</td>
</tr>
<tr>
<td>TX</td>
<td>3.285</td>
<td>5.964</td>
<td>10.491</td>
</tr>
<tr>
<td>TRAUMA</td>
<td>0.955</td>
<td>0.652</td>
<td>0.878</td>
</tr>
<tr>
<td>URO</td>
<td>13.337</td>
<td>18.604</td>
<td>28.04</td>
</tr>
<tr>
<td>VASC</td>
<td>2.636</td>
<td>4.540</td>
<td>5.659</td>
</tr>
<tr>
<td>Avg. Days</td>
<td>7.098</td>
<td>6.655</td>
<td>7.243</td>
</tr>
<tr>
<td>99% CI</td>
<td>(6.856, 7.341)</td>
<td>(6.447, 6.862)</td>
<td>(7.002, 7.482)</td>
</tr>
<tr>
<td>Patients</td>
<td>14,415</td>
<td>20,862</td>
<td>22,255</td>
</tr>
<tr>
<td>R^2(adj)</td>
<td>12.82%</td>
<td>20.49%</td>
<td>22.31%</td>
</tr>
</tbody>
</table>

Table 3: North Pavilion Average Days to DOS
block scheduling (Peters & Blasco, 2004), initial block assignments allow for outside-of-a-week planning. Since 2006, quarterly modifications to SSS block assignments yield SSS OR time blocks based on SSS case (i.e., patient) volume. Similar to marketing segmentation among demographic groups, SSS specific OR time used from historical data establish predictable average SSS case volume. Specific SSS block release rules also allow surgeons within a particular SSS to schedule OR time, not in their specific ORs, 72-hours out from day of surgery (DOS). A surgeon in any SSS can schedule OR time in any available OR 36-hours out from DOS. Additional heuristic rules define specific SSS preferences, robotic rooms, hybrid rooms, specific UHHS campus OR preferences, cystoscopy and endoscopy preferences, staff allocations, and length of OR availability per day.

The state of UHPS in early 2005 prohibited streamlining hospital-wide patient flow without first streamlining intra-operative patient flow. Likewise, the modified heuristic block scheduling improved perioperative process scheduling and the digital transformation yielded a tighter coupling to actual surgical patient demand (e.g., cases). Table 3 illustrates this improvement by SSS, listing the average days between scheduling a surgical procedure and the DOS for FY05, FY07, and FY18. FY05 is prior to the scheduling improvement implementation. FY07 is the first full year of implementation. FY18 is the most recent year reflecting the evolved heuristic scheduling rules. Although the average days between the three years are not statistically different, as indicated by the overlapping 99% CIs for each year, note the volume of patient flow increase (e.g., 54%) between FY05 and FY18. Likewise, the scheduling rules in FY18 explained more (e.g., 74%) of the scheduling variation (i.e., $R^2_{adj}$) than FY05.

**Hospital-wide EMR Integration**

The structural, process, procedural, and cultural changes achieved in UHPS over FY05 and FY06 allowed the executive committee to move forward in early 2007 to extend the clinical scheduling IS across UHHS and address hospital-wide patient flow and documentation. The new areas integrating with the CSIS were Admissions, PreOP, PACU, CSS, and all other ancillary services. The hospital-wide EMR integration encompassed 11 task forces covering surgeon’s orders, clinical documentation, electronic medical records, pharmacy, physician workflow, critical care, knowledge and content, technical metrics, communications, and testing/training/transition.

The project’s goal was improvement of patient flow, documentation, and satisfaction through extended CSIS functionality, IT capabilities, and patient tracking technology. The enterprise application integration process redesign efforts yielded the additional IS modules clustered around the CSIS in Figure 2. The most visible interface into the dissemination of perioperative process information across Admissions, PreOp, intra-operative, and PACU were electronic patient status boards. The deployed boards were in each functional perioperative area, visitor waiting area, and the patient information was HIPAA compliant. Figure 3 depicts the patient status boards in a PACU area at the North Pavilion campus.
Pre-operative Patient Evaluations

Figure 4 depicts the annual averaged on-time start (OTS) KPIs for GENORs, CVORs, and HHORs from FY05 to FY18. The hospital-wide EMR integration in 2007 omitted parts of required PreOP evaluation documentation (e.g., external medical records, PreOP assessment, as well as medical, surgical, and medication history). The GENOR OTS KPI average for FY10 was 55.8% versus a target of 70%. Upon closer analysis of the surgical case delays, 17.5% were preventable. CSIS data reflected incomplete patient information delays for over one out of six surgical cases. As a result, UHPS launched a PACT Clinic task force to redesign preoperative patient evaluations. Task force members visited four leading academic medical centers in the United States, as well as the two internal University Hospital sites, to gather a transparent and bottom-up view of different perspectives to preoperative evaluation processes. The external sites were located in: (1) Baltimore, MD; (2) Boston, MA; (3) Rochester, MN; and (4) Cleveland, OH.

Essential elements of the redesign required EMR inclusion of all pertinent external records with the initial UHHS referral and the PreOP assessment appointment is made simultaneously with the initial surgeon appointment. Patient screening and standardized co-morbidity risk stratification occurs by telephone, the Internet, or by the surgical clinic making the referral. The best practices identified during the site visits afforded University Hospital the opportunity to redesign their preoperative patient evaluation into a preoperative assessment, consultation, and treatment (PACT) clinic. A “clinic without walls” in that the PACT clinic exists only within the CSIS and evaluations can occur anywhere within UHHS. Since the PACT Clinic implementation in FY12, the OTS KPI target of 70% on-time has been achievable as illustrated in Figure 4.

PACU EMR Documentation

UHPS developed and configured CSIS nursing documentation as EMRs to document and manage patient care accountability across perioperative workflows. PACU nurses receive surgical patients from the OR and continue acute care per surgeon’s orders until patient recovery. As a critical care unit similar to the OR suite, the CSIS collects PACU clinical data from bio-medical equipment and monitoring sensors (i.e., BMDIB in Figure 2). Within the PACU area, nurses have four EMR types to document patient care and events. The PACU Nursing Record EMR documents acute care delivery. The ICU/After Hours PACU Overflow Record EMR, via the CSIS, documents acute care for patients that are over-nighting in PACU due to overflow conditions in the ICU. Both PACU acute care EMRs capture patient UOS charges as depicted in Figure-2. As surgical patients recover from anesthesia, the need for acute care lessens. Within the CSIS, a PACU Phase-II Nursing Record EMR posted to the patient’s surgical case identifies when PACU acute care ends. When surgical patients completely recover from anesthesia, the attending PACU nurse discharges the patient from Phase-II and discontinues documentation to the patient’s surgical case. Likewise, the PACU staff discharge outpatients per surgeon orders, while in-patients are transported to a hospital bed.
CSIS nursing EMRs differentiate patient care for charge billing and resource allocations. Within PACU, the Phase-II and ICU nursing records also facilitate PACU workflow balancing and bed/resource utilization. Within PreOP and PACU, a finite number of acute care beds are valued resources, when compared to ambulatory care beds. The PACU Phase II Nursing Record allows ambulatory nursing documentation via the CSIS in any University Hospital ambulatory bed. Hence, PACU Phase II patients are transferable to PreOP or floor beds when PACU beds are in critical supply. Moreover, the ICU Overflow EMR identifies ICU capacity issues and avoids unplanned ICU discharges (Utzolino et al., 2010). PACU Phase-II EMRs document ambulatory care that has lower patient UOS charges and allows any UHHS hospital bed having ambulatory patient care to become PACU Phase-II. Hence, PACU Phase-II Nursing Record EMRs via the CSIS create a virtual PACU allowing more critical patients to remain in PACU acute care beds. Table 4 lists the current UHHS Nursing Record EMRs used across the perioperative sub-processes within the GENOR, CVOR, HHOR, and TKC labs.

### Table 4: CSIS Nursing Documentation and UOS

<table>
<thead>
<tr>
<th>CSIS Nursing Record EMRs</th>
<th>FY Start</th>
<th>UOS Std.</th>
<th>UOS Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ancillary Record - Family</td>
<td>2007</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>PreOP Nursing Assessment</td>
<td>2012</td>
<td>1.93</td>
<td>Time</td>
</tr>
<tr>
<td>Endo PreOP Nursing Record</td>
<td>2014</td>
<td>--</td>
<td>Procedure</td>
</tr>
<tr>
<td>Endo Sedation Nursing Record</td>
<td>2014</td>
<td>2.1</td>
<td>Time</td>
</tr>
<tr>
<td>PreOp Regional Block Nursing Record</td>
<td>2014</td>
<td>2.21</td>
<td>Time</td>
</tr>
<tr>
<td>CSS</td>
<td>2003</td>
<td>3.52</td>
<td>Load</td>
</tr>
<tr>
<td>OR Nursing Record - CVOR</td>
<td>2007</td>
<td>9.04</td>
<td>Time</td>
</tr>
<tr>
<td>OR Nursing Record - Cardiac Perfusion</td>
<td>2012</td>
<td>4.22</td>
<td>Time</td>
</tr>
<tr>
<td>OR Nursing Record - GENOR</td>
<td>2003</td>
<td>7.45</td>
<td>Time</td>
</tr>
<tr>
<td>OR Nursing Record - ENDO</td>
<td>2014</td>
<td>6.92</td>
<td>Procedure</td>
</tr>
<tr>
<td>Ancillary Record – Room Cleanup</td>
<td>2005</td>
<td>--</td>
<td>Time</td>
</tr>
<tr>
<td>PACU Nursing Record</td>
<td>2010</td>
<td>2.71</td>
<td>Time</td>
</tr>
<tr>
<td>ICU/After Hours PACU Overflow Record</td>
<td>2014</td>
<td>2.71</td>
<td>Time</td>
</tr>
<tr>
<td>PACU Phase-II Nursing Record</td>
<td>2014</td>
<td>1.93</td>
<td>Time</td>
</tr>
</tbody>
</table>

### ANALYSIS AND DISCUSSION

Previous sections on case background and observed effects demonstrate the BPR opportunity during the digital transformation of the UHHS perioperative process. CSIS integration and BPM efforts support a tight coupling between patient care, perioperative workflow (i.e., patient flow), and the integrated hospital IS. Moreover, the CSIS data yield aggregated KPI metrics to further understand, manage, and improve perioperative workflow, resources, and performance. The following sub-sections discuss digital maturity, defensive for offensive IT impact, as well as UHPS digital transformation CSFs with respect to the literature, case, and observed effects.

#### Digital maturity

Organizational digital maturity is a CSF for digital transformation that reflects strategy, culture, and talent (Kane et al., 2015). For strategy, digital transformation requires reconfiguring processes to exploit health IT abilities and information through digital technologies integrated across people, processes and functions. Increasing health IT impact on core capabilities (e.g., Figure 1) moves an organization from incremental improvement (i.e., CPI) to business process redesign (BPR). To this end, UHPS uses CSIS data to improve perioperative sub-processes via business analytics, OLAP, and data mining (e.g., see Table 2). Likewise, having high IT impact on core strategy and increasing IT impact on core capabilities moves an organization from emerging opportunity to business transformation. The modified heuristic block schedule, patient status boards, PACT Clinic, and PACU EMRs are examples of implementing health IT innovatively. Organizational culture and employee talent are visible via the BPM
efforts and perioperative improvements listed in Table 2. UHHS also uses KPI targets and BPM efforts as annual goal objectives for personnel and SSSs to meet in the strategic plan (Ryan et al., 2016).

In a digital transformation strategy, an operational backbone and a digital services platform are essential enterprise architecture assets (Sebastian et al., 2017) to execute internal operational excellence (i.e., defensive IT impact) and external customer experience (i.e., offensive IT impact). The CSIS is the UHHS operational backbone providing a single source of reconciled perioperative data. U.S. hospitals eligible for CMSEHRIP (e.g., 95%) have a similar operational backbone (ONC, 2017). The HIPPA compliant Web services and BMDIB within the UHHS integrated IS (e.g., Figure 2) constitute a digital services platform to facilitate rapid development and integration of digital innovations.

**Defensive for offensive IT impact**

The BPM efforts applied to perioperative scheduling has positioned UHHS to achieve a level of operational excellence, as evidenced by its BPM efforts, improved patient flow, and OTS KPI metrics. In turn, operational excellence positions UHHS to pursue external customer experience centered on enhanced collaboration between perioperative stakeholders (e.g., healthcare providers, patients, and their families).

With respect to the IT Impact Map (i.e., see Figure 1), measured efficiencies in CPI and BPR of OR scheduling, hospital-wide EMR integration, PreOP patient evaluations; and PACU EMRs moved UHHS from Support to Factory Modes and yielded defensive IT impact. Innovatively applying measured efficiencies gained through BPR and the digital transformation of the perioperative process adds to UHHS patient experience and patient satisfaction surveys. The enhanced customer experience moved UHHS into Turnaround Mode and yielded offensive IT impact. Likewise, using patient experience KPIs as strategic goals to foster provider-patient collaboration (Ryan et al., 2014) has moved UHHS into Strategic Mode and yielded offensive IT impact.

**UHPS Digital Transformation CSFs**

Digital transformation offers workflow productivity via IT applications, the ability to better manage process performance via data availability and visibility, as well as the ability to meet customer experience expectations (IDG, 2018). UHHS was not seeking these particular benefits when it changed UHPS' governance in FY05, but the change evoked continuous data-driven improvement. To this end, UHPS’ digital transformation has evolved over time. The following observed CSFs, summarized from the case, provide an a priori framework for UHPS’ digital transformation:

- The agile, integrated CSIS as an operational backbone, with the HIPPA compliant Web services and BMDIB as a digital services platform.
- Changed governance using matrix-style management from cross-functional departments.
- CSIS implementation and EMR integration was phased to achieve proof of concept—first in intra-operative and CSS, moving later upstream to PreOp, then downstream to PACU, and then hospital-wide.
- Accessible and visible data via the CSIS having high data quality and data integrity.
- Empowered multi-disciplinary teams and integrated knowledge workers who are perioperative subject matter experts and IT literate.
- An organizational culture focused on continuous improvement using data-driven decision-making.
- A BPM approach to perioperative performance and improvement that is aligned to hospital strategy.

**CONCLUSION AND LIMITATIONS**

This paper fills a healthcare literature gap noted by Agarwal et al. (2010) in examining the integration and use of CSIS data and EMRs leveraged as health IT. Likewise, this study contributed to the healthcare IT literature
by examining perioperative digital transformation through the lens of IT impact to prescribe an a priori framework to foster the occurrence. Moreover, empowered teams, integrated IS coupled to workflow, leveraged health IT, and a holistic BPM approach supported this study’s observed effects in the digital transformation of a hospital’s perioperative process. The observed effects demonstrated CPI, BPR and BPM as adaptable practices when leveraging health IT for digital transformation within the hospital environment. Likewise, the analysis, evaluation, and synthesis cycle of CPI, BPR, and BPM within the observed effects demonstrated communication, innovation, as well as individual and collective organizational learning.

This study has limitations. One limitation to the study’s generalization to other hospitals would be if a hospital’s IS architecture lacked the digital services platform required to facilitate implementation and integration of digital innovation opportunities. The study is also limited to a single case, where future research should broaden focus as well as address other limitations inadvertently overlooked.

Overall, the study results were exploratory and need further confirmation. The case examples can serve as momentum for perioperative methodology, complexity comprehension, and improvement extension. Researchers may choose to further or expand the investigation, while practitioners may apply the practices and BPM framework within their perioperative environment.

REFERENCES


Pressure Injury and Restraint Prevalence Surveys: Saving Time and Dollars for Patient Care by Automating Manual Chart Abstraction

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Abstract: Bronson Healthcare Group performs quarterly pressure injury and restraint audits as part of the National Database of Nursing Quality Indicators (NDNQI). The chart abstraction portion of the audit previously required nurses to manually abstract 31 data points. To save time and cost, we used Lean and PDSA process improvement tools to automate the chart abstraction portion of the audit, reducing the number of data points requiring manual abstraction to 2. We validated the automated abstraction by comparing it to abstractions done manually by the audit nurses. We found that an automated process has the potential to reduce the impact of human error inherent in manual abstraction.

BACKGROUND

Clinical Significance of Pressure Injuries

A pressure injury is defined as “localized damage to the skin and underlying soft tissue usually over a bony prominence or related to a medical or other device” (Ratliff et al., 2017). In the United States, 2.5 million people develop pressure injuries each year. In addition to being painful for the patient, pressure injuries increase the risk of infection and additional health care utilization. Hospitals must strive to prevent hospital-acquired pressure injuries (HAPIs), not only for their patients’ benefit, but because the Centers for Medicare & Medicaid (CMS) no longer reimburse hospitals for the additional care required to treat a hospital-acquired pressure injury (Dan Berlowitz et al., 2014).

In 2014, an extensive clinical practice guideline was published by international experts representing the National Pressure Ulcer Advisory Panel, the European Pressure Ulcer Advisory Panel, and the Pan Pacific Pressure Injury Alliance. This guideline consists of 575 recommendations for the care and prevention of pressure injuries (Haesler, Kottner, & Cuddigan, 2017). To develop these guidelines, experts critically examined 356 papers and assessed the level of evidence of the research in the paper. From this they assessed the strength of the evidence for the recommendation, and finally the strength of the recommendation itself. In this assessment, 94% of the recommendations received a strength of recommendation score indicating it “should be implemented.” (Haesler et al., 2017)

National Database of Nursing Quality Indicators (NDNQI)

The National Database of Nursing Quality Indicators provides “a national database and Registered Nurse (RN) surveys for examining relationships between nursing and patient outcomes” and in so doing “delivers evidence to support the importance of nurse sensitive measures in overall patient experience strategy” (“NDNQI - National Database of Nursing Quality Indicators,” n.d.).
Bronson Methodist Hospital in Kalamazoo, MI we participate in NDNQI surveys as part of its overall quality improvement strategy. One component of the NDQI is the Pressure Injury and Physical Restraint prevalence survey. Bronson does its Pressure Injury and Physical Restraint prevalence surveys quarterly, on the second Tuesday of the second month of each quarter. On the day of the 1st quarter 2019 survey, there were 456 patients admitted to the 21 hospital units that are included each quarter in the survey.

**Pressure Injury and Physical Restraint Surveys**

The purpose of the NDNQI Pressure Injury Surveys are to track the rate of hospital-acquired and unit-acquired pressure injury occurrence, and to study the connections between nursing assessments, interventions, and the development of pressure injuries. These surveys also benefit the individual healthcare organization by helping to facilitate quality assessments and quality improvement efforts (National Database of Nursing Quality Indicators, 2018).

Required items on the pressure injury surveys assess the use of nursing skin assessments and risk assessments, the interventions used for at-risk patients, and counts of the total number of pressure injuries (including type and stage information) and counts of total hospital-acquired and hospital unit-acquired pressure injuries.

**Origin of Process Improvement Effort**

Our project to improve this process began with the following IT Help Desk ticket submitted by our NDNQI site coordinator:

> “I was wondering about the possibility of creating a new report to streamline the monthly prevalence hospital acquired injury survey that the nursing team has to complete. The attached are two worksheets that are used every month. There are many fields that could potentially be captured from nursing documentation automatically on survey day from my way of thinking which would save a bunch of time for the auditors on survey day – I am not sure who in IT could possibly help improve this process for us.”

**METHODS**

**Process Improvement - Discovery and Assessment of Existing Process**

Since the primary goal of the project was to increase efficiency and decrease waste, we decided to use the Lean Process Improvement methodology and PDSA (a methodology that often stands on its own but is also a key component of Lean). For this effort, we found it effective to use the six steps of Lean’s “A3 Problem-Solving” methodology, with a focus on the five underlying principles of Lean.

**A3 Problem-Solving Methodology**

According to Ozkaynak, et. al., the six steps of the A3 Problem-Solving Methodology are:

1. Defining the problem or gap in performance
2. Understanding the current process
3. Determining the root causes of the problem
4. Developing actions to address root causes
5. Implementing the plan
6. Collecting follow-up data

*Step 1: Define the problem or gap in performance*
In reviewing the site coordinator’s Help Desk ticket requesting automation of the process using the EMR, several issues were identified:

- Each quarter, pressure injury and restraint surveys are done on 21 units in three of our four hospitals, and take two staff members per unit (a nurse and a patient care assistant) up to five hours to complete. The amount of time to complete varies by the number of patients on the unit at the time of the survey. Due to this time commitment, units need extra staff (at extra cost) on prevalence days in order to maintain appropriate levels for patient care.
- Much of the work involved in the survey is manual chart review, which required the surveyors to hunt through multiple different areas of the chart looking for the data points required.
- Following the surveys, the administrative assistant spends two to three full work days entering the survey results into NDNQI’s website. Each patient is entered individually and there are typically several hundred patients to enter. NDNQI now has the capability to accept electronic uploads to the site, which has the potential to save most of this time spent by the administrative assistant.

With that understanding, we identified our gaps in performance as:

- We rely on manual chart abstraction to accomplish a goal that could easily be automated by the EMR’s reporting tools.
- We require nurses to go to the different areas of the chart where the information is contained, rather than using available EMR tools to bring all the relevant data to them in a single location.
- We rely on manual data entry of hundreds of patients’ data instead of leveraging available technology tools to automate data submission.

**Step 2: Understanding the Current Process**

We used workflow process mapping with the Lean principle of value stream mapping to understand the current process. This value stream mapping is discussed in detail below.

**Step 3: Determining the Root Causes of the Problem**

In assessing the root causes of problems 1 and 2 above, we identified that the primary cause is that while using the EMR’s tools to automate these steps is possible, it isn’t something that the surveyors would have been able to create for themselves. The task requires the kind of access and EMR expertise that IT staff have but is not typically available to end users. A contributing cause is the fact that the vendor doesn’t provide a tool that works out-of-the-box for automating the prevalence survey process, even many organizations participate in the NDNQI survey.

The root cause of problem 3 is similar in that the automatic upload process requires a great deal of IT expertise to configure.

**Steps 4, 5, and 6, i.e., Developing Actions to Address Root Causes, Implementing the Plan, and Collecting Follow-Up Data**, are described in detail below.

**How Lean’s Underlying Principles Supported Our Problem-Solving Process**

The five underlying principles of the Lean strategy are:

1. Define value
2. Value stream mapping
3. Create flow between steps
4. Provide just in time response
5. Pursue error free work (Amador, 2013)
Step 1: Defining Value

While Lean efforts in healthcare focus on defining value to the patient, the value to the patient in this process is abstract. Participation in the NDNQI surveys benefits Bronson patients indirectly by helping to monitor pressure injury and restraint prevalence over time so that we can improve our rates, which benefits the patient.

We identified in this process the opportunity to provide additional value to the patient and the organization by reducing clinician time spent on the surveys, which frees up time and money for additional patient care activities, and saves the organization money in a time where most healthcare organizations, including Bronson, need to “do more with less” from a financial perspective.

Step 2: Value Stream Mapping

Figure 1 shows the map of the existing process for the surveys at Bronson. We identified waste in four key steps:

- Reviewing charts in Epic for 31 data points
- Entering chart review info on data collection form
- Physically assessing patients
- Manually entering data into NDNQI website

Upon initial review of the data collection form (Appendix A), it appeared we would be able to eliminate all four of the wasteful steps by automatically extracting data from the EMR. However, conversation with our Site Coordinator and consultation of the NDNQI Guidelines for Data Collection clarified that physically assessing the patient to count pressure injuries is a required part of the survey process (National Database of Nursing Quality Indicators, 2018). Since the data reported to NDNQI is used for research on pressure injury and restraint prevalence, it is extremely important that the data submitted on the counts of pressure injuries is accurate, and therefore pulling data only from the EMR is not sufficient to achieve this level of accuracy.

We identified that eliminating waste from the steps of Reviewing the chart for 31 data points and Entering chart review data on the collection form could be accomplished via the same solution of creating a report from Epic’s real-time reporting tool (Reporting Workbench) that automatically pulls the data points that were previously abstracted manually, and could be exported and printed.

To eliminate waste from the step of Manually entering data into the NDNQI website, we planned to start using NDNQI’s automated upload process, which allows uploading a file with all the data, rather than manually entering the data for each patient in each of our hospitals.
Step 3: Create Flow Between Steps
Challenges that we encountered in creating flow between steps and achieving automation included:
- Inability to control formatting of Excel exports from Epic
- No consistent schedule for when units begin the surveys
- Functional limitations in Epic for formatting of printed reports and inclusion of blank columns for physical assessment results

Despite these challenges, we were able to arrive at a solution that allowed for an improved work-flow between steps and met the requirement that the printed report be only one page wide in order to be a usable instrument for surveyors as they performed the physical assessment of the patient. A sample of the report the surveyors can print for data collection is included in Appendix B.

An additional opportunity to improve work-flow was found in the two remaining data points that require clinical judgment based on manual abstraction of chart data by the audit nurses. We were able to streamline abstraction by building additional information into the view of the report that the nurses would view in the EMR when they prepared to print the report.

Step 4: Provide Just-in-Time Response (or “Establish Pull”)
Providing just-in-time response was achieved effort by implementing a new work-flow between steps allowing nurses to generate the report at the moment they were going to start the survey, rather than “pushing” it out to them.

Step 5: Seek Perfection (or “Pursue Error-Free Work”)
We established a methodology for validating the report, verifying its usefulness, and continuing to improve it.

Figure 2 shows the map of the final, revised process we arrived at through this process improvement, as it was on the day the new process was piloted.

![Figure 2: Map of Final Process after Improvement Process](image)

Development of Requirements and Prototype, and Concept Validation with Users

Development of Requirements and Prototype
After initial investigation into the technical details of the automatic upload process, we determined that due to time constraints it was necessary to split the project into two phases, with the first phase focused on addressing the waste in the data collection process, and the second phase focused on adoption of the automated upload process.
In the first phase we created an automated report in a test environment similar in structure and content to the manual data collection spreadsheet surveyors were filling out in the existing process. Data in the automated report was validated by our NDNQI site coordinator as meeting all NDNQI data collection guidelines (National Database of Nursing Quality Indicators, 2017, 2018).

We then built a working prototype with real patient data and gave a demonstration to the site coordinator and five of the surveyors. After analysis, we determined that there were too many documentation values fully automate the process of reporting the full data set for each patient. Clinician interpretation of the data was still required. However, it was determined that we could pull enough relevant information into the report to greatly assist surveyors in making the clinical judgments.

Implementation

To implement the plan (Lean A3 step 5), we devised a pilot process to test the effects of the improved process and to validate the accuracy of the report (Lean A3 step 6). We piloted the report in large units with many patients to insure that it would work in the real setting in Q1 of 2019, with the goal of rolling it out to all units for Q2 2019.

Training the surveyors who would pilot the process was conducted using provided tip sheets with step-by-step instructions for printing the report and instruction in how to use the report to facilitate their survey efforts.

Collecting Follow-Up Data (A3 Step 6)

To test the effects of the new process, we collected anecdotal feedback about the ease of the new process compared to the existing process from the pilot units as well as information about how much time each unit (pilot and non-pilot) spent doing the survey, especially in comparison with previous surveys using the old process.

Validating the accuracy of the report was accomplished by also running reports for the units that were NOT participating in the pilot (the control group) and comparing what the report returned against the surveyors’ manual chart abstraction. We then investigated each discrepancy between what was on the report and what the surveyor reported to determine the cause of the discrepancy.

RESULTS

Execution of Validation, Investigation, and Classification of Discrepancies

We reviewed 82 patients, with 105 individual discrepancies, since a single patient could have multiple discrepancies. To investigate the causes of each discrepancy and determine whether the report was accurate or the surveyor was accurate, we opened each chart to examine the documentation associated with the data point in question, and documented the summary of the findings. We identified the following types errors:

- If the surveyor or the report simply did not match what was in the chart, we counted each occurrence as a "Report Error" or "Surveyor Error." (If the Surveyor or the Report made a systematic mistake, such that a large number of patients would have been categorically affected, we counted this as a single error but tracked the number of patients affected.)
- If the discrepancy was "time-dependent" and the report was shown to be correct based on the time it was run, we did not count this as a true error.
- If the discrepancy was the result of incorrect or incomplete specifications found in the requirements-gathering step, we counted each specific cause once as "Incorrect/Incomplete Requirements" and tracked the number of patients affected.
- If an error was made but was inconsequential because the data could easily be assumed to not be necessary, we labeled this as "Inconsequential."
- If users made data entry errors when charting this was classified as “Error in source documentation”
- Situations where there might have been clinical judgment involved that we couldn’t validate but the report was correct based on the specifications of the NDNQI guidelines we classified as “Can't classify, Report correct.”
Report Validation - Errors

The number of errors and affected patients for each error classification are shown in Table 1.

<table>
<thead>
<tr>
<th>Error Classification</th>
<th>Number of Errors</th>
<th>Affected Patients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Report Error</td>
<td>7</td>
<td>26</td>
</tr>
<tr>
<td>Incomplete Requirements</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>Surveyor Error</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td>Systematic Surveyor Error</td>
<td>2</td>
<td>49</td>
</tr>
<tr>
<td>Time-Dependent</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>Inconsequential Error</td>
<td>3</td>
<td>174*</td>
</tr>
<tr>
<td>Can't classify, report correct</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Error in Source Documentation</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

* Each of the 3 inconsequential errors affected the same 58 patients, for a total of 174.

Report errors

Aside from the report errors categorized as incomplete or incorrect requirements, there were 7 report errors that affected 26 patients.

Causes of the errors were identified and the report modified to try to eliminate them. At the time of this report, revalidation had not yet occurred.

Time Savings

On the Extended Medical Care Unit (EMCU) a non-pilot unit that had 33 patients on survey day, the surveyors spent an hour doing the manual chart review and 1.5 to 2 hours doing the physical assessments. On the Neonatal Intensive Care Unit (NICU), a non-pilot unit which had 41 patients on survey day, it took less than an hour to do their survey.

For the Oncology unit, a pilot unit with 31 patients on survey day, it took only 50 minutes to do the survey, which does suggest improvement over the non-pilot EMCU.

However, this time savings data is imprecise and incomplete because we did not do an effective job of capturing objective data on the time savings with the new process and relied on anecdotal reports of the surveyors.

DISCUSSION

Value of the Process Improvement Effort

Reduction in Workload

Using the paper data collection sheet surveyors had to manually search for, abstract and record up to 31 unique data points for each patient surveyed. After introduction of the automated report, surveyors were only required to manually abstract 2 of those 31 data points, and only in a subset of patients who were classified as “at risk”. While as noted above, we did not have good objective measures of time savings, it is reasonable to conclude that the large reduction in the number of data points requiring manual abstraction will lead to significant time savings for the surveyors.

Improvement in Accuracy
Our new process also resulted in improved accuracy by reducing the impact of human error. During the validation process we identified 10 errors generated by the automated report affecting 39 patients. In contrast, the validation of the data manually abstracted by surveyors uncovered 38 transcription errors affecting 38 patients, and 2 systematic abstraction process surveyor errors that affected 58 patients each. We determined that errors in the automated report were due to faulty logic or incorrect identification of requirements which we were able to correct. But there was no similarly easy way to systematically reduce the human errors. Despite the fact that surveyors undergo a program of initial training as well as subsequent review training before each survey and an annual inter-rater reliability study (National Database of Nursing Quality Indicators, 2018), we saw 38 instances of surveyor error in our validation sample of 82 patients.

### Systematic errors - whether of human or system origin - affect more patients per error than Surveyor errors.
However, systematic errors can be systematically fixed.

![Systematic errors chart]

- **Report Error**: 7 errors affecting 26 patients
- **Incomplete Requirements**: 3 errors affecting 13 patients
- **Surveyor Error**: 38 errors affecting 38 patients

---

**Potential Uses of the Tool Beyond Survey Day**

Along with our surveyors, we observed that new report had other unanticipated value beyond the quarterly survey. Since the report was easy for users to run, it could be run on a daily basis to help unit leaders spot gaps in care for individual patients. Similarly, the report could catch patients who have not had timely skin or risk assessments done, or who are at-risk and do not have adequate interventions in place. It could also be used to catch data entry errors in the documentation.

**Strengths and Limitations**

Strengths of the new process include the dramatic reduction in data points that must be manually abstracted. A reduction from 31 data points to 2 could make a significant difference in the work effort required from the surveyors. It also has the potential to improve nursing satisfaction with the EMR, since streamlining workflows and being able to easily “get data out of the EMR” tend to be some of the ways in which clinicians feel that the EMR has fallen short of its promise.

This project was also a good model of a way to make any recurring manual abstraction task easier by both pulling data automatically where possible, and where not possible, pulling the relevant data into one place so that users don’t have to jump around the different areas of the chart looking for it.

One significant limitation of the new report is the technical complexity. In order to facilitate the complex NDNQI requirements in a way that accommodated our users’ documentation, the logic was complicated and often involved several layers of records to accomplish a single data point. This is a challenge because it will make support and maintenance of the report difficult in the future. Even the IT analyst who built it will likely have to study the build each time an issue comes up in the future or a change is made to NDNQI requirements or the way our nurses document. Analysts who are not intimately familiar with the build will have even more difficulty troubleshooting the report. To mitigate this limitation, we plan to make careful diagrams of the way the build records fit together as a way of visual...
aid. Using this documentation, we can facilitate conversations with other analysts to help them understand how it works. Figure 3 shows a simplified example of such a diagram. This example illustrates the relationships between the records for one data point of the report.

![Figure 3: Simplified Build Diagram Illustrating Relationships between the Records for a Single Column](image)

**CONCLUSIONS**

*Lessons Learned*

We learned that when making the plan for testing the change in the PDCA cycle, it’s critical to go into great detail and have a specific, formal plan for collecting the data necessary to measure effectiveness. Despite holding planning meetings in the weeks leading up to the pilot, and assurances from the site coordinator that we would be able to get information from the surveyors about how much time they spent on the survey, we were not successful in getting this information from most units. This was likely because we relied on informal reach-outs from the site coordinator to the surveyors (via phone and email), rather than a formal instrument for collecting this information. It would also have been helpful to have communicated directly with all of the surveyors (pilot and non-pilot) in advance to make sure
each understood the importance of capturing this data. In addition to information on the time spent, a more formal approach could have helped us get better data from the pilot units on the new process and how we might improve it before rolling out to all units.

It would have been helpful to establish relationships with the non-pilot units before the survey day. Most of the units not piloting the new process weren’t aware that a new process was being trialed. We were so focused on developing the new tool that our collaborations with surveyors was almost exclusively with the units that planned to pilot the new process. While the lack of awareness on the part of the non-pilot units might have had some benefit in blinding the non-pilot users to the trial, it meant that we didn’t have the opportunity to follow up with them on questions about their responses on the data collection form as we performed the validation. In particular, it would have been helpful to have some of the non-pilot surveyors involved in reviewing their own discrepancies and providing insight on what led them to a conclusion that conflicted with the data in the chart and the report. Leading up to the pilot, our work was incredibly focused on the new process and the users who would pilot it, while our work after the pilot was heavily shifted toward validating the new report against those who used the old process.

SUMMARY

Effective use of the EMR and the support of IT analysts can automate the abstraction process for any particular audit. This saves time, improves accuracy, and gives back time for patient care, saving the organization money and improving care.

To have confidence in the impact made, it is important to give as much thought to the process of how to measure the improvement as it is to the technical details of the planned intervention. A validation approach involving comparing users’ manual assessments with the output of the automated tool is a valuable way to find errors in the design, misunderstood requirements, and situations where the real-world documentation does not match what we expect is happening.

REFERENCES


### Appendix A: Restraint and Pressure Injury Data Collection Sheet

**Restraint & Pressure Injury Survey Monthly Report**

(for data collection purposes only)  See NDNQI Guidelines for data collection directions. See Pressure Injury Training on how to stage pressure injuries and differentiate from other types of wounds.

<table>
<thead>
<tr>
<th>Date</th>
<th>For Year</th>
<th>For Month</th>
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<table>
<thead>
<tr>
<th>Unit Name:</th>
<th>Unit Number:</th>
<th>Number Surveyed:</th>
<th>Number Excluded:</th>
<th>Note on Unit:</th>
<th>Reason:</th>
<th>Unclear for Pt:</th>
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<table>
<thead>
<tr>
<th>Unit Assigned Pressure Injury Reporting:</th>
<th>Yes</th>
<th>No</th>
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</thead>
</table>

- Risk Assessment (RA): Scale used on this unit:  
  - Braden (67)  
  - Braden (B37)  
  - Braden (B27)  
  - NSRAS (NS)  
  - Norton (N)  
  - NSRAS (NS)  
  - Multiple Scales  
  - Clinical Factor (CF)

#### Restraint Survey

<table>
<thead>
<tr>
<th>Age</th>
<th>Gender</th>
<th>Resident to Use</th>
<th>Restraint Method (choose all that apply)</th>
<th>Chemical restraint (choose one)</th>
<th>Physical restraint used (choose one)</th>
<th>Patient at Risk (choose one)</th>
<th>Pressure Injury Survey</th>
<th>Degree of Pressure Injury</th>
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<tbody>
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#### Admission Assessment

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#### Last Assessment

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#### Types of Preventive Interventions in Use

<table>
<thead>
<tr>
<th>Preventive Intervention</th>
<th>Within Past 24 Hours for At Risk Patients Only</th>
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<tbody>
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</table>

#### # of Pressure Injuries

<table>
<thead>
<tr>
<th>Each Patient</th>
<th>Unit-Associated Plus Disconnected Before</th>
</tr>
</thead>
<tbody>
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</table>

**Note:** This table is a sample and should be customized to fit specific institutional needs and guidelines.
APPENDIX B. New Data Collection Form with Automated Chart Abstraction

| Patient | Age | Sex | Race | Marital Status | Insurance | Chief Complaint | History of Present Illness | Other Pertinent History | Pain Location | Pain Duration | Pain Quality | Pain Relief | Pain Management | Pain Score | Treatment Plan | Other Comments |
|---------|-----|-----|------|----------------|------------|----------------|--------------------------|-------------------------|---------------|--------------|--------------|-------------|-------------|----------------|------------|---------------|----------------|
| E0201 | 45 | M  | White | Single | Yes | Chest pain    | History of MI | None                    | Abdominal pain | No | 2 hours     | Severe     | Yes | None        | 7           | Medication  | None  |
| E0211 | 54 | F  | Black | Married | Yes | Headache     | History of HTN | None                    | None          | Yes | >24 hours   | Mild       | Yes | None        | 3           | Therapy     | None  |
| E0221 | 65 | M  | Hispanic | Single | Yes | Knee pain    | History of OA | None                    | None          | Yes | 6 months    | Moderate   | Yes | None        | 8           | Physical    | None  |

*Note: The table continues with more rows.*
Patient Trust and Resistance towards Patient Portals

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Abstract: Health information technologies (HITs) as facilitators of chronic disease self-management remains an ongoing topic for information system researchers. This research addresses a gap in knowledge surrounding patient trust and resistance towards using these technologies, specifically patient portals. The method used to accomplish this study is through the dispersion of a quantitative survey to participants in Ontario, Canada. This survey focused on questions related to the four variables that have been identified through the literature to be important in determining patient resistance of HITs. The results indicate the importance of patient trust in mitigating their resistance to using these technologies.

INTRODUCTION

Patient access to personal health information (PHI) results in numerous benefits. These benefits may include improved quality of care and safety, increased efficiency and consumer engagement, and decreased costs (Ancker, Edwards, Miller & Kaushal, 2012; Walker, Pan, Johnston, Adler-Milstein, Bates & Middleton, 2005). Despite this, resistance to the use of HITs is strongly prevalent for patients (Samhan, 2017; Samhan & Hauck, 2018). Additionally, there is a lack of literature addressing this trust as it pertains to the resistance of HITs (Li, James, & McKibben, 2016; Platt, Jacobson & Kardia, 2018). Trust is characterized as “a multidimensional dynamic between two parties defined by an expectation or willingness to impart authority and accept vulnerability to another in fulfilling a given set of tasks” (Platt, Jacobson & Kardia, 2018). Although trust has been determined as an important indicator in the reduction of uncertainty (Liang, Laosethakul, Lloyd, & Xue, 2005), the volume of literature on this topic is greatly lacking and should be explored further. To assist in mitigating these gaps in the literature this study will examine factors that contribute to patient resistance and more specifically focusing on trust concerns of patient portals. Patient portals are a HIT that allows patients to access PHI through a secure online website at any time as long as an internet connection is available (Kruse, Argueta, Lopez, & Nair, 2015). Therefore, this study seeks to address the research question of: How does patient trust affect resistance behaviors towards the use of patient portals?

BACKGROUND

Over the past several years the notion of patient portals has become a prevalent topic in literature (Kruse, Argueta, Lopez, & Nair, 2015). Patient portals enable patients to have 24-hour access to PHI via secure online websites; these websites may be accessed anywhere as long an internet connection exists (Kruse, Argueta, Lopez, & Nair, 2015). These portals provide patients with the opportunity to better manage and understand their current health situations (Kruse, Argueta, Lopez, & Nair, 2015; Ammenwerth, Schnell-Inderst, & Hoerbst, 2012; Dohan & Tan, 2014). Patient portals differ from personal health records (PHR) in that data on the portals is updated whenever updates are made to the electronic health record (EHR), as opposed to PHRs, where data is only updated by patients (Kruse, Argueta, Lopez, & Nair, 2015). There are numerous different features that can be provided by patient portals including; access to information regarding recent office visits, summary of discharges, medications and lab results with more advanced options being prescription refill requests, scheduling of appointments, and communicating via secure messages with practitioners (Kruse, Argueta, Lopez, & Nair, 2015; Ammenwerth, Schnell-Inderst, & Hoerbst, 2012).

Although information sharing in healthcare is accomplished in various ways, the overall goal is to present patients as digital managers of their health data and information (Gordon & Catalini, 2018). The management of chronic diseases is essential to maintain a good quality of life and to mitigate health emergencies, complications and possibly even death (Dadgar, Majid, & Joshi, 2018), therefore information sharing could provide substantial benefits here. There are numerous self-management activities that patients with a chronic disease must manage in their everyday lives. These activities include communicating with healthcare providers, medication management, lifestyle management,
management of psychological consequences, use of social support systems and symptom management (Dadgar, Majid, & Joshi, 2018). Although most research on information sharing has focused on the provider perspective, research on Health Information Exchanges (HIEs) has investigated information sharing from the patient perspective (Esmaeilzadeh & Sambasivan, 2017). HIE technologies has shown great potential in improving safety and quality of care, increasing efficiency and consumer engagement, and reducing cost (Ancker et al., 2012; Walker et al., 2005). These benefits are not just acquired by individual groups such as providers, but all participants in the healthcare system including patients, providers, payers and the entire community (Murphy, 2013).

Despite these benefits, the success of information sharing depends on the degree of trust users feel towards the experience (Platt, Jacobson & Kardia, 2018). Trust as it relates to HITs has been determined to increase patients' improved decision making and use of HIE systems (Kisekka & Giboney, 2018). When individuals trust that the system will provide them with quality information, the chances of continued use are increased (Kisekka & Giboney, 2018). Further, it was found by (Kisekka & Giboney, 2018), that there is a positive relationship between information trust and optimistic attitudes towards using HIE technologies among providers. Trust entails that the implementer of a technology will deal with any related issues that emerge (Rivard & Lapointe, 2012). With regards to trust and patient portals, a patient must establish trust with both the organizations providing the information as well as trust with their physicians (Li, James, & McKibben, 2016; Platt, Jacobson & Kardia, 2018).

Given that these patient portals amount to some sort of investment, and that they have the potential to be an important part of normal care routines, it is imperative that patients’ attitudes and behaviours related to resisting use of the technology be addressed. Resistance is an important factor here to take into account, as it captures the potential users consideration and subsequent rejection of a technology (Bhattacherjee & Hikmet, 2007). This can potentially lead to resistance behaviours beyond simple non-adoption, such as sabotaging change processes or open hostility towards change agents (Bhattacherjee & Hikmet, 2007), for examples.

Gaps in Research

Given the obstacles associated with the adoption of HITs to facilitate interoperability and manage chronic disease, as well as the benefits that may be attained with the implementation of these technologies, there are still several gaps in the literature that should be explored. The first gap identified concerns the lack of literature on patient resistance behaviors of HITs and more specifically patient portals (Samhan & Hauck, 2018). Within the healthcare industry, the resistance of users is considered a major contributor to the failure of systems. Given the importance of mitigating patient-user resistance, there is a lack of literature addressing the resistance of patients toward HITs (Samhan, 2017; Samhan & Hauck, 2018; Kim & Kankanhalli, 2009). For this gap to be addressed, patients perceived awareness and knowledge must be examined to initiate successful technological change directed towards patients. Second, there is a lack of literature addressing trust as it pertains to the resistance of HITs and more specifically patient portals (eg. Li, James, & McKibben, 2016; Platt, Jacobson & Kardia, 2018). Trust has been identified as an important factor in the reduction of uncertainty (Liang, Laosethakul, Lloyd, & Xue, 2005), but the volume of literature on this topic is lacking and should be explored further to find out how patient trust affects the resistance behaviors towards HITs such as patient portals.

THEORETICAL BACKGROUND

To address the aforementioned gaps in research, several theoretical approaches will be integrated into a model. First, constructs from Commitment-Trust Theory (Wang, Wang & Liu, 2016) will be employed in order to capture trust-related constructs. Second, Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh & Davis, 2000) will be used to capture traditional variables related to personal use of technology and the context of its use.

Commitment-Trust Theory

The commitment-trust theory is a theory fixated on explaining the growth of long-term relationships among exchange parties (Wang, Wang & Liu, 2016). Specifically, this theory focuses on the concurrent adoption of relationship commitment and trust as critical indivisible factors for the formation and maintenance of business relationships between exchange parties (Wang, Wang & Liu, 2016). This theory thus proposes that the trust between exchange parties can aid in the reduction of the vulnerability of relationships, ultimately resulting in enhanced relationship
commitment (Wang, Wang & Liu, 2016; Yuan, Lai, & Chu, 2019). Although, this theory is generally used in the context of relational exchanges within the relationship marketing field (Morgan & Hunt, 1994), it similarly offers a powerful theoretical basis for the explanation of online service usage such as the use of patient portals within the healthcare field (Yuan, Lai, & Chu, 2019).

**Unified Theory of Acceptance and Use of Technology**

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a cognitive theory focused on understanding and predicting human behavior as it relates to the adoption and use of technology (Venkatesh et al., 2003; Venkatesh et al., 2016). It incorporates various cognitive theoretical foundations that focus on the intention of an individual to use technology (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong & Xu, 2016). Four main factors are posited to predict the intention to use a technology: performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2016). This model is very popular, and has been applied to explain factors related to the technology and context of its use, and their effect on the intention to use technology. Previous studies have reported empirical evidence integrating the four UTAUT predictors along with resistance in investigations on patient use of cloud computing (Hsieh, 2016).

**HYPOTHESIS DEVELOPMENT**

As previously stated, the research question used to guide this study is: *How does patient trust affect resistance behaviors towards the use of patient portals.* Figure 1 (below) describes the theoretical model used in this research.


The first hypothesis refers to the ability of performance expectancy to positively impact user resistance behaviors towards patient portals. Performance expectancy is defined as the extent to which an individual believes the use of a system will provide them with their desired outcomes (Venkatesh & Davis, 2000; Venkatesh et al., 2003). There is a positive impact associated with a high degree of performance expectancy, which results in user acceptance or reduced resistance (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2016). Here, the perception related to the ability of the patient portal to help the patients achieve their health goals will be a compelling argument for them to use the technology, thereby lowering their resistance-related attitudes towards it. Therefore, hypothesis 1 is:

\[ H1: \text{As the “Performance Expectancy” of patient portals increases, the overall resistance of the patient portals will decrease.} \]
The next hypothesis refers to social influence and its impact on resistance behaviors toward patient portals. Social influences can be characterized as the degree to which an individual perceives that people significant to them believe in the use of the technology (Venkatesh et al., 2003). Positive or encouraging social influences would encourage an individual to perform or in this case be accepting of patient portals, and this has been hypothesized and supported in other contexts (Samhan, 2017; Oreg, 2006). The second hypothesis is:

**H2:** As the “Social Influence” towards patient portals becomes positive, the resistance to patient portals will decrease.

The third hypothesis refers to the impact of facilitating conditions on intentions to resist patient portals. Facilitating conditions can be defined as the degree that an individual is convinced that an organization and information technology exists to support the use of the specified system (Venkatesh et al., 2003). In the case of patient portals, the patient’s physician may provide varying levels of support for the use of the patient portal. Thus, hypothesis 3 reflects this relationship:

**H3:** As the “Facilitating Conditions” towards patient portals increases, the resistance to patient portals will decrease.

The fourth hypothesis refers to the impact that trust has on patient portal resistance. An ongoing concern is the trust between physicians and patients; this degree of trust affects the development of this important relationship (Li, James, & McKibben, 2016). Technology changes the way patients and physicians interact, and the degree of trust can impact whether a patient is accepting of the technology or resistant toward the technology (Li, James, & McKibben, 2016). It is expected that trust will have a moderating effect on resistant behaviors. Thus, hypothesis 4 is broken into three separate hypotheses as follows for each of the aforementioned independent variables:

**H4a:** Increased “Trust” will moderate (amplify) performance expectancy behaviors to resist patient portals.

**H4b:** Increased “Trust” will moderate (amplify) social influence behaviors to resist patient portals.

**H4c:** Increased “Trust” will moderate (amplify) facilitating condition behaviors to resist patient portals.

**METHODOLOGY**

Data was collected between February and August 2019 in Ontario, Canada. Participants were recruited via posters dispersed amongst various locations in Ontario, Canada and through posts on social media. The survey was administered online, and participants were motivated with the chance to enter into a draw upon completion of the questionnaire. The survey was comprised of three sections; the first section provided a brief explanation of patient portals to ensure participants were aware of what was being talked about. This explanation was followed demographic questions on age, gender, education, voluntariness, access frequency, and chronic disease. The main component of the survey included questions regarding the performance expectancy, effort expectancy, social influence, and facilitating conditions adapted from Venkatesh et al (2003). The trust and resistance items were adapted from Aboobucker & Bao (2018) and Bhattacherjee & Hikmet (2007), respectively. The items for each of the constructs of the model were measured on a seven-point Likert scale (Strongly Disagree – Strongly Agree). To control for common method bias and to avoid impulsive and repetitive responses, the order of the questions was randomized for each participant. Lakehead University Research Ethics Board (REB) provided ethics approval.

Analyzing the data involved the following steps. First, the dataset was examined using both a visual assessment and SPSS software for any major concerns such as missing data, suspicious response patterns, and outliers. After screening and cleaning the data, descriptive analysis was then run in SPSS to determine what trends exist in the data, whether the data set was normally distributed and to be able to describe the data. From this, it was identified that the data was somewhat negatively skewed with some indications of non-normality. Due to the nature of the data being somewhat non-normally distributed, having a smaller sample size and most variables being continuously measured, the rest of the data analysis was conducted with WarpPLS (Kock, 2018). PLS makes little to no assumptions regarding the distribution of the data and is ideal for small sample sizes (Hair et al., 2016). The outer model was tested utilizing the PLS Mode M Basic algorithm in WarpPLS and from this, it was identified that there was a presence of non-linear
relationships. The inner model was analyzed using the Warp3 algorithm, which attempts to identify relationships among latent variables that follow a pattern similar to an “S”-shaped curve using a logarithmic function (Kock, 2018).

**Descriptive Statistics**

After screening and cleaning the data, descriptive analysis was then run in SPSS to determine trends in the data. From this analysis it was determined that there was a total of 91 usable samples within this data set; of these 21 are males (23.1%), 69 are females (75.8%) and one respondent preferred not to disclose this information. Most respondents were between the ages of 19-34 years old (about 64%). Regarding the highest level of education obtained, most respondents had achieved a level of education of College or University or higher (about 81%). For the responses on the management of a chronic disease, there were only 33 respondents (about 36%) who identified to manage a chronic disease for themselves or a family member/loved one. Most individuals in this study (about 70%) indicated that they felt the use of patient portals was voluntary, followed by 24 respondents who felt it was somewhat voluntary (about 26%) and 3 respondents felt it was not voluntary (about 3%). Lastly, of the respondents who use patient portals, 36 participants used patient portals yearly (about 40%), followed by 9 monthly users (about 10%) and 4 weekly users (about 4%). The results of these tests are summarized in Table 1 (below).

<table>
<thead>
<tr>
<th>Total n=91</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Highest Education</td>
</tr>
<tr>
<td>Manage a Chronic Disease</td>
</tr>
<tr>
<td>Voluntaryness</td>
</tr>
<tr>
<td>Frequency of Use</td>
</tr>
</tbody>
</table>

**Reliability and Validity**

Internal consistency reliability is usually the first criterion evaluated for the measurement model and it is evaluated using Cronbach’s alpha and composite reliability (Hair et al., 2016). Convergent validity can be described as the degree that an indicator positively correlates with other indicators from the same construct (Hair et al., 2016). Outer loadings between 0.4 and 0.7 will be deleted under the circumstance that deletion increases the AVE and composite reliability, while loadings below 0.4 will be deleted immediately (Hair et al., 2016). It is also noted that an acceptable AVE is any value above 0.5 (Hair et al., 2016). Discriminant validity will be assessed with the cross-loadings and the Fornell-Larker criterion. For this approach, the square root of the AVE should be greater than any inter factor correlations (Hair et al., 2016).

**Structural Model Estimation**

Following the confirmation of validity and reliability of the construct measures, the next phase assesses the structural model, also referred to as the inner model (Hair et al., 2016; Kock, 2018). The examination of the inner model involves both the model’s predictive capabilities and the relationships between constructs (Hair et al., 2016). Specifically, the procedure for assessing the structural model begins by assessing the model for any collinearity issues; collinearity is discussed further in the following section (Hair et al., 2016). The main criteria for assessing the inner model are displayed in table 3 (below) and include the assessment of the model’s structural paths, coefficient determination, effect size and predictive qualities (Hair et al., 2016; Kock, 2018). Also included in table 3 are the criteria for the analysis of the goodness of fit which includes several indices used to assess quality (Kock, 2018). Specifically, quality is assessed by the Average Path Coefficient (APC), Average R² (ARS), Average Adjusted R² (AARS), Average
Block VIF (ABVIF), and Average Full Collinearity VIF (AFCVIF), all of which should be below 5 or 3.3 (Kock, 2018). The VIFs below 5.0 are acceptable to assume collinearity is not present (Hair et al., 2016).

**Alternative Model Evaluation**

Several alternative models were compared using the goodness of fit tests as well as by examining the overall model fit and quality indices presented by WarpPLS. The model presented was the best one.

**RESULTS**

104 participants provided responses. After screening and cleaning the data, there were 91 usable samples. The data was screened and cleaned for any major concerns using SPSS software. With regards to missing data, four cases were removed due to a large percentage of unanswered questions. The threshold used for missing data was 15% (Hair et al., 2016). Upon examination, there were nine cases of straight-lining that were removed from the data set. There were no outliers identified in the data.

**Reliability and Validity**

All Cronbach’s alphas and composite reliabilities were greater than the 0.7 thresholds (Hair et al., 2016). In analyzing the data there were several indicators that were dropped due to high cross-loadings with regards to their component loadings: SocInf1 and Trust4. There were few other indicators that were below the threshold of 0.708 that were examined further but due to their deletion not having any improved impact on the Adjusted R², they were retained. The AVEs of most of the constructs are all larger than 0.5 suggesting an acceptable level of convergent validity (Hair et al., 2016). Two cases do not meet this criterion, they include trust as a moderator for social influence and facilitating conditions. The cross-loadings were confirmed for all independent variables, although some issues did arise with the moderating variables. This criterion was satisfied for the Fornell-Larcker criterion, although there were two violations for trust as a moderator for social influence and facilitating conditions. The reliability and validity analysis results are presented in Table 2 (below).

**Table 2: Average Variance Extracted (AVE), Cronbach’s Alpha (α), Composite Reliability, Latent Variable Correlations and Square Root of AVE (italicized on the intersections). The bolded numbers are the violations of the discriminant validity. PE: Performance Expectancy. SI: Social Influence. FC: Facilitating Conditions. T: Trust.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>AVE</th>
<th>α</th>
<th>CR</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 PE</td>
<td>0.653</td>
<td>0.851</td>
<td>0.881</td>
<td>0.808</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 SI</td>
<td>0.736</td>
<td>0.821</td>
<td>0.893</td>
<td>0.615</td>
<td>0.858</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 FC</td>
<td>0.621</td>
<td>0.759</td>
<td>0.828</td>
<td>0.570</td>
<td>0.558</td>
<td>0.788</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Trust</td>
<td>0.674</td>
<td>0.754</td>
<td>0.860</td>
<td>0.695</td>
<td>0.553</td>
<td>0.425</td>
<td>0.821</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Resistance</td>
<td>0.627</td>
<td>0.724</td>
<td>0.833</td>
<td>-0.209</td>
<td>-0.137</td>
<td>-0.108</td>
<td>-0.090</td>
<td>0.792</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>6 T*PE</td>
<td>0.551</td>
<td>0.944</td>
<td>0.935</td>
<td>-0.328</td>
<td>-0.250</td>
<td>-0.222</td>
<td>-0.372</td>
<td>-0.238</td>
<td>0.742</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 T*SI</td>
<td>0.470</td>
<td>0.869</td>
<td>0.887</td>
<td>-0.296</td>
<td>-0.133</td>
<td>-0.260</td>
<td>-0.291</td>
<td>-0.243</td>
<td>0.740</td>
<td>0.686</td>
<td></td>
</tr>
<tr>
<td>8 T*FC</td>
<td>0.491</td>
<td>0.880</td>
<td>0.896</td>
<td>-0.253</td>
<td>-0.206</td>
<td>-0.242</td>
<td>-0.264</td>
<td>-0.282</td>
<td>0.847</td>
<td>0.649</td>
<td>0.701</td>
</tr>
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</table>

**Structural Model**

The final model using the PLS Mode M Basic Algorithm with the Warp3 algorithm meets most of the overall model fit criteria (APC=0.162, P= 0.027; ARS= 0.276, P= 0.001; AARS= 0.224, P= 0.006; AVIF= 1.827 < 3.3; AFVIF= 2.617, < 3.3) (Kock, 2018). Figure 3 (below) summarizes the structural model, as well as Table 6 (below), presents the full results of the significant relationships in the structural model. Additionally, the block VIFs are all below the
threshold of 5.0, thus it is assumed that collinearity is not a problem (Hair et al., 2016). The path coefficients, effect size ($f^2$), coefficient of determination ($R^2$) are all used to interpret the results (Hair et al., 2016).

The $R^2$ for the dependent variable resistance is weak with a value of 0.28 (adjusted $R^2 = 0.22$) (Hair et al., 2016). Additionally, the supported hypotheses 1 and 2 have a small effect size, while hypotheses 4a, has a medium effect size (Hair et al., 2016). The confidence levels for each of the hypotheses were also assessed and are illustrated above in Table 6 for reference. The confidence levels for the supported hypotheses 1 and 2 are not significant, while hypothesis 4a yielded a significant confidence interval. Out of the six hypotheses included in the model, three are supported at the .05 level.

**DISCUSSION**

The purpose of this research was to determine the influence that trust has on the resistance behaviors towards the use of patient portals. From the results presented above, there was support for trust as a moderator of performance expectancy. Performance expectancy is characterized as the degree that a patient believes that the use of a system will contribute to the attainment of their desired outcome (Venkatesh et al., 2003). With higher degrees of trust, as performance expectancy increases, the resistance behaviors decrease. This result generally implies that trust is important for patients to adopt and use patient-focused HIT. More specifically, it implies that trust is important for patients to understand that the system will provide the intended benefits of the system. This result is in line with previous studies that suggest that trust plays an important role in the usage intentions of a system as well as having a positive effect on relationships (Yuan, Lai & Chu, 2019; Hashim & Tan, 2015). The effect of social influence on resistance was also significant. This result differs from that of previous studies (Samhan, 2017) although it uses a specific patient portal in a more tightly defined context. The moderation of trust on the relationship between social influence and resistance as well as facilitating conditions and resistance were both not supported (H4b and H4c). As this model yielded a small effect size for hypotheses 2 and hypothesis 3 was not supported, it is not surprising that hypothesis 4b and 4c were also not supported. Both of these results could imply that any action to increase trust in the

![Figure 2: Structural Model Test Results. Significant relationships are denoted by bold lines, and non-significant relationships are denoted by dashed lines.](image)
technology will not improve any resistance due to any social influences or perceptions regarding workloads necessary to use the HIT. Taken together, these results underline the importance of conducting more and larger-scale research on the role of trust in patient HIT adoption and use.

Limitations and Future Research

The chief limitation of this project pertains to its small sample size and the fact that participants self-selected. Being a small-scale research project, this limits its generalizability to any larger population. As well, the sample had a few shortcomings, such as the low proportion of participants who actually managed any chronic diseases. Finally, effort expectancy (Venkatesh et al., 2003) had to be dropped from the model, as the construct could not be found in the dataset. Future studies could focus more strongly on various aspects of the population, such as patients with certain chronic diseases. Future studies could also focus on certain interventions that are designed to address trust issues in a defined user base.

CONCLUSION

There has been a lack of literature focusing on the resistance behaviors toward HITs such as patient portals. The factors identified to be most important in reducing resistance include performance expectancy, social influence, and trust as a moderator to performance expectancy. These factors that identify to be most prevalent in contributing to resistant behaviors can thus be properly addressed in hopes of fully adopting patient portals as principal enablers of health management. Although many barriers exist in mitigating resistance behaviors such as trust concerns, this study is a step forward to not only contributing to the lacking literature but in facilitating change and complete adoption of patient portals.

REFERENCES


“Real World” Research Using Practice Based Research Networks (PBRN): A Systematic Review

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Abstract: Objective: While the randomized control clinical trial (RCT) has long been viewed as the “gold standard” for evidence based medicine, researchers and clinicians have also recognized limitations of RCTs when applied to clinical practice. These limitations arise from the fact that the results of interventions and procedures of RCTs conducted in controlled institutional settings often differ significantly from results obtained when the same interventions are applied in clinical practice. Consequently, there are increasing calls for more research to be carried out in the “real world” setting of clinical practices treating heterogeneous groups of patients. Studies conducted in clinical practices are referred to as “pragmatic clinical trials” or “pragmatic studies” and practice based research networks (PBRNs) have been proposed as ideal environments for conducting pragmatic clinical trials. The purpose of this study is to investigate how well PBRNs have performed in fulfilling this promise in the US.

Materials and Methods: A study protocol was developed based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to identify clinical research studies of patient health outcomes that were conducted in a PBRN setting. The PubMed database was queried for journal articles in English that contained the search terms “practice based research network” in the abstract or the title of the article. Existing PubMed filters designed to select only clinical research studies were then applied. Duplicates were removed and the remaining articles were reviewed by 2 researchers for relevant inclusion and exclusion criteria. Each article in the final group was reviewed to determine study design, experimental setting, outcome measures used, main findings, citations count and impact factor of the journal in which the study appeared.

Results: The initial query of the PubMed database returned 571 articles. After applying filters 42 articles remained. Manual inspection of the full text of the remaining articles yielded a remaining total of 10 studies that met inclusion criteria. The studies reviewed were a heterogeneous group with a wide range of objectives, methodologies, patient outcomes and results. Citation counts for all articles were higher than the median citation count for articles in the journals in which they were published. All articles reviewed were published in journals with relatively high journal impact factors (JIF) with JIF percentile rankings ranging from the 68th to the 89th percentiles in their respective journal categories.

Conclusion: Despite the large number of articles returned by the initial search, very few of these turned out to be clinical studies of patient outcomes. The articles that were not clinical trials covered a wide range of topics including case studies of the formation of PBRNs, editorials advocating for the creation of PBRNs, calls for funding of PBRNs, quality improvement studies, provider attitude and opinion surveys, and histories of the PBRN movement. The studies that were judged to be clinical trials tended to focus on interventions such as use of mailed reminders or training of family caregivers designed to change patient health related behaviors as opposed to direct medical interventions or changes in patient treatment protocols. The articles that were judged to be clinical studies of patient outcomes were of high quality based on citation counts and journal impact factors.
INTRODUCTION

Practice based research networks (PBRNs) have been in existence in the U.S. dating back to the 1970s. Initially developed as collaborations between community based physician practices, their focus encompassed improving patient outcomes in primary care, epidemiological and prevalence studies, and conducting studies intended to improve primary care practices such as the assessment of prophylaxis treatment for acute otitis media by community based pediatricians. In 1979, a group of physicians and researchers proposed the formation of the Ambulatory Sentinel Practice Project of North America (ASPPN) following a meeting of the North American Primary Care Research Group (NAPCRG). The ASPPN project later received grant funding from the Rockefeller foundation in 1981 and was subsequently shortened to Ambulatory Sentinel Practice Network (ASPN) (1).

The formation of new PBRNs continued throughout the 1980s and 1990s. In response, the federal government Agency for Health Care Research and Quality (AHRQ) began to provide funding to build capacity for practice-based research and PBRN projects. The Journal of the American Board of Family Medicine published a special issue in 1994 on practice-based research that contained the results of a survey indicating that there were 28 active networks in North America. Since then the number of PBRNs increased to 173 in 2016, involving 29,455 practices and 153,736 clinicians and serving over 86 million patients. Types of networks included 34% mixed specialties; 30% family medicine; 13% pediatric; 3% each for internal medicine, pharmacy, and dental; and 14% “other”(2).

In a 2011 comprehensive study of PBRNs based on self-reported data collected from registration forms from PBRNs applying for formal recognition by the AHRQ for inclusion in a the AHRQ national registry of PBRNs, Peterson et al. reported that “PBRNs are growing in experience and research capacity. With member practices serving approximately 15% of the US population, PBRNs are adopting more advanced study designs, disseminating and implementing practice change, and participating in clinical trials. PBRNs provide valuable capacity for investigating questions of importance to clinical practice, disseminating results, and implementing evidence-based strategies. PBRNs are well positioned to support the emerging public health role of primary care providers and provide an essential component of a learning health care system”(3). The study designs used as reported by the PBRNs included: observational epidemiology; health systems/outcome research; best practice research/modeling; implementation research; clinical trials; Comparative effectiveness research; methodological research; nonpractice-based community health interventions, and; pharmaceutical clinical trials.

Ford et al. have identified problems with the majority of published clinical trials in that “…clinical trials do not adequately inform practice because they were optimized to determine efficacy. Because such trials were performed with relatively small samples at sites with experienced investigators and highly selected participants, they could be overestimating benefits and underestimating harm. This led to the belief that more pragmatic trials, designed to show the real-world effectiveness of the intervention in broad patient groups, were required.”(4) Califf et al. added the argument that, “the need for high-quality evidence to support decision-making about health and health care by patients, physicians, care providers, policymakers is well documented. However, serious shortcomings in evidence persist. Pragmatic clinical trials (PCTs) that use novel techniques and emerging information and communication technologies to explore important research questions rapidly and at a fraction of the cost incurred by more ‘traditional’ research methods promise to help close this gap (5).” Heintzman et al. have asserted that a “…particular strength of PBRNs is their ability to participate in pragmatic trials, which differ from standard clinical trials in that they are performed in real-world clinical environments and account for variation in routine clinical practice. Pragmatic trials are essential to testing the translation of experimental findings into heterogeneous settings and to balancing internal and external validity” (6).

The present study represents an attempt to determine how successful PBRNs have been in conducting pragmatic clinical trials of interventions that directly impact patient outcomes in the United States. If PBRNs are playing an important role in “the translation of experimental findings into heterogeneous settings” as suggested above, we hypothesize that there should be a large number of articles reporting the results of clinical studies conducted in PBRN settings published in well regarded medical journals. In addition, these studies should be widely cited in other research and review articles.
This study was limited to PBRNs in the US because the funding and operation the US health care delivery system (and consequently the PBRNs that function as a part of that system) are unique among all other developed countries in the world (7).

Materials and Methods

Search strategy

The study protocol was developed based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The PRISMA guidelines were developed in 2005 because, “Systematic reviews and meta-analyses are essential to summarize evidence relating to efficacy and safety of health care interventions accurately and reliably. The clarity and transparency of these reports, however, is not optimal. Poor reporting of systematic reviews diminishes their value to clinicians, policy makers, and other users.” (6) In response to this situation, an international group that included experienced authors and methodologists developed the PRISMA statement in 2005, originating from the QUOROM (Quality Of Reporting Of Meta-analysis) Statement, consisting of a 27 item checklist deemed essential for transparent reporting of a systematic review and a four-phase flow diagram, (8). The PRISMA guidelines have since been widely recognized as a preferred guide for the generation of study protocols for systematic reviews and meta-analysis. See Appendix 1 for a copy of the PRISMA checklist.

The PubMed database was searched to identify medical research studies published in English conducted in a medical practice-based research setting in the United States that focused on patient health outcomes. The PubMed Advanced Search Build was use to generate and filter the article queries. The search was conducted on 3/1/2019. No date parameters were used. We searched for the exact phrase, “practice based research network” in the title or abstract. Articles were then filtered by the article type using PubMed’s’ article type filters: clinical trial; clinical trial-phase 1; clinical trial-phase 2; clinical trial-phase 3; clinical trial-phase 4; controlled clinical trial; observational study; pragmatic clinical trial, and; randomized controlled trial. Titles and abstracts, and, if required, the full text of the article were reviewed independently by 2 reviewers for inclusion and exclusion criteria. Articles were considered to be clinical studies and included in the final review if they were judged to meet one of the study type definitions listed below.

Study Type Definitions

Case Control Study

“A study that compares patients who have a disease or outcome of interest (cases) with patients who do not have the disease or outcome (controls), and looks back retrospectively to compare how frequently the exposure to a risk factor is present in each group to determine the relationship between the risk factor and the disease

Case control studies are observational because no intervention is attempted and no attempt is made to alter the course of the disease. The goal is to retrospectively determine the exposure to the risk factor of interest from each of the two groups of individuals: cases and controls. These studies are designed to estimate odds. Case control studies are also known as ‘retrospective studies’ and ‘case-referent studies.’” (9)

Randomized Controlled Trial

“A study design that randomly assigns participants into an experimental group or a control group. As the study is conducted, the only expected difference between the control and experimental groups in a randomized controlled trial (RCT) is the outcome variable being studied.” (9)

Cohort Study

“A study design where one or more samples (called cohorts) are followed prospectively and subsequent status evaluations with respect to a disease or outcome are conducted to determine which initial participants exposure
characteristics (risk factors) are associated with it. As the study is conducted, outcome from participants in each cohort is measured and relationships with specific characteristics determined.”(9)

**Outcome Measures**

To be included in the final group for review the study needed to focus on patient health outcomes.

**Primary outcome**

The primary outcome was objectively measured patient health outcomes (i.e., mortality, morbidity, patient-reported outcome measures, physiological measures of health or disease, etc.).

**Secondary outcomes**

Given the anticipated wide variation in settings, participants, and study designs for studies that met inclusion criteria we also included indirect measures assumed to be related to patient health. These included: process outcomes (i.e., measures of patient compliance with medication orders and treatment plans), and; adverse events.

**Data Collection and Analysis**

A standardized data sheet was prepared for recording the relevant information from each study that qualified for inclusion. The data recorded included type of study; number of subjects; objectives of the study; study location; data collected; outcome measures used; outcome measures results; statistical analyses used (if any); study authors’ conclusions; citation count, and: impact factor of journal in which the article was published. See Appendix 2 for a copy of the data sheet used.

The count of times the article has been cited by other articles and impact factor of the journal in which the article was published were used as proxies for a measure of the quality of the published article.

The citation count theoretically informs the reader of the author’s or journals impact in that scientific community. “Impact Factor is not a perfect tool to measure the quality of articles but there is nothing better and it has the advantage of already being in existence and is, therefore, a good technique for scientific evaluation. Experience has shown that in each specialty the best journals are those in which it is most difficult to have an article accepted, and these are the journals that have a high impact factor.

Most of these journals existed long before the impact factor was devised. The use of impact factor as a measure of quality is widespread because it fits well with the opinion we have in each field of the best journals in our specialty.”(10) The journal’s impact factor is derived by 2 elements: the numerator, which is the number of citations in the current year to items published in the previous 2 years, and the denominator, which is the number of substantive articles and reviews published in the same 2 years.(7). Citation counts are included in the metadata of most articles contained in the PubMed database. Impact factors are published each year in the Clarivate Analytics Journal Citation Report. Impact factors for this study were taken from the 2018 report ([https://jcr.clarivate.com/JCRLandingPageAction.action](https://jcr.clarivate.com/JCRLandingPageAction.action)).
Figure 1: Journal’s Impact Factor

Full articles that met the final inclusion criteria were read by 1 reviewer who extracted relevant information into the data collection form. These data collection forms were then reviewed by a second reviewer. All disagreements about the accuracy of a given data element were resolved through discussion until consensus was reached.

Results

The initial search yielded 571 articles containing the phrase “practice based research network” in the title or abstract. The PubMed article filters were then applied sequentially as follows: clinical trial (filter with the most significant reduction in articles); clinical trial-phase 1 (no effect); clinical trial-phase 2 (no effect); clinical trial-phase 3 (no effect); clinical trial-phase 4 (no effect); controlled clinical trial (no effect); observational study (articles increased in count by 8); pragmatic clinical trial (no effect), and; randomized controlled trial (no effect). After application of the filters 42 full text articles remained.

Duplicate articles were removed resulting in 38 full text articles to be reviewed for inclusion in the final set. Of these 38, 4 were excluded for non USA setting, 6 were excluded for no patient outcomes, 6 were excluded as QI only studies, and 12 were excluded for miscellaneous other reasons (see Figure 2). A final number of 10 articles were identified as clinical studies that and were included in the content summaries and quality evaluation (citation count and journal impact factor).
The studies reviewed were a heterogeneous group with a wide range of objectives, methodologies, patient outcomes and results. See table 1 for a summary of the 10 articles that met the inclusion criteria.
<table>
<thead>
<tr>
<th>Study</th>
<th>Journal</th>
<th>Study Design</th>
<th>Setting and Intervention</th>
<th>Key Findings</th>
<th>Number of citations</th>
<th>Impact factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearce et al 2008, Cardiovascular Risk Education and Social Support (CARRESS): Report of a Randomized Controlled Trial from the Kentucky Ambulatory Network (KAN)</td>
<td>The Journal of Family Medicine</td>
<td>Clustered randomized controlled trial</td>
<td>Kentucky; Test a practice-based intervention to foster involvement of a relative or friend in the reduction of cardiovascular risk in patients with type 2 diabetes after 9 to 12 months, the intervention had no significant effect on systolic blood pressure, HbA1C, health-related quality of life, patient satisfaction, medication adherence, or perceived health competence. Power was insufficient to detect an effect on low-density lipoprotein cholesterol. Baseline cardiovascular risk values were not very high; mean systolic blood pressure at 140 mm Hg; mean HbA1C at 7.9%; and mean low-density lipoprotein at 137 mg/dL. Patient health care satisfaction was high.</td>
<td>12</td>
<td>2.515</td>
<td></td>
</tr>
<tr>
<td>Rodriguez et al 2014, Real-World Implementation and Outcomes of Health Behavior and Mental Health Assessment</td>
<td>The Journal of the American Board of Family Medicine</td>
<td>Prospective mixed methods study</td>
<td>Greater Los Angeles, California, northeastern Vermont and rural Appalachian Virginia, urban Richmond, Virginia. Assessing patient-reported health behaviors in a critical first step in prioritizing prevention in primary care. We assessed the feasibility of point-of-care behavioral health assessment in 9 diverse primary care practices. Most nonurgent patients (71%) visiting the participating practices during the implementation period completed the health assessment, not even versus dpy practice (range, 59% to 68%). Unhealthy diet, sedentary lifestyle, and stress were the most common patient problems, with similar frequencies observed across practices. The median number of &quot;positive screens&quot; per patient was similar among FQHCs (3.7 positives; standard deviation [SD] 1.9), practice-based research network practices (3.3 positives; SD 1.9), and the Veterans Affairs (4.1 positives; SD 2.0). Primary care clinicians discussed assessment results with patients about half of the time (54%), with considerable variation between practices (ranges, 13% to 69%). Lowest use among FQHC clinicians. Although clinicians were interested in routinely implementing assessments, many reported not feeling confident of having resources or support to address all patients' behavioral health needs.</td>
<td>9</td>
<td>2.515</td>
<td></td>
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<tr>
<td>Levy et al 2012, Mailed Fecal Immunochemical Testing Plus Educational Materials improves Colon Cancer Screening Rates in Iowa Research Network (IRENE) Practices</td>
<td>The Journal of the American Board of Family Medicine</td>
<td>Randomized observational study</td>
<td>Iowa Research Network family physician offices; test whether mailed educational materials and a fecal immunochemical test (FIT), with or without a scripted telephone reminder, led to FIT testing. A total of 373 individuals received educational materials (including a FIT) and 231 (62%) returned a posteducation survey. The mean age was 61.2 years; 52% were women, 59% were white, 39% had a high school education or less, 39% had a total family income of less than $50,000, and 7% had no insurance. The written materials were read by 82%, understood by 91% (of those who read them), and 82% felt their knowledge was increased. The DVD was viewed by 69%, understood by 94% of those who viewed it, and 80% felt the DVD increased their knowledge. Compared with baseline, individuals reported being significantly more likely to bring up CRC screening at their next doctor's visit (P &lt; .001) and being more likely to be tested for CRC in the next 6 months (P &lt; .001). Comparing baseline with follow-up, summary attitude scores improved (P &lt; .001), readiness scores improved (P &lt; .001), and there were fewer barriers (P = .034, Wilcoxon signed rank). The FIT return rate increased from 9% to 45.2% in the education alone group and from 0% to 48.7% for the group receiving education plus the telephone call (P &lt; .001 for each group individually and overall when compared with Medicare beneficiaries in Iowa).</td>
<td>30</td>
<td>2.515</td>
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<tr>
<td>Study</td>
<td>Journal</td>
<td>Study Design</td>
<td>Setting and Intervention</td>
<td>Key Findings</td>
<td>Number of citations</td>
<td>Impact factor</td>
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<td>Ferrel et al. 2009, A Medical Assistant-Based Program to Promote Healthy Behaviors in Primary Care</td>
<td>The Annals of Family Medicine</td>
<td>Randomized control trial</td>
<td>San Antonio (TREN), studied the effectiveness of a medical assistant-based program to identify and refer patients with risk behaviors to appropriate interventions</td>
<td>Follow-up data were available for 55% of participants at a mean of 12 months. The medical assistant referral arm referred a greater proportion of patients than did usual care (67% vs 21.8%; P &lt; .001) but did not achieve a higher success rate for improved behavioral outcomes (21.7% vs 16.9%; P = .19). Qualitative interviews found both individual medical assistant and organizational effects on program adoption.</td>
<td>36</td>
<td>4.54</td>
</tr>
<tr>
<td>Mold et al. 2014, Implementing Asthma Guidelines Using Practice Facilitation and Local Learning Collaboratives: A Randomized Controlled Trial</td>
<td>The Annals of Family Medicine</td>
<td>Cluster Randomized Controlled Trial</td>
<td>Greater Los Angeles, California, southeastern Vermont, and rural Appalachian Virginia, urban Richmond, Virginia; Assessing patient reported health behaviors is a critical first step in prioritizing prevention in primary care. Assessing the feasibility of point-of-care behavioral health assessment in 9 diverse primary care practices.</td>
<td>Overall, adherence to all 6 recommendations increased (P &lt; .002). Examinations of improvement by study arm in unadjusted analyses showed that practices in the control arm significantly improved adherence to 2 of 6 recommendations, whereas practices in the PF arm improved in 3 practices in the LLCs improved in 4, and practices in the PF+LLC arm improved in 5 of 6 recommendations. Multivariate modeling, PF practices significantly improved assessment of asthma severity (odds ratio [OR] = 2.5, 95% CI, 1.5-3.8) and assessment of asthma level of control (OR = 2.3, 95% CI, 1.5-3.5) compared with control practices. Practices assigned to LLCs did not improve significantly more than control practices for any recommendation.</td>
<td>28</td>
<td>4.54</td>
</tr>
<tr>
<td>Hunt et al. 2004, Impact of educational mailing on the blood pressure of primary care patients with mild hypertension.</td>
<td>Journal of General Internal Medicine</td>
<td>Prospective, randomized controlled single-blind trial</td>
<td>Primary care practice-based research network in which 9 clinics located in Portland, Oregon participated. To assess the effectiveness of mailed hypertension educational materials on blood pressure control</td>
<td>No significant difference was found in mean blood pressure between intervention and control patients (137.77 mmHg vs 137.77 mmHg, P = .229). Patients in the intervention arm scored higher on a hypertension knowledge quiz (7.48 ± 1.6 vs 7.06 ± 1.6, P = .019), and reported higher satisfaction with several aspects of their care. No significant difference was seen in the prevalence of home blood pressure monitoring ownership or use.</td>
<td>38</td>
<td>4.005</td>
</tr>
<tr>
<td>Steiber et al. 2015, Using a Web-Based Nutrition Algorithm in Hemodialysis Patients</td>
<td>Journal of Renal Nutrition</td>
<td>Prospective observational study</td>
<td>HD outpatient units in five different countries; The purpose of this study was to test the ability of a newly developed nutrition algorithm on (1) clinical utility and (2) ability to capture patient outcomes</td>
<td>At the initial screening step, 8 of the 14 factors led to chain with random selection pattern (by z-test with P &lt; .05). In the subsequent diagnostic step, patients diagnosed within the insufficient protein group (n = 38), increased protein intake by 0.11 g/kg/d (P = .022). In patients with a diagnosis in the high PTH group, PTH decreased by a mean of 176.85 pg/mL (n = 19, P = .011) and in those with a diagnosis in the high phosphorus group, serum phosphorus decreased by a mean of 0.91 mg/dL (n = 39, P = .006).</td>
<td>5</td>
<td>2.651</td>
</tr>
<tr>
<td>Study</td>
<td>Journal</td>
<td>Study Design</td>
<td>Setting and Intervention</td>
<td>Key Findings</td>
<td>Number of citations</td>
<td>Impact Factor</td>
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<tr>
<td>Howard-Thompson et al 2013, Pharmacists-physician collaboration for diabetes care: cardiovascular outcomes.</td>
<td>The Annals of Pharmacotherapy</td>
<td>Prospective, multicenter, cohort study</td>
<td>University of Tennessee, Knoxville; Evaluate the effect of pharmacists-physician collaboration on attainment of cardiovascular-related goals in patients with type 2 diabetes</td>
<td>For the 206 patients enrolled, the average age was 59.7 years; the majority were male (59.7%) and white (66%). When compared with baseline, the postintervention mean systolic (P &lt; .0001), diastolic blood pressure (P = .0003), and LDL (P &lt; .0001) decreased significantly. The proportion of patients achieving a blood pressure of &lt;130/80 mm Hg increased 21.8% (P &lt; .0001), and the proportion of patients achieving an LDL of &lt;100 mg/dL increased 12% (P = .0023).</td>
<td>8</td>
<td>2.765</td>
</tr>
<tr>
<td>Degenhardt et al 2014, Preliminary Findings on the Use of Osteopathic Manipulative Treatment: Outcomes During the Formation of the Practice-Based Research Network, DO-Me.net</td>
<td>The Journal of the American Osteopathic Association</td>
<td>A retrospective medical record review and a prospective observational study</td>
<td>A.T. Still University-Kirkville and Penn State Hershey; To assess the current use of OMT and associated patient-reported outcomes</td>
<td>In the medical record review, 17 of the top 22 diagnoses (77%) were related to musculoskeletal conditions. In the prospective study, 18 of the top 24 medical diagnoses (75%) were related to musculoskeletal conditions. Immediately after OMT, patients at 276 office visits (92%) felt better or much better, those at 5 (2%) felt worse. After 7 days, patients at 126 of 175 office visits (72%) felt better or much better, and those at 10 (6%) felt worse. Average and worst symptoms severity decreased until post-OMT days 4 and 5, respectively, when severity leveled off. There was decreased interference of symptoms with quality of life from before OMT to 7 days after OMT in usual general activities, sleep-mood, and relationships (all P &lt; .05).</td>
<td>7</td>
<td>N/A</td>
</tr>
<tr>
<td>Ratanawongsa et al 2014, Diabetes Health Information Technology innovation to improve Quality of Life for Health Plan Members in Urban SafetyNet</td>
<td>Journal of Ambulatory Care Management</td>
<td>&quot;The quasi-experimental evaluation used a waitlist variant of a stepped-wedge design, in which SF-12 scores were randomized participants to waitlist or immediate intervention during 4 recruitment waves.&quot; Retrospective: Pre-postobservational</td>
<td>Community Health Network of San Francisco (CHN SF), California; The SelfManagement Automated and Real-Time Telephonic Support Study (SMARTSteps/ PassoPositivo) is a controlled quasi-experimental evaluation of the program’s impact on HRQOL, diabetes self-management, patient centered care, and cardiovascular outcomes.</td>
<td>Compared to waitlist, immediate intervention participants had greater 6-month improvements in overall diabetes self-care behaviors (standardized effect size [SES] = 0.29, P = .01) and 12-Item Short Form Health Survey physical scores (SES = 0.25, P = .03); changes in patient-centered processes of care and cardiovascular outcomes did not differ.</td>
<td>9</td>
<td>N/A</td>
</tr>
</tbody>
</table>
Citation counts for all articles were higher than the median citation count for articles in the journals in which they were published. All articles reviewed were published in journals with relatively high journal impact factors (JIF) with JIF percentile rankings ranging from the 68th to the 89th percentiles in their respective journal categories.

<table>
<thead>
<tr>
<th>Study</th>
<th>Number of Articles</th>
<th>Median Article</th>
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</thead>
<tbody>
<tr>
<td>Hunt et al. 2004</td>
<td>31</td>
<td>2</td>
</tr>
<tr>
<td>Ferrel et al. 2009</td>
<td>36</td>
<td>2</td>
</tr>
<tr>
<td>Levy et al. 2012</td>
<td>30</td>
<td>1</td>
</tr>
<tr>
<td>Mold et al. 2014</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>Pearce et al. 2008</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Ratanarungs et al. 2014</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Rodriguez et al. 2014</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Howard Thompson et al. 2013</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Degenhardt et al. 2014</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>Steen et al. 2015</td>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

**Figure 3: Included Journal Summary**

**CONCLUSION**

Despite the large number of articles returned by the initial search, very few of these turned out to be clinical studies of patient outcomes. The articles that were not clinical trials covered a wide range of topics including case studies of the formation of PBRNs, editorials advocating for the creation of PBRNs, calls for funding of PBRNs, quality improvement studies, provider attitude and opinion surveys, and histories of the PBRN movement. The studies that were judged to be clinical trials tended to focus on interventions such as use of mailed reminders or training of family caregivers designed to change patient health related behaviors as opposed to direct medical interventions or changes in patient treatment protocols. The articles were of high quality based on citation counts and journal impact factors.

**DISCUSSION**

The relatively small number of PBRN based clinical studies reported in the literature that we found in our research does not support the conclusion that PBRNs are currently “hot beds” of pragmatic clinical trial research in the U.S. During our search process we reviewed some articles that cited barriers to conducting clinical studies in PBRN settings. Fernald et al. reported difficulties in recruiting physicians to participate in PBRN pragmatic clinical trials because participation often requires significant modifications in the practices of individual physicians that they are unwilling to make (11). Rhyne et al., report that with the recent termination of major sources of funding from the AHRQ and other government agencies, maintaining the activities of PBRNs has become increasingly more difficult (2). Mello et al. describe a number of privacy and legal barriers to conducting research using existing health information exchange infrastructures (12). Given the similarities between HIEs and PBRNs it is reasonable to assume that many of the same barriers apply to PBRNs. Lastly, like the HIE movement, the PBRN movement may be losing momentum due to shrinking grant funding and lack of workable business cases. While performing initial preparatory research for this study we clicked on several links to individual PBRNs listed in the AHRQ PBRN registry at https://pbrn.ahrq.gov/pbrn-registry. We found that a number of the links were broken. Additionally, PBRNs are typically made up of small independent physician practices and it is likely the case that given the current massive consolidation occurring in the U.S. health care system (13) that PBRNs are being replaced by vertically integrated health care systems and consequently pragmatic clinical trials are being conducted in those settings.
This study contains some limitations. Limiting the study to the U.S. could mean that the finding of low numbers of PBRN-based pragmatic clinical trials is a function of the idiosyncrasies of the U.S. health care system. This would be a good area for additional research. Due to time and resource limitations, we did not search for additional articles based on manual inspection of the reference section of articles that were included in the final group for review. However, prior to conducting this study we read a number of systematic reviews of various types and determined that secondary reference searches contribute relatively few new articles to the final selection. Finally, the PRISMA guidelines call for an estimate of the bias included in each of the articles selected for final inclusion. This was not done due limitations in the skill set of the author of this paper at the present time.
## APPENDIX 1

<table>
<thead>
<tr>
<th>Section/Topic</th>
<th>#</th>
<th>Checklist Item</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TITLE</strong></td>
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</tr>
<tr>
<td>Title</td>
<td>1</td>
<td>Identify the report as a systematic review, meta-analysis, or both.</td>
</tr>
<tr>
<td><strong>ABSTRACT</strong></td>
<td></td>
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</tr>
<tr>
<td>Structured summary</td>
<td>2</td>
<td>Provide a structured summary including, as applicable, background, objectives, data sources, study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.</td>
</tr>
<tr>
<td><strong>INTRODUCTION</strong></td>
<td></td>
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<tr>
<td>Rationale</td>
<td>3</td>
<td>Describe the rationale for the review and the content of what is already known.</td>
</tr>
<tr>
<td>Objectives</td>
<td>4</td>
<td>Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICO/S).</td>
</tr>
<tr>
<td><strong>METHODS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Protocol and registration</td>
<td>5</td>
<td>Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.</td>
</tr>
<tr>
<td>Eligibility criteria</td>
<td>6</td>
<td>Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.</td>
</tr>
<tr>
<td>Information sources</td>
<td>7</td>
<td>Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.</td>
</tr>
<tr>
<td>Search</td>
<td>8</td>
<td>Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.</td>
</tr>
<tr>
<td>Study selection</td>
<td>9</td>
<td>Specify the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).</td>
</tr>
<tr>
<td>Data collection process</td>
<td>10</td>
<td>Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.</td>
</tr>
<tr>
<td>Data items</td>
<td>11</td>
<td>List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.</td>
</tr>
<tr>
<td>Risk of bias in individual studies</td>
<td>12</td>
<td>Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.</td>
</tr>
<tr>
<td>Summary measures</td>
<td>13</td>
<td>State the principal summary measures (e.g., risk ratio, difference in means).</td>
</tr>
<tr>
<td>Synthesis of results</td>
<td>14</td>
<td>Describe the methods of handling and combining results of studies, if done, including measures of consistency (e.g., I²) for each meta-analysis.</td>
</tr>
<tr>
<td>Risk of bias across studies</td>
<td>15</td>
<td>Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).</td>
</tr>
<tr>
<td>Additional analyses</td>
<td>16</td>
<td>Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.</td>
</tr>
<tr>
<td><strong>RESULTS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study selection</td>
<td>17</td>
<td>Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.</td>
</tr>
<tr>
<td>Study characteristics</td>
<td>18</td>
<td>For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.</td>
</tr>
<tr>
<td>Risk of bias within studies</td>
<td>19</td>
<td>Present data on risk of bias of each study and, if available, any outcome-level assessment (see Item 12).</td>
</tr>
<tr>
<td>Results of individual studies</td>
<td>20</td>
<td>For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group and (b) effect estimates and confidence intervals, ideally with a forest plot.</td>
</tr>
<tr>
<td>Synthesis of results</td>
<td>21</td>
<td>Present results of each meta-analysis done, including confidence intervals and measures of consistency.</td>
</tr>
<tr>
<td>Risk of bias across studies</td>
<td>22</td>
<td>Present results of any assessment of risk of bias across studies (see item 15).</td>
</tr>
<tr>
<td>Additional analysis</td>
<td>23</td>
<td>Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression) (see item 161).</td>
</tr>
<tr>
<td><strong>DISCUSSION</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summary of evidence</td>
<td>24</td>
<td>Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., health care providers, users, and policy makers).</td>
</tr>
<tr>
<td>Limitations</td>
<td>25</td>
<td>Discuss limitations at study and outcome level (e.g., risk of bias), and at review level (e.g., incomplete retrieval of identified research, reporting bias).</td>
</tr>
<tr>
<td>Conclusions</td>
<td>26</td>
<td>Provide a general interpretation of the results in the context of other evidence, and implications for future research.</td>
</tr>
<tr>
<td><strong>FUNDING</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Funding</td>
<td>27</td>
<td>Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.</td>
</tr>
</tbody>
</table>

DOI:10.1371/journal.pmed.1003100.t001
APPENDIX 2

Data Collection Sheet

Study:

Type of study:

Number of subjects:

Objectives of the study:

Study location:

Data collected:

Outcome measures used:

Outcome measures results:

Analyses used (if any):

Study authors’ conclusions:

Citation count:

Impact factor of journal in which the article was published based on Clarivate Analytics Journal Citation Report 2018

Reviewer 1 comments:
APPENDIX 3

Articles meeting inclusion criteria


REFERENCES


Peterson, K. A., Paula Darby Lipman, Carol J. Lange, Rachel A. Cohen, & Steve Durako, Supporting Better Science in Primary Care: A Description of Practice-based Research Networks (PBRNs) in 2011 (J Am Board Fam Med 2012;25:565–571.)


Study type definitions (Himmelfarb Health Sciences Library. https://himmelfarb.gwu.edu/tutorials/studydesign101/casecontrols.cfm  -
Impact of EHR Usability on Provider Efficiency and Patient Safety in Non-Hospital Settings

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Abstract: Healthcare organizations may reap benefits transitioning to electronic health records (EHRs), such as decreased healthcare costs and better care. However, severe unintended consequences from implementation and design of these systems have emerged. Poorly implemented EHR systems may endanger the integrity of clinical or administrative data. That, in turn, can lead to errors jeopardizing patient safety or quality of care. A literature review of 40 sources identified how EHR implementation and design can impact provider centric, patient centric, and outcomes. These categories provided the basis for a comprehensive EHR impact model that was evaluated in non-hospital settings through focus groups interviews.

INTRODUCTION

Electronic health record usability refers to the efficiency and effectiveness of the system’s use and the satisfaction of the users when accomplishing specific tasks within their environment; this includes user-friendly workflow design supporting efficient, effective quality care. The lack of standard user interfaces remains a challenge for clinicians who work in multiple care settings (Middleton, 2013) potentially influencing provider productivity and patient safety. EHR-related errors, their potential impact on patient safety, quality of care, and usefulness, have been widely documented.

Given that EHR issues have the potential to impact patient wellness, provider burnout, and general healthcare, mitigating potential problems as well as improving EHR usability poses one possible way to improve healthcare as well as better facilitate general wellness. Healthcare organizations are motivated to transaction to EHR’s as they reap substantial benefits such as decreased healthcare costs and improved care. The United States healthcare spending per GDP is approximately twice that of other developed countries, yet fails to deliver high-quality healthcare based on international standards (Baron, 2007). While this may lead to the assumption that United States healthcare is an improvement on other healthcare systems in developed countries, this is far from the case. The US excels on dimensions involving chronic disease management, the doctor-patient relationship, shared decision-making between primary care and specialty providers, end-of-life discussions, and performed moderately better on wellness counseling linked to healthy behaviors. The US performs poorly on numerous coordination measures, however, including information flows between primary care, specialty, and social service providers (Doty, 2017).

Technology has proven its potential to increase patient safety, but only if we can minimize the risk tradeoff. Health information technology (HIT), which includes EHRs, health information exchanges, and patient portals, has been promoted as powerful leverage in healthcare reform. When designed and implemented adequately, health IT can expedite patient engagement and care coordination (National Patient Safety Foundation, 2015 February).

The broad use of health IT has led to valid reductions in medical errors. Computerized physician order entry (CPOE) has demonstrated a decrease in medication errors by nearly 50% in acute care settings (Bates, Leape, Cullen et al. 1998). More importantly, electronic ordering has the potential to drastically lessen dosing errors, prescription theft, prescription forgery, and identified medication allergy errors (Knoll, M. 2016). Health IT has also reduced errors related to clinical care by using techniques such as bar-coding and smart pumps for transfusion. These types of technology can also improve patient outcomes; for example, implementation of high-level EHRs have been associated with declines in mortality among hospitalized patients (National Patient Safety Foundation, 2015 February).

Healthcare IT may also introduce new adverse events, however, such as patient misidentification, alert fatigue, copy and paste errors, or even software malfunction. A recent study validated the existence of these adverse events, stating that they had potential to lead to “an appreciable incidence of severe harm and death,” (National Patient Safety Foundation, 2015 February). Some systems may be faulty. A simulation study of a CPOE system at 62 hospitals discovered that the system failed to recognize 52% of potentially fatal errors (Declerck, Aimé, 2014). Poor interoperability between systems results in integration failure, and thus interrupts the transfer of data across the care continuum (Premier, 2014). Some systems also produce poor usability, which can provoke new errors.

Health IT has also been connected to clinician burnout; primary care providers utilizing EHR systems with numerous complex functions had higher burnout rates than others utilizing systems with fewer complex functions. Underlying these concerns is the absence of clear, enforceable criteria for the development and use of these
systems. Even when regulations do exist, adherence is not guaranteed (Harrington, 2013).

Although EHR-related errors and their impact on patient safety, quality of care, and usefulness have been documented for years, considerable work still needs to be done to assess the occurrence of these errors, determine the causes, and implement resolutions. System certifications exist, but this does not guarantee successful implementation, operational use, or patient safety.

METHODS

Literature Review

We used a grounded approach to search for relevant articles. Articles were included if the title contained the terms "electronic health records," "EHR usability," "EHR alert fatigue," "EHR workarounds," “EHR implementation” or "EHR patient safety". As a synonym for “EHR,” “electronic medical records (EMRs)” were used interchangeably with the above search terms. The exhaustive literature review used PubMed, ProQuest, and Google Scholar databases, and focused on case studies and research studies rather than overview papers or opinion pieces. After a preliminary review of all articles for relevance to the purpose, the collection included over 300 articles. This number was refined to the five most frequently cited articles for each subcategory.

Survey and Interview Questions

After analysis of the results of the literature review, the identified categories and subcategories provided the basis for tailored survey and set of interview questions to add to the effort of evaluating the various aspects of EHR systems. A preliminary electronic survey to be used prior to focus groups was developed to gather basic demographic information as well as questions pertaining to electronic health records. These questions focus on seven different areas of interactions with EHR’s: design, implementation, workload, quality, care coordination, safety, and patient-provider relationship. The focus group questions delve further into these categories and allow for participants to expand and verbalize their thoughts in an open-ended format.

Focus Groups

A co-sponsorship with Michigan Medical Group Management Association (MiMGMA) was established in an effort to recruit medical offices for focus group participation. Additional networking was also conducted to enlist offices willing to volunteer. Participants in the study are informed of the goal of the research and will be given the results of the general research. The survey is administered to focus group participants prior to the interview and the interview questions are informed by the survey results.

RESULTS

The selected articles were reviewed for key themes and topics, which were then grouped into appropriate categories and sub-categories. A total of three categories (provider centric, patient centric, and outcomes) and eight sub-categories (design, implementation, workload, safety, quality, care coordination, patient-provider relationship, and health outcomes) emerged.
A model was developed (Figure 1), based on the categories/subcategories, that addresses the EHR challenges of interaction complexity within the socio-technical context, specific clinical collaboration patterns, and challenges of measuring the influence on clinical outcomes. The model depicts the various relationships and interconnections between the eight sub-categories and links them to findings from the literature. This model was the basis for evaluating EHR use in primary care offices through surveys and interviews. It is expected that the evaluation research aspect of this project will further refine the model to better understand the very complex and challenging aspects of EHRs use in healthcare, and thus ultimately improve patient safety and health outcomes. This study is in the data collection phase and recruiting participants for focus groups.

**CONCLUSIONS**

Electronic health records have the potential to impact all areas of healthcare. Using the comprehensive literature review, it was determined that three main areas of effect can be observed: what the physician sees, the safety of the patient both electronically and medically, and how the electronic records impact the relationship a provider develops with the patient. Additionally, the literature review revealed that most analyses of electronic health records were conducted at the hospital setting, thereby making the model most appropriate for that setting. With future focus group work specifically aimed at the non-hospital settings of healthcare, it is anticipated that this model will further develop and be improved upon for specifically non-hospital settings.
REFERENCES


The Dynamics of Real-Time Online Information and Disease Progression: Understanding Spatial Heterogeneity in the Relationship

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Abstract: The re-emergence of infectious diseases such as measles and polio is creating logistics challenges for the state authorities to curb their spread and contain them. (CL, 2015) Real-time surveillance of infectious diseases is important to detect possible epidemics in advance to prevent shortages of medications (FDA, 2018). The outbreak of an infectious disease creates panic in the community and is accompanied by a sudden increase in the online interest in knowing more about the disease and its symptoms. Prior studies have found a strong relationship between web-based information and disease outbreak but the influence of dynamics of web-based information in real-time is often not considered (Zhang, 2017). The dynamics or rate of change of the online interest in a disease can inform or misinform about perspective cases of the disease in a region. Oftentimes, especially in this connected world individuals overreact to the situation which may send spurious online signals regarding the disease progression. Hence, we study the relationship between the dynamics of online information and the infectious disease outbreak. We also investigate if this relationship could be influenced by regional demographic factors. We analyze weekly online interest dynamics for five infectious diseases over a period of three years across 50 states of the United States. We control for several factors (including weather, demographics, and travelers) and utilize hierarchical functional data models to incorporate real-time dynamics and clustering at the regional level. Preliminary findings suggest that online interest dynamics have a significant relationship with disease outbreak and the effect is segregated at the regional level. These findings are important to develop a system for real-time surveillance and account for the influence of heterogenous online interest during an endemic outbreak.

BACKGROUND

Infectious diseases are a risk to public health and wellness. In the year 2016, the deaths caused by infectious diseases were ranked in the top 10 leading causes of deaths worldwide, mostly occurring in low-income countries (WHO, 2016). The prediction of the progression of these diseases based on historical estimates can help save lives by preventing drug shortages and is of increasing interest in studies (M.F.Myers, 2004). This is no dearth of research on explaining the outbreak of infectious disease, however, due to their erratic transmission patterns, it is still challenging to predict outbreaks with an acceptable level of accuracy (Presanis, 2011).

The federal care organizations at the state level are authorized to take steps for preventing the outbreaks of the infectious disease and providing adequate care for the infected. However, the duration between when the infection is contracted, treatment and reporting make it difficult for them to track or predict the future cases of the disease (Jajosky, 2004). Nowadays due to the abundance of medical resources on the internet the patients are encouraged to seek the medical advice or investigate the cause of their symptoms from the online sources.

The role of online search trends related to a disease in predicting its outbreak is an emerging area of research. Prior studies have found a strong correlation between online search trends and the active cases of an infectious disease. These studies, however, did not control for a variety of factors that can influence the impact of online activity and the
actual disease count. For instance, regions where patients are not tech-savvy there they might not leave any footprints on the internet. Similarly, in the regions where health services are easy to avail or are less costly the patients there may not seek medical information on the internet. It is important to understand the regional factors which might impact the relationship between online activity and disease progression for developing a robust and effective disease surveillance system.

Over the years the internet has become a reliable and cheap source of medical information while the Medicare costs have risen consistently in the United States. It is not a surprise that about a third of the online search today is for medical information. It is possible that this high cost of availing health services in drawing some of the internet traffic for medical information. For some individuals, the cost of reaching out to physicians for medical advice might to too high to immediately approach them as the symptoms appear. The financially constrained patients may prefer to first verify their symptoms and their severity from online information sources before reaching out to the physicians.

Hence, in this study, we first investigate if there are any regional variations in the relationship between online search activity of a disease and its progression. Next, we study the role of Medicare costs in a state in determining the direction of this relationship. We investigate if the higher Medicare costs strengthen the positive association between the online search for a disease and its actual cases or not. The findings from this study would help the stakeholders to better understand the dynamics of online search activity and disease progression. This could be the first step for developing a more robust disease surveillance system. While form the policy perspective the finding can have implications for the healthcare expenditures for the state.

We investigate the progression of 5 infectious diseases over a period of five years across all 50 states of the United States to answer the above questions. We control for several variables that may contribute the cases of infectious disease including weather, travelers, population density, income and age of the residents. We multilevel modeling approach to account for the unobserved heterogeneity across the states. We also allow the relationship between the search activity and disease cases to vary across each state by incorporating random coefficient hierarchical models. The next sections discuss prior work, data, methods and key findings from this study.

PRIOR WORK

Internet search queries have shown to help improve the disease prediction by several prior studies (Santillana, 2015) (Chae, 2018) (Zhang, 2017) (Fuente, 2018) (Milinovich, 2014). A survey study found that people having trouble getting access to health care might be more likely to query the internet and can help the accuracy and reliability of surveillance systems (Lee, 2015). However, no team was able to predict influenza season milestones using the online data during a challenge sponsored by the Center for Disease Control and Prevention (CDCP). The problem with forecasting models proposed by most teams during the challenge was the lack of interactions between model developers and public health decision-makers as well as a limited amount of data.

The geospatial studies have shown that there is likely an effect of long-range airline transportation on the spread of diseases (Duygu Balcan, 2009). Along with long-range geospatial effect, the short-distance spatial infectious disease spread is likely to affect school season resulting in faster close proximity spread and slower long-distance spread (Gog, 2014). As one might expect the close proximity and higher density of population have shown likely to affect disease rate spread (Hu, 2013). Different diseases have different responses in spread rate in varying weather conditions as well as other descriptive and predictive studies have shown (Chae, 2018) (Song, 2015)

There is also some evidence that individuals living in poor conditions are more inclined to obtain and transmit infectious diseases that those living in an affluent environment (Xia, 2013). Some studies have also found that the demographics of the population essentially the age group of the individuals living in an area also impact the progression of an infectious disease (Valle, 2014). These different sited environmental factors have all be used in these studies either for prediction or assessing if they are relevant factors in improving infectious disease surveillance systems. In this study, we control for most of the factors cited in the prior studies that could have an impact on the progression of the disease. The table 1 below discusses the prior work in detail.
Table 1: Literature Review

<table>
<thead>
<tr>
<th>PAPER</th>
<th>OBJECTIVE</th>
<th>METHOD</th>
<th>Online Search</th>
<th>FINDINGS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ray, E. L. (2018)</td>
<td>Predicting influenza progression.</td>
<td>Featured weighted density ensemble models</td>
<td>No</td>
<td>Component models showed more variability and ensemble methods showed slightly better average performance</td>
</tr>
<tr>
<td>Milinovich, G. J. (2014)</td>
<td>To investigate the potential of using internet search data for early warning of a wide range of disease.</td>
<td>Correlation Analysis</td>
<td>Yes</td>
<td>17 Diseases were found to be significantly correlated with a search result</td>
</tr>
<tr>
<td>Biggerstaff, M. (2016)</td>
<td>Predicting the timing of start, peak and intensity of influenza</td>
<td>Multiple prediction models</td>
<td>Yes</td>
<td>No team was entirely accurate in forecasting influenza season milestones.</td>
</tr>
<tr>
<td>Chretien, J.-P. (2014)</td>
<td>To review influenza forecasting models</td>
<td>Literature Review</td>
<td>N/A</td>
<td>Comparing the accuracy of the forecasting applications in prior studies is difficult as forecasting methods, outcomes, and validation metrics varied widely.</td>
</tr>
<tr>
<td>Shaman, J. (2012)</td>
<td>To predict influenza disease outbreaks in New York from 2003-2008</td>
<td>SIRS-EAKF ensemble method</td>
<td>Yes</td>
<td>Real time skillful predictions of peak timing possible up to 7 weeks in advance</td>
</tr>
<tr>
<td>Duygu Balcan. (2009)</td>
<td>To analyze the geospatial effect of transportation methods on global epidemics.</td>
<td>Generalized Linear Models</td>
<td>No</td>
<td>The spatiotemporal patterns of disease spreading are mainly determined by long-range airline transportation.</td>
</tr>
<tr>
<td>Chowdhury, F. R. (2018)</td>
<td>To study the effect of weather on disease spread</td>
<td>ANOVA test</td>
<td>No</td>
<td>Heterogeneity in impact of temperature and humidity on disease progression.</td>
</tr>
<tr>
<td>Chae, S. (2018)</td>
<td>To use big data to deep learning to help reduce disease reporting delays</td>
<td>Deep Neural Network, ARIMA</td>
<td>Yes</td>
<td>The deep learning methods DNN performed much better that time series approaches like ARIMA.</td>
</tr>
<tr>
<td>Song, Y. (2015)</td>
<td>To study the usefulness of weather variables in the prediction of hand foot and mouth disease.</td>
<td>Time series method (SARIMA)</td>
<td>No</td>
<td>Strong relationship between weather and the progression of diseases considered</td>
</tr>
<tr>
<td>Fuente, M. O. (2018)</td>
<td>To estimate the rate of influenza epidemics using information from public sources</td>
<td>GLS regression models</td>
<td>No</td>
<td>The GLS estimators performed much better than OLS estimators.</td>
</tr>
</tbody>
</table>
Most of the prior studies focused on a specific disease such as influenza or utilized black-box approaches (e.g. machine learning methods) to predict disease progression. To our knowledge, none of the prior studies investigated the heterogeneity in the relationship between online activity and disease progression. In this paper, we aim to observe the combination of most of the previously studied environmental factors in a more comprehensive study to find out how Medicare costs are associated with disease transmission.

DATA

To understand the relationship between the online search trend of a disease and its reported cases, we combined data from multiple databases. First, we obtained the states level disease data from the National Notifiable Disease Surveillance System (NNDSS, 2019). The NNDSS system coordinates the data gathering and organization from several state-level reporting systems managed by the Center for Disease Control (CDC). We collected weekly from 50 states for five different diseases including Chlamydia, Gonorrhea, Campylobacteriosis, Salmonellosis, and Syphilis for the years 2015-2017.

To account for online search activity associated with each of the aforementioned diseases, we collected weekly google trends search results associated with each disease across all the states under consideration. The Google search trend measure associated with a disease is scaled between 0 -100 and is adjusted at the geography and topic level to make comparison easier between the terms. It should be noted however that different regions that show the same search interest don't always have the same total search volumes. The Google search data is an unbiased sample of the actual searches and only a percentage of online search sample is used to compile trends. We picked the most relevant search terms for each of the diseases, for example, the disease ‘Campylobacteriosis’ did not have as much information as the more commonly searched term is ‘Campylobacter’ which refers to the same disease. This was the only one of the diseases where the scientific name of the disease was not used in the google trends search.

The Medicare cost per capita data for each state were obtained from the Centers for Medicare and Medicaid Services (CMS,2019). The CMS works with the state authorities to monitor the distribution of the Medicaid and health insurance portability standards. The key state-level Medicare cost variables collected included, the actual per capita Medicare costs, hospital inpatient (IP) per capita actual cost and hospital outpatient (OP) per capita actual costs.

To control for the tourists arriving in the state which may lead to an increase in the count of infectious disease we collated the air travel data. The travel data was obtained from the bureau of transportation statistics website (Transstat, 2019). The dataset contains information on the number of arrivals and departures for each airport for each state in the U.S.

We also control for the weather conditions in a state during a certain week by obtaining data from the Automated Surface Observing System (ASOS) database. The information of this database covers all weather stations in each state containing weather observations on multiple variables every 20 minutes for each station. To reduce processing time for gathering the weather data we decided to pick 10 stations for each state in the U.S. that were picked on the spatial proximity to other weather stations locations in that state. We extracted two different weather variables including the air temperature and relative humidity and standardized them at the state and week level.

We also control for various state-level characteristics including the population density, median age, and median income for each state from the U.S. census bureau from the US census website. These variables are estimated at the annual level, the table xxx below describes the data used in the study.
Table 2: Variables Description

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Descriptive Statistics</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disease_Count (Count)</td>
<td>Min = 0, Mean = 72.25, Max = 4331.00</td>
<td>This is a daily count of disease from the NNDSS aggregated and summed by week from 01-02015-12-2017</td>
</tr>
<tr>
<td>Online_Trend</td>
<td>Min = 0, Mean = 18.02, Max = 100</td>
<td>Search trend for the disease in past one week.</td>
</tr>
<tr>
<td>Week</td>
<td>Time series</td>
<td>This is the week of the year</td>
</tr>
<tr>
<td>Temperature</td>
<td>Min = -12.4, Mean = 54.14, Max = 92.11</td>
<td>The average air temperature in Fahrenheit in the state over the week.</td>
</tr>
<tr>
<td>Humidity</td>
<td>Min = 14.17, Mean = 69.51, Max = 95.21</td>
<td>The average relative humidity in % over the week.</td>
</tr>
<tr>
<td>Population Density</td>
<td>Min = 1.292, Mean = 200.7, Max = 1208.66</td>
<td>This is population estimates for each year divided by the area per square mile in each state</td>
</tr>
<tr>
<td>Median_Income</td>
<td>Min = 40037, Mean = 58966, Max = 81084</td>
<td>This is median income per year estimates from U.S. Census Bureau for each state.</td>
</tr>
<tr>
<td>Arrival_Rate</td>
<td>Min = 0, Mean = .04, Max = .25</td>
<td>The average number tourist visiting each week as a % of total population</td>
</tr>
<tr>
<td>Median_Age</td>
<td>Min = 30.10, Mean = 38.06, Max = 44.30</td>
<td>This is the Median Age for each state for each year from the U.S. Census Bureau</td>
</tr>
<tr>
<td>Medicare Cost</td>
<td>Min = 29539, Mean = 574115, Max = 2725203</td>
<td>Actual per capita Medicare costs</td>
</tr>
<tr>
<td>Inpatient Cost</td>
<td>Min = 10017, Mean = 183555, Max = 766103</td>
<td>Hospital inpatient (IP) actual costs as a percent of total actual Medicare costs</td>
</tr>
<tr>
<td>Outpatient Cost</td>
<td>Min = 4111, Mean = 103517, Max = 376058</td>
<td>Hospital outpatient (OP) actual per capita Medicare costs</td>
</tr>
</tbody>
</table>

EMPIRICAL ANALYSIS AND RESULTS

The data structure considered in this study consists of repeated weekly observations for each state on the disease count, weather, online search, state demographics, and Medicare cost variables. The observations are not independent and are clustered at the state level. One of the questions of interest in our study is the relationship between the online search trends for a disease and its actual cases in the state and how this relationship varies for a different state. To account for the multilevel structure of the data we use a multilevel model with random coefficient to investigate heterogeneity in the relationship between online interest and the actual count of infectious disease. The model equation is described below:

\[
\text{Count}_{ij} = \beta_0 + \beta_1 \text{Online Trend}_{ij} + \beta_2 \text{Temperature}_{ij} + \beta_3 \text{Humidity}_{ij} + \beta_4 \text{Population Density}_{ij} + \beta_5 \text{Arrival Rate}_{ij} + \beta_6 \text{Median Income}_{ij} + \beta_7 \text{Median Age}_{ij} + \beta_8 \text{Medicare Cost}_{ij} + \beta_9 \text{Week}_{ij} + \sum_j \beta_j \text{Disease}_{ij} + \sum_k \beta_k \text{Year}_{jk} + \epsilon_{ij} \tag{1}
\]

\[
\beta_{1i} = \gamma_{00} + U_{0i} \tag{2}
\]

The dependent variable of interest in our model is the number of cases for a disease ‘j’ in the state ‘i’ (Count_{ij}). We account for state-level fixed effects through the coefficient \(\beta_{0i}\) while the disease-specific effects are accounted by the coefficients \(\beta_j\). To account for heterogeneity in the disease count cases due to unobserved year-specific event we control for the ‘Year’ of observation in our model. We also control for the weather, demographics, and Medicare-related variables in our model. The level 2 model the random part \(U_{0i}\) which is normally distributed with mean zero.
accounts for heterogeneity in the relationship between the search trend and the weekly cases for a disease. Both level 1 and level 2 models are estimated using the restricted maximum likelihood method which has been shown to be better than the typically used MLE estimation method. We compare multiple models in table 3 and 4 below to test the robustness of the hierarchical modeling structure.

Table 3: Model Results

<table>
<thead>
<tr>
<th></th>
<th>Model 1 Linear Regression</th>
<th>Model 2 Random Intercept</th>
<th>Model 3 Random Coefficient Fixed Intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>810.53262</td>
<td>52.11749</td>
<td>753.46739</td>
</tr>
<tr>
<td></td>
<td>(493.60455)</td>
<td>(189.30897)</td>
<td>(398.83138)</td>
</tr>
<tr>
<td>Online interest</td>
<td>0.41248***</td>
<td>0.40728***</td>
<td>4.40549**</td>
</tr>
<tr>
<td></td>
<td>(0.08291)</td>
<td>(0.08287)</td>
<td>(1.58178)</td>
</tr>
<tr>
<td>Week</td>
<td>0.11197</td>
<td>0.11144</td>
<td>0.08870</td>
</tr>
<tr>
<td></td>
<td>(0.06100)</td>
<td>(0.06086)</td>
<td>(0.04926)</td>
</tr>
<tr>
<td>Temperature</td>
<td>0.16731**</td>
<td>0.16907**</td>
<td>0.18893***</td>
</tr>
<tr>
<td></td>
<td>(0.06297)</td>
<td>(0.06278)</td>
<td>(0.05083)</td>
</tr>
<tr>
<td>Humidity</td>
<td>-0.13684</td>
<td>-0.14731</td>
<td>-0.15480</td>
</tr>
<tr>
<td></td>
<td>(0.11394)</td>
<td>(0.11351)</td>
<td>(0.09199)</td>
</tr>
<tr>
<td>Population density</td>
<td>-0.60472</td>
<td>0.08601</td>
<td>0.27498</td>
</tr>
<tr>
<td></td>
<td>(0.81784)</td>
<td>(0.04604)</td>
<td>(0.66031)</td>
</tr>
<tr>
<td>Median income</td>
<td>-0.00005</td>
<td>-0.00012</td>
<td>-0.00023</td>
</tr>
<tr>
<td></td>
<td>(0.00057)</td>
<td>(0.00051)</td>
<td>(0.00046)</td>
</tr>
<tr>
<td>Arrival rate</td>
<td>113.09268</td>
<td>119.88411</td>
<td>40.69653</td>
</tr>
<tr>
<td></td>
<td>(124.86290)</td>
<td>(115.52776)</td>
<td>(100.80944)</td>
</tr>
<tr>
<td>Median age</td>
<td>-21.79922</td>
<td>-3.73173</td>
<td>-20.96897*</td>
</tr>
<tr>
<td></td>
<td>(12.38203)</td>
<td>(4.82108)</td>
<td>(10.00208)</td>
</tr>
<tr>
<td>Total per-capita cost</td>
<td>0.00006</td>
<td>0.00013***</td>
<td>0.00009</td>
</tr>
<tr>
<td></td>
<td>(0.00009)</td>
<td>(0.00003)</td>
<td>(0.00007)</td>
</tr>
<tr>
<td>Disease Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.38684</td>
<td>0.3925</td>
<td>0.807</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>39000</td>
<td>39000</td>
<td>39000</td>
</tr>
<tr>
<td>AIC</td>
<td>514784.5</td>
<td>514997.36179</td>
<td>498138.46452</td>
</tr>
<tr>
<td>Num. groups: state</td>
<td>50</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>Var: state (Intercept)</td>
<td>6386.28272</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var: Residual</td>
<td>31571.60789</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var: state online_interest</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1
Table 4: Model Results

<table>
<thead>
<tr>
<th>Random Coefficient Fixed Intercept</th>
<th>Model 4 (Total per-capita cost)</th>
<th>Model 5 (Outpatient cost)</th>
<th>Model 6 (Inpatient costs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>823.56289*</td>
<td>311.37766</td>
<td>898.20245*</td>
</tr>
<tr>
<td>(399.02551)</td>
<td>(416.03195)</td>
<td>(385.67617)</td>
<td></td>
</tr>
<tr>
<td>Online interest</td>
<td>-2.37955</td>
<td>0.89658</td>
<td>-1.48232</td>
</tr>
<tr>
<td>(1.83843)</td>
<td>(1.67893)</td>
<td>(1.90155)</td>
<td></td>
</tr>
<tr>
<td>Week</td>
<td>0.08946</td>
<td>0.08938</td>
<td>0.09007</td>
</tr>
<tr>
<td>(0.04925)</td>
<td>(0.04924)</td>
<td>(0.04926)</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.18815***</td>
<td>0.18653***</td>
<td>0.18897***</td>
</tr>
<tr>
<td>(0.05083)</td>
<td>(0.05082)</td>
<td>(0.05083)</td>
<td></td>
</tr>
<tr>
<td>Humidity</td>
<td>-0.15648</td>
<td>-0.14849</td>
<td>-0.15844</td>
</tr>
<tr>
<td>(0.09198)</td>
<td>(0.09202)</td>
<td>(0.09196)</td>
<td></td>
</tr>
<tr>
<td>Population density</td>
<td>0.38973</td>
<td>0.58321</td>
<td>0.32557</td>
</tr>
<tr>
<td>(0.66663)</td>
<td>(0.66268)</td>
<td>(0.65945)</td>
<td></td>
</tr>
<tr>
<td>Median income</td>
<td>-0.00021</td>
<td>-0.00021</td>
<td>-0.00019</td>
</tr>
<tr>
<td>(0.00046)</td>
<td>(0.00045)</td>
<td>(0.00047)</td>
<td></td>
</tr>
<tr>
<td>Arrival rate</td>
<td>37.98723</td>
<td>45.55041</td>
<td>34.93340</td>
</tr>
<tr>
<td>(100.80423)</td>
<td>(100.76199)</td>
<td>(100.79987)</td>
<td></td>
</tr>
<tr>
<td>Median age</td>
<td>-19.62189*</td>
<td>-8.86586</td>
<td>-21.44970*</td>
</tr>
<tr>
<td>(10.00468)</td>
<td>(10.60499)</td>
<td>(9.83232)</td>
<td></td>
</tr>
<tr>
<td>Total per-capita cost</td>
<td>-0.00013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.00009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online interest: Total per-capita cost</td>
<td>0.00001***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outpatient cost</td>
<td>0.00005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.00026)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online interest: Outpatient cost</td>
<td>0.00003***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.00001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inpatient cost</td>
<td></td>
<td>-0.00044</td>
<td></td>
</tr>
<tr>
<td>(0.00024)</td>
<td></td>
<td>(0.00001)</td>
<td></td>
</tr>
<tr>
<td>Online interest: Inpatient cost</td>
<td></td>
<td>0.00003***</td>
<td></td>
</tr>
<tr>
<td>(0.00001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>498140.51932</td>
<td>498131.06150</td>
<td>498144.52389</td>
</tr>
<tr>
<td>Adj. R Squared.</td>
<td>0.774</td>
<td>0.7935</td>
<td>0.7737</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>39000</td>
<td>39000</td>
<td>39000</td>
</tr>
<tr>
<td>Num. groups: state</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Var: state*online interest</td>
<td>86.15747</td>
<td>110.46377</td>
<td>90.89845</td>
</tr>
<tr>
<td>Var: Residual</td>
<td>20558.57534</td>
<td>20549.56109</td>
<td>20561.62823</td>
</tr>
</tbody>
</table>

*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1

The proposed modeling structure (Model 3 in Table 3) explains about 80% of the variations in the observed data which is significantly higher than the linear model (Model 1) and the models with state-level random effects (Model 2). The model fit statistics AIC and likelihood values also suggests that the model that accounts for the randomness in the relationship between online search and the disease count explains most variation in the observed
data. The model statistics described in Table 4 confirm the interaction effect of Medicare costs on online search activity. For instance, the interaction coefficient (Online interest: Total per-capita cost) is significant and positive in Model 4. We also investigate the interaction effect of inpatient (Model 5) and outpatient cost (Model 6) per capita and we observe a similar relationship. This finding further confirms the robustness of the proposed relationship. This indicates that the states where Medicare costs are higher the effect of online activity on disease count would also be higher. Figure 1 below described the variation in the effect size of online search for a disease on disease count for low (first quartile) and high (second quartile) levels of Medicare costs across the states under consideration.

![Effect of Online Search on Disease Count](image)

**Figure 1: Effect of Online Search on Disease Count**

**RESULTS AND DISCUSSION**

The findings of our study suggest that there is a significant variation in the relationship between the online search activity related to a disease and its actual cases in the following week across 50 states of USA. On further investigation, we found that medicare costs play a key role in explaining this heterogeneity in the relationship across states. The states where medicare cost is higher the online search activity has a stronger influence on the actual reported cases of the disease in the coming weeks. One of the reasons for this finding could be the hesitations of the residents to avail medical services in the states with higher medicare costs. Instead to spending money on tests for medical diagnosis the residents in these states prefer to go online and look for information relevant to their symptoms. Hence, in states with higher costs of Medicare services a sudden rise in online search activity related to a disease should be taken more seriously as it might bring a sudden rise in number of disease cases.

We also find that for the five infectious diseases that we have considered the effect on online activity is not moderated by the inpatient cost. This finding reflects upon the severity of the diseases under consideration. As the diseases considered are not fatal in nature inpatients visits are not required to treat them. Hence, higher inpatient costs does not have any significant impact on the relationship between online activity and disease cases. The future disease surveillance systems should account for this heterogeneity in the effect of online search activity on disease cases for an improved forecast. The proposed linear model that accounts for state and disease level fixed effects as well as the heterogeneity in the relationship through random coefficient explains the maximum (~80%) amount of variation in the cases of infectious diseases in near future. The variation explained is about twice of that that explained by the models that only account for state level random effects.

**LIMITATIONS & FUTURE WORK**

We used weekly information from the CDC which is the standard for national disease surveillance systems research. This weekly CDC information oftentimes is unable to capture all the disease occurrences as only the individuals who
choose to seek medical treatment at the hospitals are reported. In addition, variables such as arrival rate that we have controlled for in our models does not capture the information of number of individuals arriving in the state via road, trains or any personal transport.

The majority of diseases in this study were related to sexual based diseases and do not account for variables that could be instrumental to the spread of such diseases, for example, number of conversation interactions between users of an online dating application or number of social meeting locations in a state or city. We leave this investigation to future research. Our findings are based on search data shared by Google which is used in about 75% of global internet searches. We collected data on search trends linked to the exact names of the diseases under consideration. We do not collect trends data on other synonyms or local names of the disease that users might search. In addition, it is difficult to determine if the search trends were generated by true disease enquiries or due to associated events such as research breakthroughs or new treatment drugs. Prior studies have also argued that search data may be spurious for the diseases with high media exposure as non-patient searches would drive most of the online activity. On the other hand the extensive weekly collection of search data for five disease for over three years help control for some of the biases that may arises due to unconventional events.

Future work in this direction can understand the spillover effect of the online activity in neighboring states on the disease cases in the home state. The effectiveness of the real-time dynamics or rate of change of online activity on disease progression could also be investigated. The research also opens a potential debate on the implications of online search behavior for health care policy. How can online search activity inform heath care policy makers? Is excessive online health information seeking an indicator of inaccessible medical services in a geographical region?

REFERENCES


Modeling Big Medical Survival Data Using Decision Tree Analysis with Apache Spark

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Abstract: In many medical studies, an outcome of interest is not only whether an event occurred, but when an event occurred; and an example of this is Alzheimer’s disease (AD). Identifying patients with Mild Cognitive Impairment (MCI) who are likely to develop Alzheimer’s disease (AD) is highly important for AD treatment. Previous studies suggest that not all MCI patients will convert to AD. Massive amounts of data from longitudinal and extensive studies on thousands of Alzheimer’s patients have been generated. Building a computational model that can predict conversion form MCI to AD can be highly beneficial for early intervention and treatment planning for AD. This work presents a big data model that contains machine-learning techniques to determine the level of AD in a participant and predict the time of conversion to AD. The proposed framework considers one of the widely used screening assessment for detecting cognitive impairment called Montreal Cognitive Assessment (MoCA). MoCA data set was collected from different centers and integrated into our large data framework storage using a Hadoop Data File System (HDFS); the data was then analyzed using an Apache Spark framework. The accuracy of the proposed framework was compared with a semi-parametric Cox survival analysis model.

INTRODUCTION

Dementia is an irreversible neuro-degenerative disorder that leads to progressive loss of memory and cognitive function. In 2015, the number of people with dementia worldwide is estimated at 46.8 million that number is expected to raise to 75 million in 2030 and 131.5 million in 2050 (Prince, M., Comas-Herrera, A., Knapp, M., Guerchet, M. and Karagiannidou, M, 2016). Early detection of AD at the pre-clinical stage is of great importance in terms of patient management. Mild cognitive impairment (MCI) is considered as a transitional stage between aging and AD. MCI is considered by physicians as a pre-Alzheimer’s condition, however, not all people with MCI develop Alzheimer’s, and a significant proportion of individuals with MCI revert to normal cognition or remain cognitively stable on follow-up. Moreover, it is more challenging to identify patients suffering from AD at the MCI stage, because these subjects have cognitive impairments beyond that which is expected for their age and education but do not meet the neuro-pathological criteria for AD (Long, X., L. Chen, C. Jiang, and L. Zhang, 2017).
Clinical trials, doctor’s notes, claims data, lab results, and gene sequences provide rich information that can become even more useful when combined in novel ways to produce new insights that can help us better understand the disease. Accordingly, such data will provide doctors with a more complete and detailed picture for patients and as such doctors will be able to define how patients respond to a specific treatment and can identify patients at risk before a health issue arises.

Gathering medical data for years has been costly and time consuming. In 2011, the U.S health-care system data reached 150 billion gigabytes which is expected to reach 2314 billion gigabytes in 2020. Therefore, we need to deal with this data in a smart way. Current incentives are changing as well: many insurance companies are switching from fee-for-service plans (which reward using expensive and sometimes unnecessary treatments and treating large amounts of patients quickly) to plans that prioritize patient outcomes (Raghupathi W, 2014). One of the promising techniques that is used in the big data world is Apache Spark. Apache Spark is a data processing system that run on top of Hadoop which enables complex computations on data that is stored in Hadoop HDFS or another database storage. Apache Spark improves the performance of data analysis and quickly extracts intelligence from massive data sets. (Xu, B., Li, C., Zhuang H., Wang, J., Wang Q., Wang, C., Zhou X, 2017)


Recent studies showed that the survival decision tree (SDT) is a good alternative to parametric and semi-parametric survival analysis approaches. (Alsaedi, A., Abdel Qader, I., Fong, A., & Niaz, M, 2018). models the dependencies among the clinical variables with Bayesian network used later for data imputation in order to allow the decision tree to be applied on the complete dataset. The researchers concluded that Bayesian networks are a promising method to handle missing values especially in datasets where the number of missing data is considerably high and the number of samples are small. The study also showed that by using Bayesian networks, patients can be divided into more precise groups.

P. M. Rancoita, M. Zaffalon, E. Zucca, F. Bertoni, C. P. De Campos (2016), used two types of competing risks trees. event trees are designed for analysis of the event of interest, while composite event trees are used for competing events. Ensembles were built using these two different trees. The study depended on nine real data and simulated data set. One conclusion from this study showed prediction error of the individual trees and the other methods are similar, however the Cindex results differ from the FineGray sub distribution hazard model and the FineGray regression with backward elimination. Kretowska, M. (2018), used a decision tree to model the survival data with competing risk. The researchers proposed a Survival Classification and Regression Tree (SCART) technique to analyze survival data by modifying classification and regression tree (CART) algorithm to handle censored data for both regression and classification problems. The study showed that SCART improve upon the existing classical method for analysis of survival data with competing risks.

A study that was presented by Dauda, K., Pradhan, B., Shankar, U., & Mitra, S (2019), proposed fitting proportional hazards models to censored survival data. The research developed a tree-based method for censored survival data, based on maximizing the difference in survival between groups of patients represented by nodes in a binary tree. Another study (Al-Nachawati H, Ismail M, Almohisen A, 2010) proposed using tree-based identification to identify subsets of time-varying covariate risk factors that affect survival while adjusting for possible confounders. The technique that was used in this study was developed from data from the Bypass Angioplasty Revascularization Investigation 2 Diabetes clinical trial to find combinations of modifiable time-varying cardiac risk factors. [20] modeled time-to-event data using classification tree analysis. By using empirical data, the study showed that it is possible to identify all statistically valid, reproducible, longitudinally consistent, and cross generalizable classification tree analysis (CTA) survival models. This study concluded that the classification tree analysis survival model offered many advantages over Cox regression. Another study, Al-Nachawati H, Ismail M, Almohisen A, 2010, proposed several methods for selecting one representative model out of multiple decision trees induced from different slices of the same massive dataset. The goal of this study was to overcome challenges for selecting one representative model.
for big data and secured environments. A semantic approach called SySM that is based on a decision tree structure was suggested. The suggested methods were applied to six different big benchmark datasets.

Survival Decision Tree (SDT) is a nonparametric machine learning algorithm that flexible; it can be fit to many functional forms. Moreover, there is no assumption needed about the underlying function for that SDT consider as powerful algorithm that can be applied [20]. Lastly, SDT has a high performance for prediction. However, one of the limitations of SDT is that it requires a lot of training data to estimate the mapping function. Also, it is slower to train because it often has far more parameters to train (Weinberg AI, Last M, 2019). In this work we aimed to apply a decision tree to analyze big data on cloud to overcome previous limitations. The dataset provided from NACC-UDS. A prediction and classification system that used decision tree using MoCA was combined with other demographic predictors was proposed. The structure of this paper is as follow, first we will introduce some tools that were used to identify AD. Next, a big data framework will be described and finally the results will be introduced and discussed.

**CLINICAL DEMENTIA RATING (CDR)**

The Clinical Dementia Rating is a scale that is used to evaluate the stage of severity of Dementia, primarily for diagnosing Alzheimer’s. CDR is a five-point scale where CDR=0 indicates a person with no cognitive impairment, and the other four points are:

- CDR = 0.5: very mild dementia
- CDR = 1: mild
- CDR = 2: moderate
- CDR = 3: severe

Six domains are used to construct the CDR, these domains are: Memory, Orientation, Judgment and Problem solving, Community Affairs, Home and Hobbies, and Personal Care.

**MONTREAL COGNITIVE ASSESSMENT (MOCA)**

The Montreal Cognitive Assessment (MoCA) is a 30- question test that is used to help assess people for dementia. It is a written test that takes 10 to 12 minutes to complete and assesses multiple cognitive domains including memory, language, executive functions, visuospatial skills, calculation, abstraction, attention, concentration, and orientation (O’Bryant SE, Waring SC, Cullum CM, et al, 2008).

Different types of cognitive abilities assessed by MoCA:

- Orientation
- Short-Term Memory/Delayed Recall
- Executive Function/Visuospatial Ability
- Language Abilities
- Abstraction
- Animal Naming
- Attention
- Clock-Drawing Test

MoCA is used to detect subjects with MCI due to Alzheimer’s disease and to distinguish them from healthy controls. In order to use MoCA to accurately identify and diagnose dementia, the test should be paired with other screenings. We suggest adding some predictors with MoCA to increase the accuracy of its prediction (https://www.MoCAtest.org/MoCA-clinic-data/)
BIG DATA TECHNOLOGIES AND PLATFORMS

Big Data: A brief introduction

Big data is massive and complex data that cannot be processed and handle by traditional systems. Big data is characterized by Volume, Velocity, and Variety. Volume refers to the amount of data; terabytes (1012 bytes) to petabytes (1015 bytes) and exabytes (1018 bytes), are all produced through different sources. Velocity refers to the speed at which data is generated and accumulated. Variety refers to all the structured and unstructured data that has the possibility of getting generated. From previous definition of big data and its characteristics, health-care data reaches the biggest data barrier (Biundo, R. et al. 2016).

Storing, managing, and analyzing massive amounts of datasets are the main challenges that are facing Biomedical scientists. Big data requires powerful and novel technologies to extract useful information and enable more broad-based health-care solutions. With such diversity in format, type, and context, it is difficult to merge big healthcare data into conventional databases, making it enormously challenging to process, and hard for industry leaders to harness its significant promise to transform the industry (Mayo CS, Matuszak MM, Schipper MJ, Jolly S, Hayman JA, Ten Haken RK, 2017).

Apache Spark

Spark is an open source project from Apache. It is one of the most commonly used analytic engines for big data and machine learning. Spark is commonly used with the open source Apache Hadoop, but it also can be used with other data sources like MongoDB, Amazon3, and Cassandra. Spark can ensure fast iterative access to data sets because it use an in-memory processing engine to allow data workers to efficiently execute streaming, machine learning or SQL workloads. Spark has distributed and massive parallel computing capabilities that offers the processing of datasets that traditional systems cannot. Spark can access several data sources like HDFS, Amazon S3 (Amazon Simple Storage Service) or HBase. Moreover, Spark provides machine learning algorithms, SQL and streaming data processing (Grover, A., Gholap, J., Janeja, V. P., et al, 2015).

SAMPLE DATA

Dataset Description

The data set used in this work was taken from the National Alzheimer’s Coordinating Center (NACC) Uniform Data Set (UDS). The UDS is a repository of data that has been collected from different Alzheimer’s Disease Centers across the United States supported by the National Alzheimer’s Coordinating Center (NACC). Table 1 shows a statistic for UDS data sets that were considered in this study. In figure 1 displays the distribution of participants according to MoCA score. The data set of interest represents a study that took place from March 2015 until October 2018 on different participants ages (see figure 2-A), for more information regarding the UDS see (El aboudi, N., & Benhlima, L, 2018 & Morris JC, Weintraub S, Chui HC, et al, 2006) The NACC UDS includes data on cognitive function using MoCA. The UDS data contains MoCA screening for 2798 subjects that did the MoCA screening with age ranging from 50 to 100.

Dataset Preprocessing

Data needs to be ready to work with; processing raw data may require extra computational resources. To prepare the UDS in such a way that it could fit to our model, a preprocessing process was needed. Data filtering was the first step to discard any data that is not required in the prediction system. Data Cleaning was the next step that was needed for noise reduction. Finally, and the most important in our work, was Missing Data Management; the data that we dealt with had a Censoring Problem that will explain in detail in the next section. Since our goal is to investigate the early stages of AD, subjects who were aged 50 years or older were included in the proposed model. Next, only subjects that had at least one MoCA screening were included in the data set. Exclusion also includes patients that missed one of the
other questionnaires or demographic covariant. The number of subjects in the data set after previous filtering was 2798 subjects.

The resulting data set was divided randomly into training (2099 subjects) and the rest (700 subjects) was used for testing. Considering figure 2-B, we can see that most participants falling in MoCA score between 23 and 30. this means that we need to take the advantage of knowing the other participants (MoCA between 0 and 22) to predict the time of conversion from one stage to another (Normal to MCI or MCI to AD).

**Figure 1: Boxplot of the Distribution of Participant according to MoCA Score**

**Figure 2: Histogram of Participants Ages (A) and Participants MoCA Score (B)**
Table 1: Formatting Specifications

<table>
<thead>
<tr>
<th>Covariant</th>
<th>Value</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>MoCA</td>
<td>Greater than 26 Avg of 22.1 16.2</td>
<td>normal controls MCI AD</td>
</tr>
<tr>
<td>Gender</td>
<td>1</td>
<td>Male</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Female</td>
</tr>
<tr>
<td>Education Level</td>
<td>&gt;= 12   16 18 20</td>
<td>High school/GED Bachelor’s degree Master’s degree Doctorate</td>
</tr>
<tr>
<td>Handness</td>
<td>1</td>
<td>Left-handed</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>right-handed</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Ambidextrous</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Unknown</td>
</tr>
</tbody>
</table>

METHODOLOGY

This study applied a Survival Decision Tree on medical data. To better understand the SDT, we will first introduce some concepts that were used with survival analysis.

Censoring

Environmental data often includes data that are reported as below some value (data<value), above some value (data>value), or even as an interval (value1<data=value2), this data is called censored data (Weintraub S, Salmon D, Mercaldo N, et al, 2009). Generally, censored data can be Left Censored, Right Censored or Interval Censored; as shown in figure 1. In medical research field, censored data is defined as data that does not have the correct interval length. Generally, censoring is present when information on time to event is not available for all study participants. The data is not available due to loss to follow-up or non-occurrence of the outcome event before the trial ended (L. Wrobel, A. Gudys, M. Sikora, 2017 & Cook, R. J., & Lawless, J. F, 2011)

Survival Function

The probability that an individual survives until time t is called survival function S(t) (Weinberg AI, Last M, 2019 & Cook, R. J., & Lawless, J. F, 2011).
**Hazard function**

Another function that is frequently used in survival analysis is called hazard function \( h(t) \) which indicates the instantaneous rate of death at a certain time \( t \) (WROBEL ukasz, 2012 & Dooneief GMarder KTand MXStern Y. 1996).

**COX proportional Hazard Regression (COXPH)**

COXPH is a semi-parametric model that is widely used in survival data analysis. In COXPH a parametric assumption makes for the effect of explanatory variables and no assumption makes for the nature of hazard function (Alsaedi, A., Abdel Qader, I., Fong, A., & Niaz, M, 2018). The relation between hazard function and explanatory variables can be written as: where \( \theta(t) \) is the baseline hazard, \( X \) is a vector of explanatory variables and is a vector of regression coefficients. Cox proportional hazard model frequently used in analyzing survival data due the fact that we do not need to specify the probability distribution for the baseline hazard function.

**SURVIVAL DECISION TREE**

Survival Decision Trees (SDT) are becoming popular alternatives to linear regression and linear discriminant analysis. In SDT, trees generally require fewer assumptions than classical methods and handle a wide variety of data structures. Moreover, in decision trees the assumptions about the underlying distribution of the data is not required and unlike the parametric models, in SDT there is no need to consider monotonic transformations such as logarithms. Generally, in tree-based models, the data is recursively partitioned based on a splitting criterion, and the objects that are like each other based on the event of interest will be placed in the same node (Lee, M.-L. T., Gail, M., Pfeiffer, R., Satten, G., Cai, T., & Gandy, A, 2013). The main difference between traditional decision tree and survival tree is in the splitting criterion.

In survival tree, the terminal node value is a survival function and the patient survival can be estimated using those terminal nodes. Whereas in classification and regression trees, the terminal node values are a single value. Moreover, the splitting rule is an essential part and may play a key role in its prediction performance (Moore, D. F, 2016). As investigated by, there is no specific recommended splitting rule for survival tree that performs uniformly optimally under different situations. In survival tree, since the goal is the comparison of survival distributions of two or more groups, one of the statistical test most that commonly used is log-rank test. The log-rank test compares the hazard functions of the two groups at each observed event time (Gepp, A., & Kumar, K, 2015).

**IMPLEMENTATION**

The proposed framework consists of data storing and data analyzing using machine learning algorithms. Our work depends on applying Survival decision Tree (SDT) to analyze and predict the conversion from MCI to AD.

**Data storage**

Dealing with large datasets is one of the challenges that traditional systems are not suitable for. Big data systems can handle this challenge by storing large datasets in HDFS, S3, Hbase, MongoDB, etc. These storage components are scalable and fault tolerant; storing faults can be handled by the process of replica creation; copying (replicating) the data from one service to another and synchronizing the destination service dataset with the source service dataset, based on a specified replication schedule (Biundo, R. et al, 2016 & Mayo CS, Matuszak MM, Schipper MJ, Jolly S, Hayman JA, Ten Haken RK, 2017).

Data storage infrastructure ensures the big data is sorted in such a way that it can easily be accessed and processed by services working on big data. Also, Big data storage enables flexibility of scaling (Grover, A., Gholap, J., Janeja, V. P., et al, 2015).
Data Processing

Spark provides a scalable machine learning library that consists of common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction and more. The machine learning algorithms can be applied on datasets that are stored on the different data storages that were mentioned earlier. These machine learning algorithms rely on iterative batch processing (Mayo CS, Matuszak MM, Schipper MJ, Jolly S, Hayman JA, Ten Haken RK, 2017 & Grover, A., Gholap, J., Janeja, V. P., et al, 2015)

Proposed Spark framework

Amazon Web Service (AWS) was used as a cloud computing platform to build a cluster that will be used to execute SDT. A cluster in AWS is a logical grouping of tasks or services. We used Elastic Compute Cloud (EC2) as a service to run the task. The cluster consists of four nodes (EC2), one node is the Master node (Driver Program) while the other three are the Core nodes, and this cluster can be easily scaled up or scaled-down as needed. In the AWS cluster, we can install different services depending on what task we want to execute on our data (Machine learning algorithms, ETLs; Extract Transform Load, Streaming, etc). Since we wanted to execute machine learning algorithms on our dataset, Spark with Spark MLlib were installed in this cluster. Moreover, for data storage, S3 has been used to save the dataset, this storage can be used to store all the data that comes from screening centers. Scala is the programming language that was used to write the machine learning algorithms. The resulting algorithm then was executed as Spark job (Spark program) to be run on the EMR cluster. The results of classification and prediction were saved in S3.

SDT has been used for classification and prediction. First the model was used to classify the participants into no cognitive impairment, MCI or AD. Next, the model was used to predict the conversion from one stage to another; no cognitive impairment to MCI or from MCI to AD.

RESULTS

The results are divided into two parts; Classification and Prediction for both SDT and COXPH.

Classification

Depending on MoCA score the participants will be classified into three different subgroups. The root of the survival tree contains all 2798 participants (4881 observation). The most influential predictor that determines the stage of participants is MoCA. Education Level and Hand are the next predictors that were used by the survival tree for classification. In general, the SDT shows low cost of classification for all three different stages of the participants. The classification tree that shown in figure 4 introduced the following:

- Each branch is a decision for splitting the data into a new classification
- The decision tree split the data into three dementia stages (Normal, MCI and AD)

Generally, the SDT shows a better classification accuracy than Cox model with less cost.

Prediction

The constructed survival tree used log-rank statistics as split criterion. Figure 5 and Figure 6 show the fitted Survival Tree for MoCA with Education Level and MoCA with Hand respectively. In these figures, the survival tree displays the levels of the variables used for classification at each node. The root node (MoCA) represents a decision based on its value; the left branch corresponds to TRUE and the right branch FALSE; greater than 25. We can see that same variable can be used in next level of classification. The terminal nodes (leaves) indicate the prediction for that partition and number who has Normal, MCI or AD out of the total in that subgroup.

CONCLUSIONS

Decision tree is a supervised machine learning algorithm that is used for classification and prediction and can be applied on categorical and continuous variables. The main idea of the decision tree is to split the sample into two or
more homogeneous sets based on the most significant splitter in input variables. This paper introduced a big data framework for modelling clinical data using Survival Decision Tree. The framework offers an advantage over using Decision Trees in a traditional system. The primary limitation of decision tree in traditional system is that it requires a lot of training data to estimate. Another general limitation that it is slow since it often has more parameters to train. The proposed framework suggests using big data parallel processing to overcome the previous limitation. Another advantage that is offered by this framework is that data can be accumulative, and this makes the prediction part of this framework more precise. Thus, as much data as we can feed our system the higher the accuracy we can get.

Additionally, non-parametric decision trees introduce accurate predictions without the risk of violating statistical assumptions. Creating a model that has both high and early prediction abilities is essential to allow for earlier on treatments and to give the patient improved quality of life. Future improvement to this work will be to combine more datasets to increase prediction efficiency. Another future work can be using Random Survival Forest (RSF) and compare the accuracy of the applied survival tree.

Figure 4: Classification Tree for Participants using MoCA, Education Level, Gender and Hand
ACKNOWLEDGMENT

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REFERENCES


The Effects of Outdoor Air Pollutants on the Costs of Stroke Hospitalizations in China

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Abstract: Stroke, the most frequent cause of severe disability and the second cause of death among adults in the world, brings tremendous mental and economic burden to patients and their families. Emerging evidence indicates that the air pollution mixture contributes to strokes. Knowing the relationship between the air pollution and the hospital costs of stroke can help us predict the costs due to air pollution, provide grounds for the allocation of medical insurance funds, and provide better working arrangements for CDC. However, few studies have examined this connection. We used time series analysis with a generalized additive model to estimate the associations between ambient air pollutions and hospital costs between the period of 2015–2017. We were surprised to find that although same-day air pollutions were positively associated with stroke mortality hospital costs were found to have a negatively association. Suggestive evidence of an association between fine particles and the costs of stroke were found: more serious air pollution increases the risk of stroke, but has a dampening effect on hospital costs. This study is the first step in optimizing medical resources, which is essential for policy making, service planning, and cost-effectiveness analysis of new therapeutic strategies.

Key words: stroke, cost, air pollution

INTRODUCTION

Stroke is the most frequent cause of severe disability and the second cause of death among adults in the world, There were 5.8 million deaths in 2016 due to the stroke and it remained the leading causes of death globally over the last 16 years and the rate of stroke occurrence continues to increase this years. In the United States, beyond the morbidity, mortality, and human suffering is the staggering financial and economic cost of this disease. Stroke is the leading cause of disability and it brings tremendous mental and economic burden to patients and government medical insurance funds. There are many factors of stroke, such as high blood pressure, high BMI, cigarette smoking, diabetes, age, gender, low birth weight, genetic factors, and air pollution. It is impossible for us to change objective factors such as gender, age, low birth weight, etc., while high BMI, smoking, and high blood pressure all require long time of behavioral control, which are very difficult. Therefore, air pollution is the easiest factor we can control in the short term. As human beings have been facing huge air pollution problems and health challenges over the last five decades, and increasing number of studies have focused on the relationship between air pollution and stroke, Evidences has shown that strokes have a close relationship with air pollution, and numerous studies have shown that particulate matter in the air have a certain correlation with strokes. The disabling nature of strokes causes them to have a higher cost after discharge than other diseases, and it is lifelong. Due to the huge economic burden brought by stroke to society and families, researchers have done some studies on the cost of strokes. It is generally believed that the factors that affect the cost of strokes are type of stroke, living condition, age of onset and so on. In this paper, the study group was a group of patients who were initially diagnosed with stroke on admission. We measure cost as the cost of the patient from admission to the hospital costs.
hospital and include all costs, including surgery costs, examination costs, treatment costs, drug costs and other costs incurred in the hospital.

The health harm from air pollution leads to increased healthcare expenditures as well as labor productivity losses, which have large social costs and cause immense economic pressure. Given that China accounts for one-fifth of the world’s population and suffers from severe air pollution, a comprehensive study of the indicators accounting for the health costs in relation to air pollution will benefit evidence-based and health-related environmental policy-making. A growing study has consistently shown a positive association between exposure to air pollution and increased health costs. Jing et al. (2018) revealed that a 1% increase in yearly exposure to PM2.5 corresponds to a 2.942% increase in household healthcare expenditure. These quantitative studies only focused on the influence of the whole social medical cost of air pollution, and the overall cost may reflects the characteristics of certain kinds of diseases costs, differences in etiology, and surgical difficulty among certain kinds of diseases may be inconsistent with the overall cost. Due to the age, gender, living environment and education level, the cost may be differences among individuals. Therefore, analyzing stroke independently, which is a devastating disease associated with significant economic costs, is necessary to analyze the impact of environmental pollution on this particular kind of disease costs. Knowing the relationship between air pollution and hospital costs of stroke can help us predict the costs due to air pollution, provide grounds for the allocation of medical insurance funds, and provide better working arrangements for CDC. This research can fill a gap in theoretical knowledge in this field.

Through the quantitative analysis of real data, we selected controllable air pollution as the entry point among the numerous inducing factors of stroke, we used time series analysis with a generalized additive model to estimate the associations between ambient air pollutants and stroke hospital costs between the period of 2015–2017. This study is the first step in optimizing medical resources, which is essential for policy making, service planning, and cost-effectiveness analysis of new therapeutic strategies.

EXPERIMENT SETTING

City C, the evaluation of complex strength is NO1 in the southwest of China, It’s subtropical monsoon humid climate is different from previous studies. It has the second largest number of private cars in China, important because automobile exhaust is one of the causes of air pollution. This all makes City C very special for this study. Stroke requires timely treatment, so when patients call for an ambulance, they should take the seek medical treatment nearby. We chose hospital L as our research object, as a fixed monitoring station is 1.2km away from the hospital and environmental data reflects the exposure level can well match the hospital patients admission data (Fig.1).

The red dots is hospital L, the blue dots is the monitoring stations, and the red areas are service areas of hospital L, which can be matched with the data of monitoring stations

Data

Daily counts of hospital admissions for stroke, including all cerebrovascular diseases (ICD-10:60-64) as the principal diagnosis from year 2015-2017 were obtained from hospital L, which has a 556.98 square kilometer service area and serves population of 872,300 people. Considering the stroke risk markers and risk factors, we also computed the cost of stroke by gender, by two age groups(age<=65, age>65) and by season for subgroup analysis, all of the data was from the Hospital Management Information System (HMIS). We only consider the direct cost in this paper. Ethics approval and consent from individual subjects were not required by our institute as we used only aggregated data and not any individualized data in this study.

Air pollution data between January 1th 2015 and December 31th 2017 was obtained from the State Environmental Protection Administration of the fixed monitoring station which is 1.2 km from the hospital. We calculated daily concentration of sulfur dioxide (SO2), nitrogen dioxide (NO2), ozone (O3), carbon monoxide (CO), particle matter 10 (PM10), and particle matter2.5 (PM 2.5) from the monitoring station. The temperature and humidity data are drawn form the National Meteorological Information Center of China.
Figure 1: L Hospital is in the Patient Coverage Area of C City

Statistical Modeling

This is a retrospective study, since the relationship between cost and air pollution variables is non-linear, we chose Generalized Additive Poisson Models (GAM) to analyze the relationship between stroke cost and air pollution by using R project with packages “mgcv”. Time series analysis of the relationship between air pollution and health has attracted a lot of attention and we set up our model based on previous studies. Before setting up the GAM model, we used t step regression to select variables by taking into account meteorological factors, social factors and patient factors comprehensively through the existing data. Traditionally, length of stay has been one of the factors influencing costs. It is a big innovation to select length of stay as the research variable of patient factors. We have done a lot of work to verify the feasibility of including length of stay in the model, including multicollinearity test. The GAM model was established in two steps. The first step was the blank model, that is, air pollution variables were not added. The second step was to add air pollutants respectively. A minimum variable was selected to enter the model according to AIC (akaike information criterion, AIC). After the test of the degree of freedom(df)for the time trend, we set up our model as follows:

$$\log(E(Y)) = \alpha + S(Temp_{1-5}, df = 7) + S(Hum, df = 3) + \beta_1 \times \text{Holiday}$$

$$+ \beta_2 \times \text{Length of stay}$$
Here $E(Y)$ stands for the expected costs for stroke patients, $\alpha$ is the model intercept, $S(.)$ is the smoothing spline function for nonlinear variables, $\text{Temp}$ represents the temperature, $\text{Hum}$ represents the humidity, $\beta_1$ and $\beta_2$ are the regression coefficients. The choice of df is based on previous studies and our sensitivity analysis, according to our results, we made 7 df the temperature and 3 df the humidity.

We separately tested SO2, NO2, PM2.5, PM10, O3 for the same day and up to 14 days prior to the outcome (single-lag effect from lag0-lag14). In the subgroup comparison of gender, age and season, we used the RR value to analyze the degree of association of this factor with the cost. All tests were conducted in the statistical environment R.

In our study, we also considered the impact of the combined action of various pollutants on the cost, in which the pollutants were included in the same lag period at the same time (lag0-10). For example, in order to analyze the effects of O3 and PM2.5, we set up model as below:

$$
\text{Model} = \text{GAM(} \text{cost} \sim \text{O3} + \text{PM2.5} + S(\text{Temp}_{1-5}; \text{df} = 7) + S(\text{Hum}; \text{df} = 3) + \beta_1 \cdot \text{Holiday} + \beta_2 \cdot \text{Length of stay}\text{)}
$$

## RESULTS

### Data description

According to our statistical analysis, a total of 8,076 cerebrovascular admission data were collected in this area during the study period. Data cleansing excluded children (<=18 years old), external trauma, work and life outside the scope of the monitoring station etc. After removing outliers, a total of 1,663 cases were selected as the overall sample for the study. Among them, males accounted for 51.29% and females 48.71%. The age over and including 65 comprises 72.82% and 27.18% are those under 65 years old. The warm season accounts for 54.15% of the cases and the cool season for 45.84%. The average cost is 10750.24 RMB, with the highest cost being 171838.4RMB, and the lowest cost at 280.68RMB. The details are shown in Table 1. Average daily air concentrations of SO2, NO, CO, O3, PM2.5 and PM10 are 12.36, 50.75, 1.10, 95.85, 59 and 93.71 (unit: ug/m3) respectively.

### Table 1: Subgroup Details

<table>
<thead>
<tr>
<th>Subgroup variable</th>
<th>Mean, SD.</th>
<th>Median, 25th, 75th percentile.</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
<td>cost 1053.75 (2001.06)</td>
<td>991.97 (991.97-673.82)</td>
<td>18195440.98</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td>male 1193.63 (2472.52)</td>
<td>1056.52 (1056.52-701.01)</td>
<td>10594332.36</td>
</tr>
<tr>
<td></td>
<td>female 905.80 (1300.35)</td>
<td>926.28 (926.28-661.60)</td>
<td>7601108.62</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>old(&gt;=65) 956.16 (1227.43)</td>
<td>976.10 (976.10-669.05)</td>
<td>11377182.35</td>
</tr>
<tr>
<td></td>
<td>young(&lt;65) 1270.06 (1758.79)</td>
<td>1026.79 (1026.79-683.08)</td>
<td>6818258.62</td>
</tr>
<tr>
<td><strong>Dtype</strong></td>
<td>infarction 806.61 (918.51)</td>
<td>920.08 (920.08-646.61)</td>
<td>10613038.73</td>
</tr>
<tr>
<td></td>
<td>hemorrhage 1844.99 (3529.94)</td>
<td>1400.49 (1400.49-800.22)</td>
<td>7582402.24</td>
</tr>
<tr>
<td><strong>Result</strong></td>
<td>death 2094.35 (3249.81)</td>
<td>2092 (2092-953.03)</td>
<td>1059000.28</td>
</tr>
<tr>
<td></td>
<td>else 1022.36 (1934.93)</td>
<td>980.30 (980.30-670.66)</td>
<td>17136440.69</td>
</tr>
</tbody>
</table>

Note: This table is a comparison of the average, median, and total cost of the partial grouping.
Spearman risk correlation analysis

The Spearman Coefficient is used to measure the dependence and correlation between data. We tested the Spearman Correlation between the pollutants, as shown in Table 3. It is clear that there is a positive correlation between SO2, NO2, CO, PM2.5, PM10. O3 is significantly different from the others, its concentration is negatively correlated with other pollutants. This is an important result for the next discussion.

Table 3: Spearman Correlation Analysis

<table>
<thead>
<tr>
<th></th>
<th>SO2</th>
<th>NO2</th>
<th>CO</th>
<th>O3</th>
<th>PM2.5</th>
<th>PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>SO2</td>
<td>1</td>
<td>0.6547</td>
<td>0.4331</td>
<td>0.0017</td>
<td>0.5042</td>
<td>0.5396</td>
</tr>
<tr>
<td>NO2</td>
<td>0.6547</td>
<td>1</td>
<td>0.6833</td>
<td>-0.2688</td>
<td>0.7448</td>
<td>0.7191</td>
</tr>
<tr>
<td>CO</td>
<td>0.4331</td>
<td>0.6833</td>
<td>1</td>
<td>-0.3461</td>
<td>0.6828</td>
<td>0.6753</td>
</tr>
<tr>
<td>O3</td>
<td>0.0017</td>
<td>-0.2688</td>
<td>1</td>
<td>-0.3092</td>
<td>-0.2869</td>
<td></td>
</tr>
<tr>
<td>PM2.5</td>
<td>0.5042</td>
<td>0.7448</td>
<td>0.6828</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PM10</td>
<td>0.5396</td>
<td>0.7191</td>
<td>0.6753</td>
<td>-0.2869</td>
<td>0.9488</td>
<td>1</td>
</tr>
</tbody>
</table>

Regression results

Single-Pollutant models

In the single model, adjusted ER (95% CI) of cost and SO2, NO2, O3, PM2.5 and PM10 IQR increases for lag periods (lag0–lag14), as shown in Fig.1. Among the lag day analyses, the lag10 day was found to have the most model fit.

The results showed that PM2.5, PM10, SO2 and NO2 were significantly negatively associated with total cost, with the best model at lag10 day (10-day moving average), and the corresponding ER for per IQR increase was 0.16% (95% confidence interval (95% CI) 0.05%, 0.27%), 0.11% (95% CI 0.14%, 0.07%) and 0.34% (95% CI 0.17%, 0.17%), respectively (P < 0.05). CO was significantly associated with total non-accidental mortality only at lag1, lag4, lag5, lag12, lag13, lag14 day, the corresponding ER for per IQR increase was 7.82% (95% CI 15.2%, 0.44%) (P < 0.05) at lag10 for example. The results of O3 were significantly inconsistent with those of other pollutants. There was no statistical significance from the lag1 to lag6, but it was statistically significant since lag7 showed a positive correlation, reaching the maximum value at lag10, the corresponding ER per IQR increase was 0.16% (95% CI 0.04%, 0.27%) (P < 0.05).

As shown in Fig.2, interestingly, except O3, the air pollutants in the subgroup of age showed statistical significance for the age>=65 from lag1 to lag14, O3 showed the statistical significance from lag 3 to lag14, but no statistical significance for age<65 groups. In addition to the positive correlation of ozone at each significant time, there was a significant negative correlation between cost and other pollutants. We take lag10 to analysis, PM2.5, PM10, SO2, CO, O3 and NO2, the corresponding ER for per IQR increase was -0.14% (95% CI -0.22%, -0.05%), -0.1% (95% CI -0.16%, -0.04%), -1.01% (95% CI -0.17%, -0.32%), -1.01% (95% CI -0.17%, -0.32%), -14.63% (95% CI -23.14%, -6.11%), 0.11% (95% CI 0.05%, 0.17%), -0.42% (95% CI -0.58%, -0.26%).

We also tested the gender as a subgroup, the details can be seen in Fig. 2, Only SO2, NO2 and PM10 on the first day had a significant negative correlation with women, and the rest of the pollutants had no significant correlation with womens’ costs. However, PM2.5, PM10, NO2 and part of SO2 lag days have significant negative correlation with male’s costs while O3, CO showed no significant correlation. Based on the above analysis, we made a further comparison between elderly males and elderly females. Although each pollutant has a significant correlation with the cost of strokes in the elderly, the results of elderly males and elderly females are different, O3 has a positive correlation with the cost of elderly males and females, while NO2 and CO have a negative correlation. PM2.5 and PM10 has a significant negative correlation with elderly males in each lag period, while only part of the lag period has a significant negative correlation with elderly womens’ cost. Sulfur dioxide showed a significant negative correlation with women in all lag periods, while men only showed a negative correlation with some lag periods.
Figure 2: Excess Risk (ER) with 95% CI per IQR Increase of Daily Mean Concentration of SO2, NO2, CO, PM2.5, PM10, O3 with Different Lag Days – the Overall Sample

Figure 3: Excess Risk (ER) with 95% CI per IQR Increase of Daily Mean Concentration of SO2, NO2, CO, PM2.5, PM10, O3 with Different Lag Days – Subgroup (Age, Gender)

We also tested the disease subgroup hemorrhage and infarction. Though significant negative correlations are found for infarction, no significant correlation was found for hemorrhage. We tested a lot of subgroups such as seasons.
results, type of medical insurance, and selected meaningful parts as shown in the figure below:

Figure 4: Excess Risk (ER) with 95% CI per IQR Increase of Daily Mean Concentration of SO2, NO2, CO, PM2.5, PM10, O3 with Different Lag Days - Cold Weather, Warm Weather

Figure 5: Excess Risk (ER) with 95% CI per IQR Increase of Daily Mean Concentration of SO2, NO2, CO, PM2.5, PM10, O3 with Different Lag Days - Different Disease Type Age >=65

The two-pollutant adjusted models showed clear differences, the results of lag10 in two-pollutant adjust models were shown in Table 4. We analyzed various combinations, O3 and NO2 are interesting impact factors, for the whole group, PM2.5/O3、PM10/O3、O3/NO2、CO/NO2、SO2/NO2 showed a significant correlation, in the subgroups, only the elderly group can be seen to have a significant correlation with SO2/NO2、CO/O3、NO2/O3. The results also showed that when SO2、NO2、O3 was used as an adjusted variable, other pollutant concentrations tended to show the significant correlation with stroke hospitalization costs.
Table 4: ER of Total Cost for IQR Increase of PM2.5, PM10, SO2, O3, CO, NO2 after Adjusting for Other Pollutions in Lag10 Day

<table>
<thead>
<tr>
<th>Variable</th>
<th>IQR increases</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM2.5</td>
<td>Adj. for PM10</td>
</tr>
<tr>
<td></td>
<td>-0.0007(-0.0039,0.0025)</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2</td>
</tr>
<tr>
<td></td>
<td>-0.0014(-0.0029,0.0001)</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO</td>
</tr>
<tr>
<td></td>
<td>-0.0014(-0.0029,0.0001)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3</td>
</tr>
<tr>
<td></td>
<td>-0.0014(-0.0025,-0.0002)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2</td>
</tr>
<tr>
<td></td>
<td>0.0001(-0.0015,0.0017)</td>
</tr>
<tr>
<td>PM10</td>
<td>Adj. for PM2.5</td>
</tr>
<tr>
<td></td>
<td>-0.0006(-0.0028,0.0015)</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2</td>
</tr>
<tr>
<td></td>
<td>-0.0011(-0.0022,0.0001)</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO</td>
</tr>
<tr>
<td></td>
<td>-0.0012(-0.0023,-0.0001)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3</td>
</tr>
<tr>
<td></td>
<td>-0.0008(-0.0016,0)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2</td>
</tr>
<tr>
<td></td>
<td>0.0002(-0.0009,0.0014)</td>
</tr>
<tr>
<td>SO2</td>
<td>Adj. for PM2.5</td>
</tr>
<tr>
<td></td>
<td>-0.0018(-0.0108,0.0071)</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10</td>
</tr>
<tr>
<td></td>
<td>-0.0001(-0.0103,0.0102)</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO</td>
</tr>
<tr>
<td></td>
<td>-0.0061(-0.0166,0.0044)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3</td>
</tr>
<tr>
<td></td>
<td>-0.0055(-0.0123,0.0013)</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2</td>
</tr>
<tr>
<td></td>
<td>0.0127(0.0007,0.0247)*</td>
</tr>
<tr>
<td>CO</td>
<td>Adj. for PM2.5</td>
</tr>
<tr>
<td></td>
<td>-0.0012(-0.1257,0.1233)</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10</td>
</tr>
<tr>
<td></td>
<td>0.0207(-0.1155,0.157)</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2</td>
</tr>
<tr>
<td></td>
<td>-0.0237(-0.1687,0.1214)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3</td>
</tr>
<tr>
<td></td>
<td>-0.0539(-0.15,0.0421)</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2</td>
</tr>
<tr>
<td></td>
<td>0.157(0.0079,0.306)*</td>
</tr>
<tr>
<td>O3</td>
<td>Adj. for PM2.5</td>
</tr>
<tr>
<td></td>
<td>0.0014(0.0002,0.0026)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10</td>
</tr>
<tr>
<td></td>
<td>0.0013(0.0001,0.0024)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2</td>
</tr>
<tr>
<td></td>
<td>0.0014(0.0002,0.0026)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO</td>
</tr>
<tr>
<td></td>
<td>0.0014(0.0002,0.0026)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2</td>
</tr>
<tr>
<td></td>
<td>0.0013(0.0001,0.0024)*</td>
</tr>
</tbody>
</table>
We also compared the two-pollutant models in subgroups. Below is an analysis table for one of these subgroups, with more results to be seen in the subsequent appendix:

<table>
<thead>
<tr>
<th></th>
<th>Adj. for PM2.5</th>
<th>Adj. for PM10</th>
<th>Adj. for O3</th>
<th>Adj. for SO2</th>
<th>Adj. for CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO2</td>
<td>-0.0036(-0.0061,-0.0012)*</td>
<td>-0.0039(-0.0065,-0.0012)*</td>
<td>-0.0031(-0.0048,-0.0014)*</td>
<td>-0.006(-0.009,-0.003)*</td>
<td>-0.0056(-0.0083,-0.0029)*</td>
</tr>
</tbody>
</table>
Table 5: Compare of ER in Gender Subgroup or IQR Increase of PM2.5, PM10, SO2, O3, CO, NO2 after Adjusting for Other Pollutions in Lag10 Day

<table>
<thead>
<tr>
<th>Variable</th>
<th>IQR increases (male)</th>
<th>IQR increases (female)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM2.5</td>
<td>Adj. for PM10 -0.0032(-0.0079,0.0015)</td>
<td>0.0026(-0.0015,0.0066)</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2 -0.0029(-0.0051,0.0008)*</td>
<td>0.0004(-0.0015,0.0023)</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO -0.0031(-0.0053,-0.001)*</td>
<td>0.0001(-0.0018,0.002)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3 -0.0024(-0.004,-0.0008)*</td>
<td>-0.0002(-0.0017,0.0013)</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2 -0.0017(-0.0041,0.0006)</td>
<td>0.002(0,0.004)</td>
</tr>
<tr>
<td>PM10</td>
<td>Adj. for PM2.5 0.0005(-0.0027,0.0036)</td>
<td>-0.0024(-0.0051,0.0003)</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2 -0.002(-0.0037,-0.0003)*</td>
<td>0(-0.0014,0.0014)</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO -0.0021(-0.0036,0.0005)*</td>
<td>-0.0003(-0.0017,0.0011)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3 -0.0015(-0.0026,0.0003)*</td>
<td>-0.0004(-0.0014,0.0006)</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2 -0.0008(-0.0025,0.001)</td>
<td>0.0011(-0.0004,0.0025)</td>
</tr>
<tr>
<td>SO2</td>
<td>Adj. for PM2.5 0.0037(-0.0099,0.0172)</td>
<td>-0.0108(-0.022,0.0003)</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10 0.0052(-0.0103,0.0207)</td>
<td>-0.0092(-0.022,0.0035)</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO -0.0072(-0.023,0.0085)</td>
<td>-0.009(-0.0221,0.0042)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3 -0.0077(-0.0178,0.0024)</td>
<td>-0.0068(-0.0154,0.0018)</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2 0.0119(-0.0064,0.0301)</td>
<td>0.0075(-0.0073,0.0222)</td>
</tr>
<tr>
<td>CO</td>
<td>Adj. for PM2.5 .0735(-0.1113,0.2583)</td>
<td>-0.1062(-0.2633,0.0509)</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10 0.087(-0.1149,0.2888)</td>
<td>-0.0697(-0.2417,0.1023)</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2 -0.0299(-0.2482,0.1885)</td>
<td>-0.0056(-0.1862,0.1751)</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3 -0.0884(-0.2299,0.053)</td>
<td>-0.0485(-0.1706,0.0736)</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2 0.1417(-0.0813,0.3646)</td>
<td>0.137(-0.0492,0.3232)</td>
</tr>
<tr>
<td>O3</td>
<td>Adj. for PM2.5 0.0005(-0.0012,0.0023)</td>
<td>0.0022(0.0007,0.0037)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10 0.0005(-0.0013,0.0022)</td>
<td>0.0021(0.0006,0.0036)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2 0.0009(-0.0009,0.0026)</td>
<td>0.002(0.0005,0.0034)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO 0.0009(-0.0009,0.0026)</td>
<td>0.002(0.0005,0.0035)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for NO2 0.0007(-0.001,0.0024)</td>
<td>0.0018(0.0003,0.0032)*</td>
</tr>
<tr>
<td>NO2</td>
<td>Adj. for PM2.5 -0.0017(-0.0054,0.0002)</td>
<td>-0.0058(-0.0088,0.0028)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for PM10 -0.0023(-0.0064,0.0017)</td>
<td>-0.0054(-0.0086,0.0021)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for O3 -0.0034(-0.0059,0.0009)*</td>
<td>-0.0029(-0.005,-0.0008)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for SO2 -0.0062(-0.0107,0.0016)*</td>
<td>-0.005(-0.0087,-0.0014)*</td>
</tr>
<tr>
<td></td>
<td>Adj. for CO -0.005(-0.0097,0.0016)*</td>
<td>-0.005(-0.0088,0.0021)*</td>
</tr>
</tbody>
</table>

*P<0.05
DISCUSSION

Time series study is a quantitative evaluation method applied to the study of the health effects of acute exposure to air pollution, which was first applied to the environmental epidemiology study of air pollution by Schwartz. A large number of studies have used this model for different diseases to find links between air pollutants and daily morbidity and mortality. Previous studies have demonstrated the selection of variables in this model, such as temperature, humidity, and so on. The selection method of degree of freedom refers to previous studies and the design. We make adjustments to this study based on our literature review.

Daniela A et al.(2013) use a negative binomial regression model for the time series study, and found when the PM2.5 concentration increases by 10 mg/m³, the risk of emergency hospital admissions for cerebrovascular causes increases by 1.29% (95% CI: 0.55, 2.03). Jeffery J.Wing et al.(2010) have found an association between higher levels of PM2.5 and O3 and higher rates of ischemic stroke, but a study in Taipei found that carbon monoxide alone in air pollutants had an impact on stroke risk, the inconsistency of the results may be due to geographical location. Some studies have also focused on the effects of carbon monoxide and ozone in the air on the incidence of stroke.

According to our results, we divided the patients into the death group and the alive group. The experimental results showed that the concentration of air pollutants had no correlation with the cost of the dead patients, while for the alive patients, except O3, the concentration of other pollutants had a significant influence on the costs of the alive patients, and all showed negative correlation. After subdividing stroke diseases into cerebral hemorrhage and cerebral infarction, it was found that there was no significant difference for those with hemorrhage, but infarction was significantly correlated with all pollutants except O3.

Air pollution should be recognized as a silent killer inducing stroke whose mortality rates remain elevated by its role as a new modifiable neurovascular risk factor. Different people react differently to O3. There are significant differences in the susceptibility of Chinese adults to ozone-related stroke, and a small proportion of the population may be seriously affected by O3. Through spearman analysis of various pollutants, we found that the correlation coefficients of O3 are inconsistent with other pollutants, which may explain why O3 has a negative effect on costs, while other pollutants have a positive correlation with costs.

People's behavior is affected by air pollution levels, which can cause changes or cancellations of trips. Studies show air pollution levels induce different behaviors such as reducing time spent outdoors, use of masks, and increased air cleaner use to protect against high outdoor air pollution. Since February 29th 2012, the Chinese government has required all regions to publish PM data to the public and PM has been getting more and more attention. Therefore, when the pollution is large, the increase in people's self-protection consciousness may make the individual's exposure value much lower than the environmental exposure value. There are many causes of stroke, such as high blood pressure, high BMI, cigarette smoking, and diabetes. Although many studies have proved a positive correlation between air pollution and stroke admission, no literature has proved that air pollution is the main influencing factor, and there is no evidence that air pollution affects the severity of strokes. Hospitalization costs were correlated with age, difficulty of surgery, comorbidity, etc. Although air pollution may increase the incidence of stroke, it may also cause milder cases. This may explain why pollutants such as PM are negatively correlated with stroke costs, which is also consistent with spearman's analysis results. If our guess is correct, residents' awareness of self-protection can be enhanced through the early warning of air pollution, which may reduce the admission of stroke caused by air pollution, thus reducing the costs to society as a whole.

In the gender subgroup studies, we found that female's costs was affected by SO2 and NO2, while male's costs was significantly correlated with all pollutants except CO and O3. Most Chinese men have the behavior of smoking, and Chinese men who smoke more than 10 cigarettes a day and have been smoking for more than 10 years have CO levels in their bodies that exceed the normal value. Due to the influence of smoking behavior, the CO content in the air is lower than the long-term exposure value. This explains why men are less affected by CO, while women's costs are significantly affected by CO. There was no significant relationship between female’s costs and PM value, while the influence on men was significant. This may be because women are more sensitive to the air quality index and know how to protect themselves, such as adopting masks and reducing time outside.
In the grouped studies, we found males were more likely than females, and people over 65 years old were more likely than younger adults to be affected by air pollution in their spending. The research shows that age is the most important risk for stroke, and men are more likely to suffer from strokes than women. These are consistent with our results. A significant correlation was found among the subgroups (such as gender, season) of people over 65 years old.

In the age subgroup studies, the elderly are particularly affected by air pollution, with almost all pollutants having a significant impact on their spending. There was no significant correlation between air pollution concentration and stroke costs in young people (age<65). In the data description stage, we found that 79.57% of the elderly were admitted to hospital due to cerebral infarction, and 20.43% were admitted to hospital due to cerebral hemorrhage. Medical studies have shown that particulate matter in the air can cause cerebral infarction, but no link has been found between air pollution and cerebral hemorrhage. In the study grouped by disease type, we also found that most air pollution had a significant relationship with the cost of infarction stroke, but no significant relationship with hemorrhagic stroke. The physical weakness of the elderly makes them vulnerable to air pollution, while hospital admissions among young people are often caused by other causes.

In the cold season, only on a very few lag days could a significant negative correlation in PM analyses be found, but the relationship between pollutant concentrations and costs is more pronounced in warmer seasons. It may be that the cold season itself is a season of high disease incidence so that the costs are affected by other factors.

In the result (death and non-death) sub group, all air pollution had no significant effect on the cost of dying patients, while in the non-death patients, all pollutants except O3 had a significant effect. This further confirms our hypothesis that air pollution has only a slight effect on stroke. As we continued to divide the elderly group into gender and disease type, we found a significant correlation, particularly in the elderly infarction expenditure group, which had a greater impact than the other groups.

Although a large number of studies have found that air pollution increases medical costs, the findings of this study may be decreasing for individual stroke patients. Also, there are a few limitation in this study: firstly, we only took the total cost as the research object and did not carry on the analysis to the expenditure constitution result. Also, with only two years of data available, the amount of data is limited. We only considered the area covered by one monitoring station. Moreover, this study did not take into account the patient's own factors, such as age, history of disease, comorbidity, etc., which all affect the cost. Thus, more research needs to be done.

CONCLUSION

Our study gives us an interesting conclusion, we found a correlation between air pollution and stroke medical costs, especially in age>=65, warm season and hemorrhage subgroups. Although a large number of research has proven that air pollution is positively correlated with the incidence of stroke, most pollutants, except O3, are significantly negatively correlated with the medical cost of a stroke. Moreover, environmental problems are huge challenges facing developing countries. We need to dig deeper into the impact of environmental pollution on healthcare. More diseases are worth studying.

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Lim, L.

Cost and cost-effectiveness analysis of a bundled intervention to enhance outcomes after stroke in Nigeria: Rationale and design[J]. eNeurologicalSci, 2015, 1(2):38-45

Ethnic differences in ambient air pollution and risk of acute ischemic stroke.


Roger et al.(2006) (model choice in time series studies of air pollution and mortality), time series analysis of ambient air pollution effects daily mortality, model choice in time series studies of air pollution and mortality


Short term Effects of Fine Particulate Air Pollution on Ischemic Stroke Occurrence: A Case-Crossover Study, Power stations emissions externalities from avoidance behaviors towards air pollution: Evidence from Beijing.


The global burden of stroke: persistent and disabling (Published Online March 11, 2019 http://dx.doi.org/10.1016/S1474-4422(19)30030-4 See Articles page 439)


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# Reviewers for the Transactions of ICHITA 2019

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