AN ORGANIZATIONAL INFORMATICS ANALYSIS OF COLORECTAL, BREAST, AND CERVICAL CANCER SCREENING CLINICAL DECISION SUPPORT AND INFORMATION SYSTEMS WITHIN COMMUNITY HEALTH CENTERS

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DEDICATION

I dedicate this dissertation to my distant past, my immediate past, my present, and my future.

To my immediate past I find the four pillars of my family: my four grandparents. My maternal grandmother, Mary Lee Brown, who practically raised me and inspired me to do anything I thought possible. My maternal grandfather, Nicholas Brown, who was my best friend and the most the loyal New York Mets fan I ever met. My paternal grandmother, Virginia Carney, who suffered from breast cancer and taught me the meaning of showing strength and courage in the face of adversity. My paternal grandfather, Elder Willie Carney, taught me what being a Carney man was all about and how faith must be the true measure of a man's worth. These are four of the greatest people I could ever hope to emulate. My Great Aunt Marion, who financed my early Catholic school education and put me on the path towards high academic achievement.

To my present, I offer this work as a testimony to my mother. While in grade school, I would be sent home with notes from my teachers complimenting my mother on her job as a parent. Every compliment I have ever received or will from this day forward for my character and professionalism I attribute to her.

To my future, I extend this as a new standard for me and my family to build upon and strengthen the family for generations to come. Every generation must carve out new pathways of achievement and lay the foundation for even greater achievement. I expect my niece, nephews, cousins, and any of my future children to go well beyond anything I have ever achieved or will achieve.

Finally, to my distant past, I honor those ancestors of my heritage who built the tradition of higher learning into the fabric of their society. It is as true for me as it is for any African-American that any achievement in the area of higher learning serves as a testament to the hard work, struggle, and dedication of those that came before us. I can only hope and pray that this research endeavor and my career moving forward in some small way serves to honor that legacy.

ACKNOWLEDGEMENTS

I would not be where I am today without the kind support and encouragement family and friends provided, and the incredible guidance and insight that was so generously given by my teachers and mentors along the way. My journey to my goal of a doctoral degree has been a long, and at times misdirected one, but at each step along the way, there were wise guides who offered a helpful nudge or some sage advice to gently usher me along to the next step in my journey.

I first want to extend a debt of gratitude to Dr. David Haggstrom, who, through some incredible act of kindness or extreme generosity, began the task of helping shape this study and eventually fashion it into something meaningful. I met David during a particularly vulnerable time in my doctoral training, when my research agenda was far too broad and unformed, and compiling my degree seemed dubious. David began meeting with me weekly, set me up with a work space within the Roudebush Veteran's Administration Medical Center, and extended me the professional courtesy of allowing me to work on projects as a research assistant. David was more than a research mentor and, at times, he assumed the roles of career coach, motivator, and even counselor. This one-on-one mentorship was, I am sure, a great burden on his time and is something that I am very appreciative of and will never forget. This directed guidance helped me to understand David's work, become intimately familiar with his research data, and it eventually helped me carve out a study, the result of which is this dissertation.

Leaving the confines of secure employment to embark on a doctoral dissertation is never an easy decision. However, conversations with Dr. Anna

McDaniel helped to reassure me that investing in the idea of coming to Indiana University and pursuing a doctorate in health informatics might very well be worth it in the end. Dr. McDaniel served as my first academic advisor and she helped me to transition from full-time employee back to full-time student. She offered one-on-one academic guidance and helped shape my understanding of what doctoral training in informatics was really all about. At times, she literally took me by the hand and introduced me to key people and helped me forge long-term partnerships along the way. Dr. McDaniel has become an extremely valuable member of the committee, as she was the only member who, in some way, had a direct understanding of the three primary stakeholders this research study was meant to respond to: (1) cancer research, (2) health informatics, and (3) pre-doctoral fellowship requirements (past and present). Dr. McDaniel helped me to navigate the maze of trying to satisfy so many divergent interests under the umbrella of a single research study. This was no easy task; she helped me to navigate all of it through her monthly and, at times, impromptu mentorship meetings. Her knowledge of the field of informatics and her extraordinary skills as a research advisor has provided me with a tremendous benchmark with which to measure my future in informatics.

The chair of my dissertation committee, Dr. Josette Jones, is probably the most notable for the well wishes she includes at the end of the emails, when she writes, “Have a gentle day.” Dr. Jones has been that gentle soul who has helped me in the midst of my many academic and professional storms. When I found myself being challenged personally or professionally, her door was always open to me and I found myself enriched by her counsel. She helped usher me through every major and minor

academic, fellowship, or career issue. She would constantly serve as an advocate for my interests to her superiors. She would also work with me to make sure that I was consistently on track for graduation and she had the unenviable task of serving at times as my source for venting. She would allow me to express my frustrations and, at the end, offer some simple perspective that would help to me to better understand that I was not alone in this endeavor and that she was there to help. In fact, I give special credit to Dr. Jones and Dr. Haggstrom for helping me remain in the program when all indications were that it was time to quit and go back to working full-time. Both Dr. Jones and Dr. Haggstrom, with the assistance of Dr. McDaniel, opened doors that allowed me to continue my studies and complete my degree. This research study would not have been completed without the personalized assistance Dr. Jones extended to me throughout my time in this program. She has never hesitated to support any of my endeavors and was always the first to offer a letter of support for any of my activities.

Dr. Michael Weaver is probably the most understated, yet highly valuable member of my committee. In a way, he fell into the job by virtue of his extraordinary knowledge and expertise in statistics. I benefited from taking two statistics courses taught by Dr. Weaver. That's when I quickly realized that if I wanted to graduate, I had better seek out his assistance. To simply say that Dr. Weaver was helpful would tremendously devalue his contribution. Dr. Weaver spent many hours challenging me to describe the intent of my study, the type of data, and the desired outcomes in terms that anyone could easily understand. Dr. Weaver's editorial reviews of my drafts were the most exhaustive and the most difficult to respond to. He pushed me to make the statistical model sound, and he helped shape my interpretation and presentation of the results. It is really no exaggeration to say that I probably would not be contemplating graduation had it not been for his sound guidance. I found myself presenting some really intricate statistical procedures with relative ease after interacting with Dr. Weaver. While I would never admit to fully understanding statistics, I will say that I gained a newly found appreciation for the importance of this field as it relates to a successful career in academic research. One other note on statistics: two very helpful people from the IU Center for Statistical and Mathematics Computing, Stephanie Dickinson and Eric Applegate, provided expert assistance with aspects of my methods development and SAS installation and coding/debugging, respectively.

Dr. Palakal's role on the committee was more or less the gatekeeper. His experience in informatics research and his knowledge of complex systems made him an essential member, ensuring that my final product met the minimal required standards for the level of academic excellence he desired from all of his students. I had the pleasure of taking a class on complex systems with Dr. Palakal, and that class helped to greatly inspire the computational modeling portion of this study. I can only hope this research ultimately demonstrates the level of academic achievement Dr. Palakal entrusts in his students as representatives of this university.

I made several references to funding and predoctoral fellowships. And it must be made clear that this research would not have been possible without funding from two very special programs. First, my initial two years of academic training were generously funded by the Anthem Foundation's Anthem/Indiana Health Information Exchange (IHIE) pre-doctoral fellowship. This fellowship helped provide me with a secure foundation as I transitioned from full-time employee to full-time student. I owe Dr. Marc Overhage, Dr. David Lee, Dr. Anna McDaniel, and the IHIE staff, a debt of gratitude for selecting me for such an honor and, while this research does not specifically focus on the cohort of national health information exchanges, I did endeavor to shape a study that could serve to support the long-term organizational informatics interests of health information exchanges.

Secondly, I want to show my sincere gratitude to the Indiana University School of Nursing's Training in Research Behavioral Oncology and Cancer Control Program (TRBOCC) Pre-doctoral fellowship program. This National Cancer Institute-sponsored program, under the guidance of Dr. Victoria Champion, served to provide me with the much-needed source of funding to complete my academic training. TRBOCC provided me with a wealth of resources and exposure to the key resources that dramatically shaped my research trajectory. TRBOCC gave me the structure and foundation I needed to sharpen my understanding and skills related to a career in research. Dr. Susan Rawl provided me with one-on-one mentorship that related to building my conceptual model and she gave me a solid grounding in behavioral theory and models used in cancer research that had a huge impact on my study design. Dr. Champion taught a class in intervention research design and helped me to continually build my research proposal into something my committee would value. This fellowship exposed me to experts in the field of cancer research and allowed me the space to identify areas where informatics research, health services research, and cancer research converge. TRBOCC also provided me with structure and the support of other pre- and post-doctoral fellows who motivated and challenged me to be my best. Finally, the fellowship provided me with administrative support from Peggy Weber and Sandra Fowler, as both kept me focused and in-step with the fellowship's demands. Dr McDaniel served not only as a member of my committee but as my TRBOCC mentor, in partnership with Dr. Haggstrom. And, as I mentioned earlier, she helped me to navigate the maze of carving out a research agenda that might serve to make everyone happy. While I cannot say that I actually accomplished this, I most certainly gave it my best effort.

I also want to thank the people at the Regenstrief Institute and the Richard L. Roudebush VA Medical Center's HSR&D team for allowing me to work with them as a research assistant on some pretty cool projects during my doctoral studies. They include Brad Doebbeling, Lori Losee, and David Haggstrom, who served on my leadership team, along with all the researchers and staff at both the VA and Regenstrief who gave some of their valuable time and much needed office space.

Two unsung heroes who helped greatly in making this dissertation complete were Randi Stocker and Karen Wilczewski. Randi Stocker is an associate librarian at the IUPUI University Library and spent several hours with me in the construction of my literature review. This assistance was incredibly important in helping me to complete perhaps the most important component of this project. Karen Wilczewski is an editor and owner of Top Dog Communications. It would be an exaggeration to say that without Karen's assistance this document would not have made it through successfully.

I want to express a deep feeling of gratitude for the expert guidance and consultation provided by the professionals at Carnegie Mellon University (CMU),

Computational Analysis of Social and Organizational Systems (CASOS). They provided me with great support throughout the development and execution of my computer simulation. Dr. Kathleen Carley, director of CASOS, gave me some of her extremely valuable time in two telephone meetings. She also invited me to attend her annual seven-day training session offered each summer at CMU, which is dedicated to teaching the basics on network analysis and computational modeling. Dr. Carley and CASOS graciously awarded me a graduate student scholarship to attend this vital training session. There I met a member of CASOS and perhaps one of the most gifted simulation modelers I ever met, Geoffrey P. Morgan. Geoffrey worked with me over the course of many hours as my key subject matter expert on network analysis and computational modeling. He played a critical role in my completing the simulation portion of my research. Geoffrey took a great deal of time away from his many responsibilities at CASOS to ensure that I understood the material and was able to complete the many assignments he gave me in building the simulation. He guided me through the conceptual design, coding, and eventual running of the simulation. He was so helpful and patient with me, a relative novice in this area. His support was nothing short of tremendous!

Finally, a word about my friends, family, and faith. I have never encountered a challenge in my professional life that has pushed me so far, for such a long period of time. This has been a journey that has seen me through several trying moments that, quite honestly, at times, I never thought would come to a successful conclusion. There were people who stood by me, listened to my doubts, challenged me to keep pushing, and helped me to remember who I really was through it all. First and

foremost, my mother, who supported me in many, many ways, too numerous to mention here. My family members constantly kept me focused on the larger goal, with special thanks to Cousin Vanessa, who would often call me to pray with me over the telephone. These prayer sessions always uplifted and motivated me. My friends called, wrote, and emailed their continued support and encouragement and constantly reminded me that the life of a starving student is only temporary and would soon pass. Finally, when it comes to faith all mistakes are mine and mine alone; however, all the honor and glory for anything good that comes from this endeavor belongs to God…And this work, indeed this entire endeavor, serves as my personal testament that “I can all things through Christ which strengthens me” (Philippians 4:13)!

ABSTRACT

Timothy Jay Carney

AN ORGANIZATIONAL INFORMATICS ANALYSIS OF COLORECTAL, BREAST, AND CERVICAL CANCER SCREENING CLINICAL DECISION SUPPORT AND INFORMATION SYSTEMS WITHIN COMMUNITY HEALTH CENTERS

Purpose: A study design has been developed that employs a dual modeling approach to identify factors associated with facility-level cancer screening improvement and how community health center cancer screening performance is mediated by the use of clinical decision support. This dual modeling approach combines the principles of: (1) Health Informatics, (2) Cancer Care Delivery/Behavioral Oncology, (3) Health Services Research, and (4) Organizational Change/Theory.

Methods: The study design builds upon measures from a conceptual framework developed by Jane Zapka intended to identify system-level factors associated with health care delivery across the cancer care continuum. Broadly, these measures fall into the following categories: (1) organizational and/or practice characteristics, (2) provider characteristics, and (3) patient population characteristics. These measures were operationalized in a 2005 HRSA/NCI Health Disparities Cancer Collaborative survey of 44 community health centers in the United States. The first set of statistical models use sequential, multi-variable regression models to test for organizational factors that may account for the presence and intensity-of-use of clinical decision support (CDS) and information systems (IS) within community health centers for use in colorectal, breast, and cervical cancer screenings. A subsequent test will assess the impact of CDS/IS on provider-reported cancer screening improvement rates. The second set of computational models will use a multi-agent model method of network evolution, called CONSTRUCT^{TM}, to identify the agents, tasks, knowledge, and beliefs associated with cancer screening practices and CDS/IS use to inform both CDS/IS implementation and cancer screening intervention strategies.

Results: The results of this study demonstrate that a dual-modeling approach–utilizing both statistical and computational models to examine point-in-time survey data–can account for temporal dynamics and complex adaptive components over a 10-year period, which are not readily seen in a linear statistical model alone.

Implications: A dual-modeling approach can serve as an organizational informatics methodological approach that aims to understand organizational change that improves cancer health outcomes and/or technology adoption and use. Additionally, this dual model can serve as a multilevel intervention research design that attempts to examine changes in system-wide knowledge absorption, and influence beliefs and task performance.

Josette Jones, RN, PhD, Chair

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CHAPTER 1: THE NATURE OF THE STUDY

Introduction

Organizational issues are considered common barriers to the implementation and adoption of clinical decision support in health care settings. According to the Agency for Healthcare Research and Quality (AHRQ), there is a lack of understanding of organizational and cultural issues related to clinical decision support systems (CDS) (U.S. Department of Health and Human Services, October 2009). Implicit in this AHRQ statement is the fact that there are some organizational factors that can ultimately have an impact on the quality and performance of health through increased CDS adoption and use. Recent research suggests that structural differences as to how care is organized may explain greater performance variance than patient factors alone (Soban & Yano, 2005). Organizational factors can serve as inhibitors or facilitators in the adoption implementation of new technologies, such as clinical decision support (CDS), or the closely aligned concepts of clinical information systems (IS) (Weiner, Savitz, Bernard, & Pucci, 2004; Doebbeling, Chou, & Tierney, 2006; Reid et al., 2005; Bates et al., 2001). However, the organizational factors of U.S. community health centers, associated with the presence of CDS and IS applications, are relatively unknown. Organizational factors that can successfully predict the presence of CDS and IS should also be related to some concrete measure of health care quality and performance; however, this hypothesis, with an added emphasis on cancer screening, has yet to be tested within community health centers.

According to the National Cancer Institute (NCI), in 2009, an estimated 1,479,350 people in the United States were diagnosed with cancer, and 562,340 will die of cancer (U.S. National Institutes of Health, 2009). Currently, estimates as to the number of deaths that could have been avoided through screening vary from 3% to 35%, based on a variety of assumptions, disease progression, prognosis, environmental factors, and lifestyle factors (U.S. National Institutes of Health, 2009). Three types of cancer screening, including (1) cervical cancer screening through the use of Pap tests, (2) breast cancer screening through the use of mammography, and (3) a battery of tests for colorectal cancer screening, have been found to detect cancer at early stages and improve cancer survival rates (American Cancer Society, 2009; Centers for Disease Control and Prevention, 2005, 2009; Müller & Sonnenberg, 1995; Newcomb, Norfleet, Storer, Surawicz, & Marcus, 1992; Selby, Friedman, Quesenberry, & Weiss, 1992; U.S. Department of Health and Human Services: Healthy People, 2010, 1998; USPSTF, 1996, 2002). Despite some improvements in screening utilization, Rutten et al. explains that the rates of colorectal cancer screening lagged behind both Pap tests and mammography screenings. Colorectal cancer screening performance rates are based on national guidelines and evidence-based best practices (Centers for Disease Control and Prevention, 2009; U.S. Department of Health and Human Services: Healthy People, 2010, 1998; Walsh & Terdiman, 2003). The American Cancer Society and the U.S. Preventive Services Task Force recommends that people over age 50 should be screened for colorectal cancer, women over age 40 should receive annual mammograms, and women (starting at the point of sexual activity but no later than age 21) should get a Pap test every two years (American Cancer Society, 2009; Force, 2006). Guidelines have been available since 1997 in the case of the Pap test, however, barriers to screening remain (Finney Rutten, Nelson, & Meissner, 2004).

Several strategies have been introduced to improve the overall quality of health care (e.g., cancer screening at the systems level) by promoting the use of evidenced-based practices (EBP) (Kawamoto, Lobach, Willard, & Ginsburg, 2009). Clinical decision support (CDS) has been particularly effective in helping to achieve greater levels of EBP in health care. According to Kawamoto et al. (2009), CDS consists of "providing clinicians, patients, and other healthcare stakeholders with pertinent knowledge and/or person-specific information, intelligently filtered or presented at appropriate times, to enhance health and healthcare, and 90% of clinician-directed CDS interventions evaluated in randomized controlled trials have significantly improved patient care" (Kawamoto et al., 2009; Osheroff et al., 2007). In general, incorporating information from evidence-based practice (EBP) guidelines (Desch et al., 2000; Desch et al., 1999; Desch et al., 2005; Rex et al., 2006; Winawer et al., 2003; Winawer et al., 1997), and performance measures (Patwardhan et al., 2006; VHA, 2006a, 2006b) for the screening of colorectal, breast, and cervical cancer have been developed by federal agencies, including AHRQ and the Veteran's Health Administration (VHA). However, the organizational determinants of CDS and IS, and the corresponding influence of clinical decision support (CDS) and information system (IS) applications designed to help to meet EPB guidelines and performance benchmarks for colorectal, breast, and cervical screening practices within community health centers, remain largely unstudied (Yano, Soban, Parkerton, & Etzioni, 2007).

This research study focused on community health centers in the U.S. as the health care setting. According to the National Association of Community Health Centers' director of Health Information Technology, approximately 40% (or 3,160) of all 7,900 community health centers have some form of Electronic Health Record (EHR) in use today (Lardiere, 2010). The EHR is considered to be an essential part of the eventual deployment of specialized clinical decision support systems supporting disease-specific target areas. Lardiere explains that "approximately 70% of the community health centers with EHRs (or 2,212) use some form of clinical decision support in the form of dashboards, data repositories, tele-health technologies, kiosks, or other technologies" (Lardiere, 2010). As encouraging as this may seem, it actually translates into only about 28% of all 7,900 community health centers that use some form of clinical decision support for practices, such as cancer screening. Lardiere points out that organizational factors, such as funding and affordability, remain inhibiting factors to overall CDS adoption and use (Lardiere, 2010).

The study (1) identifies the organizational determinants of clinical decision support (CDS) and information systems (IS) within community health centers, and (2) it tests the impact of CDS and IS on colorectal, breast, and cervical cancer screening 12-month provider self-reported improvement rates within community health centers. This study also employs the use of a computational model to examine socio-technical factors (e.g., identified agents, tasks, knowledge, groups, and beliefs) associated with cancer screening, CDS, and IS use within community health centers. This study uses a framework initially proposed by Zapka et al. in 2003 to assist in conceptually defining a set of factors that can be measured in association with CDS and IS presence, intensity of use, and impact. Three constructs from Zapka et al. were identified, including (1) organizational and/or practice settings, (2) provider characteristics, and (3) patient population characteristics (Zapka, 2008; Zapka, Taplin, Solberg, & Manos, 2003).

This study will employ a dual modeling approach that includes a traditional statistical (empirical) methodology used for hypothesis testing and organizational informatics methodology that relies on principles of computational modeling and network analysis. Computational modeling will be used for hypothesis generation through simulations and *what-if* scenario analysis using a community health center performance matrix for facility-level Cancer Screening Improvement and CDS/IS practices. This study expects to provide a means of aligning community health center organizational diagnosis and design efforts with information technology efforts intended to increase the presence of clinical decision support and information systems used in colorectal, breast, and cervical cancer screenings, and ultimately compliment other quality improvement strategies (Chin et al., 2004; Haggstrom, Clauser, & Taplin, 2008; Landon & Normand, 2008; McInnes et al., 2007; Taplin et al., 2008) aimed at increasing colorectal, breast, and cervical cancer screening rates in community health centers.

Of primary interest is a composite measure of overall information systems (IS) and clinical decision support (CDS), which is currently used for cancer screening within community health centers. Recent studies measured the extent to which quality improvement interventions (McInnes et al., 2007), particularly interventions related to the Chronic Care Model (CCM) (Haggstrom et al., 2008), were performed within community health centers that participated in the Health Resources and Services Administration (HRSA) Health Disparities Cancer Collaborative (HDCC). From 2003 to 2005, the Haggstrom et al. study measured the extent to which HDCC centers implemented six components of CCM, including self-management support, decision support, delivery system design, clinical information systems, health care organization, and community resources (Haggstrom, 2008; Sperl-Hillen et al., 2004). Haggstrom et al. discovered that community health centers that were identified as HDCC participants were more likely to report CCM implementation and cancer care process improvement compared to non-HDCC participants (Haggstrom et al., 2008).

Haggstrom et al. highlighted the continuing effort of the Bureau of Primary Health Care (BPHC), the part of HRSA that oversees federally-funded health centers, to use of the collaborative strategy as a means of reducing health disparities, improve quality of care in health centers, and reduce costs (HRSA, June 2008). The model was started in 1996 by the Institute for Healthcare Improvement (IHI) Collaborative Model for Achieving Breakthrough Improvement; it also became known as the Breakthrough Series (BTS) (HRSA, June 2008). BTS represented a way to "help healthcare organizations make breakthrough improvements in quality, while reducing costs" (HRSA, June 2008). HRSA has employed the collaborative model since 1999 as a means of providing structure for health care organizations to learn from one other and be exposed to recognized experts in the specific areas identified for improvement (HRSA, June 2008). The HRSA Collaboratives have focused on a variety of areas, including health disparities (e.g., cancer, asthma, cardiovascular disease, depression, etc.), patient safety, obesity, tobacco cessation, organ donation, newborn screening, HIV/AIDS and other areas (HRSA, June 2008). Recent studies highlighted the impact of HRSA-sponsored collaboratives in a variety of areas. In 1998, Chin et al. examined 19 Midwestern health community centers to assess the level of progress made as participants in the Health Disparities Collaborative on Diabetes. The health centers were evaluated based on the level of improvement achieved as a function of their deployment of both the Plan-Do-Study-Act rapid change process and the Chronic Care Model (CCM). Chin et al. describes the *plan* as an intervention to help the health center achieve its major aim, *do* as the effort to implement the intervention on a small scale, *study* as analyzing the effects of the intervention, and finally act as a way for the health center to *act* based on study data and revise its approach, as needed (Chin et al., 2004). Chin et al. also examined several aspects of the Chronic Care Model, including patient-self management, delivery system redesign, decision support, clinical information systems, leadership, health system organization, and community outreach (Chin et al., 2004). Chin et al. found that, after 969 patient chart reviews, a review of 79 diabetes quality improvement team members, and a series of qualitative interviews, the Health Disparities Collaborative improved diabetes care in community centers over a one-year study period (Chin et al., 2004). Additionally, Landon et al. conducted a controlled study of 44 health center participants within the Health Disparities Collaborative and 20 centers, which were identified as non-participants, examining three disease focus areas of diabetes, asthma, and hypertension, for both process of care outcomes and clinical outcomes (Landon, Hicks, & O'Malley, 2007). Landon et al. found that, for those health centers that participated within the collaborative, there was a recognized improvement in process outcomes for the two or the three assessed areas, including asthma and diabetes, but not for hypertension (Landon et al., 2007). Landon et al. found no recognized improvement for clinical outcomes in any of the three areas that were studied (Landon et al., 2007) through collaborative participation. Landon et al. demonstrated that Health Disparities Collaboratives significantly improved the process of care for at least two of the three areas studied (Landon et al., 2007). These findings were consistent with the 2005 Asch et al. study, which also found that organizational participation in a common disease-targeted collaborative improved a wide range of processes of care and builds the case for utilization of collaboratives as a strategy for improving the process of care for patients with chronic disease (Asch et al., 2005).

The current study builds upon the Haggstrom et al. study by (1) analyzing data obtained from the organizational surveys performed among community health centers in 2005 and (2) specifically examining the organizational determinants of clinical decision support within this community health center population and the potential impact of CDS and IS on self-reported cancer screening performance. This study approach, which examined health center collaborative participation as a precursor for improvement, is consistent with the established studies conducted by Chin et al.; Landon, et al.; and Asch et al., through its utilization of survey data obtained from a 2005 HRSA Health Disparities Cancer Collaborative (HDCC) (Haggstrom et al., 2008). The current study assessed the strength of association between a list of identified organizational, patient, and provider factors and process of care outcomes for clinical decision support and information systems, as well as a cancer screening clinical care outcome with a sample of 44 community health centers (22 HDCC participants and 22 non-participants). With respect to clinical care outcomes, Haggstrom et al. explains that the provider self-reported cancer screening was obtained in the HDCC survey (see Appendix 2), where health center employees were asked whether their health center had "been able to improve the rate of the following cancer care processes in the past year: screening mammography, screening Pap test, colorectal cancer screening, timely notification of screening results, timely completion of additional diagnostic testing after abnormal screening results, timely beginning of treatment, and documentation of discussions about cancer screening." This study specifically assessed two very closely related aspects of collaborative activity, including (1) HDCC status at the time of the Haggstrom et al. study as either participant or non-participant and the extent to which such designation at the time of the survey was associated with the outcomes and (2) HDCC experience or prior exposure by the health center to this HRSA cancer collaborative or any other HRSA collaborative activity associated with the respective outcomes. The aims of this study are as follows:

Aim 1: To determine the organizational and/or practice setting factors, provider characteristics, and patient population characteristics that might be associated with the presence, intensity-of-use, and impact of clinical decision support (CDS) and information systems (IS) for colorectal, breast, and cervical cancer screenings in community health centers.

Hypothesis 1: Organizational and/or practice setting, provider characteristics, and patient population characteristics are associated with the presence of clinical decision support and information systems within community health centers.

Hypothesis 2: Organizational and/or practice setting, provider characteristics, and patient population characteristics are associated with the intensity-of-use of clinical decision support and information systems within community health centers.

Hypothesis 3: Clinical decision support and information systems intensity-of-use rankings scores are correlated with the 12-month self-reported breast, cervical, and colorectal screening improvement rate scores within community health centers.

Aim 2: To develop a computational model of community health center ***agents***, ***tasks***, ***knowledge***, ***groups***, and ***beliefs*** related to cancer screening practices and CDS/IS use using CONSTRUCT™ [1] that will inform both community health center CDS/IS implementation and cancer screening intervention strategies.

Aim 2a: To apply an organizational informatics methodology/technique–computational modeling and network analysis–to examine how changes in one or more organizational factor(s) (agents, tasks, knowledge, groups, and beliefs) in simulated hypothetical scenarios can impact the community center cancer screening and CDS/IS activity over time.

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[1] "Construct, developed by CASOS, is a multi-agent model of network evolution. Social, knowledge, and belief networks co-evolve. Groups and organizations are treated as complex systems, thus capturing the variability in human and organizational factors. In Construct, individuals and groups interact communicate, learn, and make decisions in a continuous cycle." http://www.casos.cs.cmu.edu/projects/construct/

Background and Significance

Several studies highlight the need for dramatic improvements in health care delivery through the application of health information technology (Doebbeling, Chou, & Tierney, 2006; Reid et al., 2005; Garg et al., 2005; Osheroff et al., 2007). Doebbeling et al. articulated well the rationale driving the national health IT and implementation of informatics efforts (Doebbeling et al., 2006):

> Technology applied within health care systems lags behind the rates of IT (information technology) adoption in other sectors. The acquisition and implementation of IT has great implications for the delivery of care in health care organizations (Lomas, 2007; McDonald et al., 1998). The rationale for IT applications include: (1) rapidly rising health care costs; (2) increasing regulatory requirements; (3) escalating patient safety and medical error concerns; and (4) calls for building better delivery systems to improve quality and eliminate waste (Bloom, 2002; Foundation for eHealth, 2003; Kohn, Corrigan, & Donaldson, 2000; Lomas, 2007; McDonald et al., 1998; Morrissey, 2003; Reid et al., 2005). The Institute of Medicine (IOM) and the National Academy of Engineering (NAE) have advocated widespread adoption of information technology (IT) to improve quality, facilitate evidence-based practice, and reduce medical errors (Bloom, 2002; Kohn et al., 2000; Reid et al., 2005). More effective health information technology (HIT) use is recommended for six key areas: (1) integrating point-of-care access with medical literature; (2) implementing evidence-based guidelines; (3) using computer decision support systems; (4) reviewing computer clinical data; (5) automating decisions to reduce errors; and (6) communicating electronically (Bloom, 2002).

The current study most closely focuses on several of the IOM and NAE priority areas. For purposes of this study, the overarching concept of HIT refers to any, all, or these six IOM areas, while two subcomponents of HIT include: (1) CDS, which represents applications specifically aimed at enhanced decision making, and (2) IS, which refers to systems designed to facilitate electronic communication and information management (Sperl-Hillen et al., 2004).

Implicit in HIT transformational efforts is the acknowledgement that organizational features are related to quality and performance. Hence, significant, sustained change to organizational environment (e.g., structure, process, design, etc.) is necessary for ongoing quality improvement (QI), including the promotion of cancer screening. Recent research suggests that structural differences in how care is organized may explain more performance variance than patient factors alone (Soban & Yano, 2005). Several studies suggest that there are a number of incentives that inspire health care organizations to adopt computerized clinical decision support (CDS), including cost savings, clinical performance improvement, improved clinician decision-making, adherence to evidence-based guidelines, medical error reduction, and more efficient information transfer (Weiner, Savitz, Bernard, & Pucci, 2004; Doebbeling, Chou, & Tierney, 2006; Reid et al., 2005; Bates et al., 2001). Research shows that clinical decision support can have an impact on the diagnosis and treatment of disease, as well as the corresponding impact on mortality, morbidty, and service quality. Garg et al. conducted a systematic review of CDS (Garg et al., 2005) and found that in "100 studies of clinical decision support [systems], "CDSS improved practitioner performance in 62 (64%) of the 97 studies assessing this outcome, including 4 (40%) of 10 diagnostic systems, 16 (76%) of 21 reminder systems, 23 (62%) of 37 disease management systems, and 19 (66%) of 29 drug dosing or prescribing systems (Garg et al., 2005)."

Doebbeling et al. asserts that the integration of CDS into clinical workflow has not reached its potential, and there has been inconsistent application of health informatics theory and practices (Doebbeling, Chou, & Tierney, 2006). In October

2005, the American Medical Informatics Association (AMIA), in partnership with the Office of the National Coordinator for Health Information Technology (ONCHIT), conducted a national workshop to outline a roadmap for national clinical decision support adoption, use, and impact evaluation within the United States (US) health care system (Osheroff et al., 2007). The committee defined clinical decision support (CDS) as any application that "provides clinicians, staff, patients, or other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care" (Osheroff et al., 2007). CDS can include a variety of applications and interventions, such as computerized alerts and reminders, clinical guidelines, order sets, patient data reports and [electronic] dashboards, documentation templates, diagnostic support, and clinical workflow tools (Osheroff et al., 2007). Studies have shown that CDS proves to be an effective tool in improving outcomes (Wright & Sittig, 2008).

The *AMIA Roadmap to National Clinical Decision Support* issued a statement that included three pillars for *fully realizing the promise* of CDS that include: (1) providing the best knowledge available when needed; (2) encouraging high clinical decision support adoption and effective use; and (3) facilitating continuous improvement of knowledge and clinical decision support methods (Osheroff et al., 2007). Both the first and second pillars highlight the importance of the timeliness and quality of data, as well as provider involvement in any potential clinical decision application and its integration into the clinical workflow (Ling et al., 2008). Provider involvement is of particular importance to colorectal, breast, and cervical cancer, because studies suggest that screening rates are positively related to provider recommendations (Lane, Messina, Cavanagh, & Chen, 2008). Some studies also demonstrate that technology may provide helpful cues-to-action and increase the likelihood of screening (Carney et al., 2008; Nease et al., 2008; Zauber et al., 2008). Beyond the provider level, system-level analyses that study the environment within which providers practice are needed to successfully determine which organizational, provider, and patient factors contribute to the presence or absence of CDS and IS. Additionally, studies are needed to determine if the presence of CDS and IS applications scaled to a level of the system can lead to measurable increases in colorectal, breast, and cervical screening rates within community health centers.

The selection of a disease focus upon cancer allows for the organizational factors to be tested in the narrower context of CDS and IS that is applied specifically for the purpose of improving cancer screening. Health care organizations influence the quality of care delivered through an array of factors that serve as the organizational context in which clinicians practice and patients experience care (Flood, 1994; Zinn & Mor, 1998).

Health Informatics is a discipline that is used to investigate and solve many complex issues involved in disseminating and implementing clinical decision support in health care organizational settings. While there are a multitude of ways health informatics is defined in practice, a clear working definition of health informatics is found in the United Kingdom (UK). The National Health Service (NHS) defines health informatics as “the knowledge, skills and tools which enable information to be collected, managed, used and shared to support the delivery of healthcare and promote health” (NHS, 2009). Health informatics is used to examine the interchange of people, processes, tools, and technologies that contribute to information collection, storage, dissemination, and patterns of usage (Bernstam et al., 2009; Collen, 1995; Friedman, 2008, 2009; Greenes & Shortliffe, 1990; Hasman, Haux, & Albert, 1996; Hersh, 2002, 2006; Hersh, 2009; Oh, Rizo, Enkin, & Jadad, 2005). The field of health informatics is being heavily relied upon to explore the many reasons for the presence and patterns of health information technology adoption throughout all levels of the health care continuum (Anonymous, 2008; Butte, 2008; Embi & Payne, 2009; Fletcher & Fletcher, 2005; Shortliffe & Cimino, 2006; Zerhouni, 2007). When specifically focused on health care organizations, organizational informatics might be considered a sub-specialized area of health informatics that more closely examines the presence of health information technology and its organizational and social-technical determinants. There is also an emerging view that the organizational setting represents a complex adaptive system consisting of many interactive parts that might better explain a particular organizational outcome.

Recent advances in social networks, cognitive sciences, computer science, and organization theory have led to a new perspective on organizations that takes into account the computational nature of organizations and the underlying social and knowledge networks (Krackhardt & Carley, 1998). At the heart of this perspective is the argument that organizations are complex, computational, and adaptive (Prietula, Carley, & Gasser, 1998). They are also synthetic agents composed of other complex, computational, and adaptive agents constrained and enabled by their position in a social and knowledge web of affiliations linking agents, knowledge, and tasks. Meaningful insights into organizational behavior can be gained through the use of computational models. The author of this research expects to find this to be true, whether the organization is a collection of people, artifacts, or any combination of the two. The only difference is that different aspects of the organizational setting (or agents) will have different cognitive and communicative abilities, including different capabilities for acquiring, processing, storing, retrieving, and communicating information (Carley, 1998).

This comprehensive application of complexity science towards understanding patterns of information science and information technology use, relative to some set of organizational predictors, contributes to the developing community of practice known as organizational informatics. The convergence of informatics, organizational studies, and cancer prevention and control is articulated in the article, "Harnessing the power of an intelligent health environment in cancer control" (Hesse, 2005). In this review, Dr. Bradford Hesse outlines how the areas of informatics (e.g., biomedical informatics, medical [health] informatics, and consumer informatics), environmental determinants (e.g., organizational, individual, and providers), and cancer prevention and control efforts are combined to formulate an overarching strategy in the "War on Cancer" (Hesse, 2005). According to Hesse, three distinct but interconnected domains of informatics will converge in the fight against cancer. The first area, bioinformatics, uses advanced computing techniques and wide area connectivity to support basic biomedical research in studying the cause, diagnosis, and treatment of cancer (Hesse, 2005). The second area consists of the expansion of medical informatics–a term that has been expanded to being synonymous with clinical or health informatics–which will focus on the application of computer technologies to the delivery of health care

(Hesse, 2005). Finally, consumer informatics describes the application of computer delivery systems–particularly over the world wide web–to individuals and their caretakers (Hesse, 2005). With respect to health informatics and the delivery of health care in the fight against cancer, which are the focus of this study, Hesse explains that information technology must play a key role in bringing the right information into the right relationship at the right time to take full advantage of the windows of opportunity in cancer care (Hesse, 2005). Hesse further defines the four types of computer applications that play a key role in both the discovery of cancer and delivery processes, including: (1) interoperable and interconnected records management systems, (2) bibliographic search and retrieval systems, (3) decision support systems, and (4) biomedical imagining systems (Hesse, 2005). The emphasis in this study is to explore how the multidisciplinary field of health informatics–more specifically organizational informatics focusing on the health care setting itself–can assist in explaining the presence of clinical decision support activity within community health centers, and the corresponding impact it would have on facility-level colorectal, breast, and cervical cancer screening rates.

Several theoretical models and frameworks, such as the Zapka et al. framework (Zapka et al., 2003), have emerged to support the investigation of clinical decision support at the health systems level as an antecedent for cancer screening improvement. These cancer control conceptual efforts have synthesized theory and frameworks from fields such as health services research, cancer care delivery & behavioral oncology, organizational analysis, and health informatics. Many of these frameworks have focused on the question of adoption of CDS and IS within a given organizational setting. Despite the heavy emphasis on adoption studies, the overall adoption rates of health information technology in the form of CDS and IS has remained relatively low (Kazley & Ozcan, 2007). In 2005, estimates of electronic medical record adoption ranged between 20% and 30% (Fonkych, Taylor, & Rand, 2005; Kazley & Ozcan, 2007). One major reason for the lack of wide-scale adoption is the vast degree of heterogeneity of hospital (health-facility) characteristics; smaller practices and organizations may have greater barriers to implementing health IT (DesRoches et al., 2008; Ford, Menachemi, Peterson, & Huerta, 2009; Samantaray et al., 2011). Each small practice or low-resource system (e.g., community health centers) must first successfully account for the barriers and facilitators of a given health information technology within its own unique setting–in this case CDS and IS–before taking on the challenge of understanding the formulation of a strategy for adoption. Informatics professionals can help in this task by employing techniques drawn from systems-thinking literature (NetLibrary, 2009) to conduct tests of how altering the predictors can increase or decrease the likelihood of adoption and have the desired impact on specific quality process measures, in this case, colorectal, breast, and cervical cancer screening rates.

CHAPTER 2: LITERATURE REVIEW

This chapter will present a review of the literature in three main sections: (1) an overview of clinical decision support in cancer screening, (2) understanding the research when defining organizational determinants or factors of clinical decision support, and (3) examining clinical decision support and knowledge management to better understand the concept of the learning organization. The study's author conducted a search of the peer reviewed literature of several online libraries, which included WorldCat, Embase, CINAHL (EBSCO), Medline (via PubMed), and Web of Science. The search included all peer-reviewed articles up to October 2011. Exceptions were excluded based on the following criteria: (1) the clinical decision support intervention or activity focused on patient decision making, behavior, or choices, as opposed to the provider or health care facility; (2) the article merely represented a review of software and made little or no reference to provider characteristics or facility-level factors; or (3) the cancer focus was on disease progression or rate of progression, not on the outcome of the cancer screening rate.

Clinical Decision Support and Cancer Screening

This chapter begins with an overview of clinical decision support systems and tools for cancer screening. In this study, clinical decision support has been previously defined in both the Zapka et al. framework and the Chronic Care Model (Wagner et al., 2001) as an activity that supports "guideline development, updating, dissemination, and the education of providers. It also involves continuing education, and protocols/critical pathways/prompts for providers" (Sperl-Hillen et al., 2004; Zapka, Taplin, Solberg, & Manos, 2003). The current study's author has also defined Clinical Information Systems (IS) as encounter reminders, flowcharts, risk lists of screenings due to the tracking of patients not adhering to screening, follow-up, or other recommendations (Sperl-Hillen et al., 2004; Zapka et al., 2003). This study combined these two very closely aligned concepts–clinical decision support and clinical information systems–into the composite construct of CDS and IS (equally represented as CDS/IS). However, this literature review treats the terms as closely aligned and/or synonymous, and as such, will only refer to CDS from this point forward within this chapter unless the two concepts are separately identified in the referenced literature. It should be noted that this review is not intended to be chronological in nature, and as such, the referenced studies and systematic reviews may be out of chronological order. Their order will be determined by their relevance to the topic being presented. The rationale is twofold: (1) the field of health information technology is fluid and dynamic and, in many instances, still unproven, and as such, may not be as dependent upon time, and (2) several of the references listed are review papers that cover previous years of activity, and as such, the publication dates may not fully represent state-of-the art health information technology. Instead, the author has chosen to focus on themes in the literature that may indeed represent either a trend or consensus in the fields of health IT and health informatics.

The search terms used in this portion of the literature review included clinical decision support in conjunction with either “cancer screening” or “cancer-screening rates.” Several databases also allowed for similar or “like” term searches and the author conducted those where appropriate.

Clinical Decision Support in Support of Quality Processes (e.g., Cancer Screening)

In 2003, Goins et al. decided to describe the system strategies used to reduce failures in the delivery of breast and cervical cancer screening (Goins et al., 2003). Their study examined breast and cervical cancer screening using several indicators, including: (1) leadership and policies, (2) clinical decision support, (3) delivery system design, (4) clinical information systems, and (5) patient self-management support. Seven large HMOs participated in an assessment of their breast and cervical cancer screening policies and procedures in an effort to reduce failures in the delivery of breast and cervical cancer screening services. These HMOs were identified as organizations that traditionally had high performance rates for these services. Goins et al. found that the guidelines were fundamentally similar across plans for both breast and cervical cancer screening for each of the five indicators, although the specific guidelines and written policy documents differed. Their study concluded that leadership commitment can be reflected in involvement in research, performance standards expectations, and financial and other incentives. Service arrangements can vary but should emphasize quality control and improvement. Clinical decision support strategies (e.g., guidelines and dissemination) are important in defining risk and periodicity, and that clinical information systems (e.g., tracking process of care) and member self-management (reminders and notifications) that reinforce clinician and patient actions are important, but mode varies and vigilance about awareness and implementation is critical. Goins et al. also concluded that variable strategies should be considered for different types of screening tests and care processes across the continuum of cancer care.

The nature of the study did not allow them to assess the relative importance of a particular indicator/strategy over another. Five of the seven HMOs were Kaiser facilities, and they may have accounted for greater consistency between facilities than what would be recognized between the other two members of the study. A more detailed assessment of these variables and their predictive power for facility-level cancer screening performance was indicated. The Goins et al. study did not fully address the question of whether or not one can successfully conclude that there is a measurable relationship between clinical decision support and cancer screening outcomes.

Ferrante et al. sought to examine the relationship between patient-centered medical home (PCMH) and preventive services (e.g., receipt of cancer screening, lipid screening, influenza vaccine, and behavioral counseling). Ferrante used the term “enhanced health IT” to represent such things as clinical decision support and clinical information systems, and within this study, enhanced health IT was tested as one of the predictors of PCMH, which also included cancer screening (Ferrante, Balasubramanian, Hudson, & Crabtree, 2010). Ferrante et al. studied 24 primary care offices with data collected between January 2006 and May 2007 in the New Jersey Family Medicine Research Network. These primary care offices participated in a randomized controlled intervention study called SCOPE (Supporting, Colorectal Cancer Outcomes through Participatory Enhancements). Ferrante et al. found that three of the four high-tech principles for quality and safety showed no statistical significance in predicting preventive services, such as cancer screening. The only high-tech indicator shown to be significant was their identified variable for clinical decision support tools. Ferrante's study concluded that overall enhanced information technology capabilities did not prove to be highly correlated with those PCMH principles that showed higher rates of preventive services. The study did not examine health information technology adoption patterns, use, or stage of implementation, and as such, the findings on health IT impact on preventive services may require additional research. Also, because this was an observational study, causality may not be conferred from their associations. This study suggested that trying to empirically define the relationship between enhanced health IT and health outcomes, such as cancer screening, may not be easy to achieve.

Millery et al. conducted a 2010 Systematic Literature Review of 105 peer-reviewed studies between 2004 and 2009, along with eight key informant interviews, in an attempt to identify evidence regarding health IT and quality outcomes in Underresourced Settings (URSs) and their corresponding impact on disparities (Millery & Kukafka, 2010). Fifteen studies were identified as having met the URS criteria and of those, 7 of the 15 studies did not focus specifically on the topic of URSs and, in fact, did not find significant evidence linking health IT and URS's quality. Key informants' comments and recommendations regarding URSs were to (1) stress the need for Health IT to be used as a tool and not an end in itself, (2) emphasize that URSs face competing priorities and face great challenges to introducing new technology, and (3) partnering among organizations and collaboration was key to implementing new technology. The study highlighted four major gaps in evidence regarding health IT, quality, and URSs: (1) there is a lack of research conducted in URSs related to barriers to implementing new technology, (2) quality impact of health IT is supported in some cases but effectiveness studies are needed to examine generalizability, (3) some levels of the health care system are largely untapped in health IT research; namely, patient, organizational, and environmental levels, and (4) there is a need for research to examine clinical quality improvement methods and health IT to improve quality. Given the small number of studies that addressed URSs, is was difficult to identify trends or aggregate findings about health IT and quality in URSs.

A closely related study and one referenced in the Millery et al. review did in fact focus specifically on health care screening in an under-resourced setting and the role that clinical decision support played in screening rates. In 2005, Steele et al. sought to determine the impact of computerized clinical decision support and guided web-based documentation on screening rates for latent tuberculosis infection screening (LTBI) (Steele et al., 2005). Their study included 8,463 patients seen at two primary care outpatient public community health center clinics in late 2002 and early

2003. The study reported that among 4,135 patients registering during the post-intervention phase, 73% had at least one CDC-defined risk factor and 610 met the alert criteria (birth in a high-risk TB country and age <40 years) for potential screening for LTBI. Adherence with the LTBI screening guideline improved significantly from 8.9% at baseline to 25.2% during the study phase (183% increase, $p<0.001$). As a result, Steel et al. concluded that computerized, clinical decision support using alerts and guided web-based documentation increased the screening of high-risk patients for LTBI. This type of technology could lead to an improvement in LTBI screening (Steele et al., 2005). Despite these findings, few studies have evaluated the use of computerized clinical decision support (CDSS) to improve screening rate outcomes. This was the only study found within these search parameters to focus exclusively on the community health center setting. There were no studies found to specifically examine the link between CDS and cancer screening specifically within this setting. This study did not examine the organizational and/or practice setting factors, patient characteristics, or provider characteristics that are unique to the community health setting, which might have an impact on screening.

Provider Acceptance of Clinical Decision Support Systems in Health Practice

Several studies examined the subject of clinical decision support and health outcomes and the role that providers have as either agents of change or end users of clinical decision support. In 2005, Zapka et al. investigated the clinician perceptions of guidelines, reminders for screening, as well as plan and practice commitment in order to assess where opportunities exist to improve the breast and cervical cancer screening process (Zapka et al., 2005). Their study included three integrated health care delivery systems: (1) a group sample of 761 primary care clinicians from the Health Cooperative, (2) Kaiser Permanente Colorado, and (3) Kaiser Permanente Northern California, with a data collection between September 2000 and December 2000. It included a combined total of 3.92 million members and 80 practice sites. They employed a two-stage cluster design based upon (1) the plan and (2) the sampling unit specialty. Zapka et al. reported that relative to Guideline Awareness, there was over 90% clinician agreement for both breast and cervical cancer screening. The study found that Guideline Content Agreement varied from 57% to 88% for breast and 78% to 98% for cervical cancer categories. Relative to Perceived Guideline Usefulness, about 87% of clinicians found it either very or somewhat useful for breast cancer screening and about 84% found it either very or somewhat useful. Clinician agreement concerning clinical information systems to promote cancer screening varied from 65% to 90% for one of four components for breast cancer and 51% to 72% for one of four components for cervical cancer. Previous studies underscored the importance of organizational strategies to increase screening. However, this study concluded that there might be differing issues at the local practice system as opposed to system-wide issues. Provider reports of congruence and perceived effectiveness were shown to be valuable to health plan polices and implementation efforts for cancer screening improvement. Since this study focused on only three very large non-profit heath care organizations, issues of generalizability were raised and future studies were suggested to further investigate the relationship among provider perceptions, CDS, and cancer screening outcomes. The complex interaction of other factors that might influence physician behavior, such as financial incentive, management strategies, structural characteristics, information strategy, and normative influence, was not examined within this study.

In 2009, Saleem et al. investigated current challenges to Colorectal Cancer (CRC) screening and follow-up, and the role that CDS can play in this outcome (Saleem et al., 2009). They, like Zapka et al., used a sample of three large health care facilities. The Saleem et al. qualitative study included three benchmark institutions for health IT: (1) the Veteran's Health Administration (VHA), (2) Regenstrief Institute (RI), and (3) Partners HealthCare System (PHS). The study employed direct observation of CDS use of 54 providers, 7 key informant interviews, 62 patient-provider encounters, and focus groups (that included 11 participants) to identify best practices and barriers to effective CRC CDS for the fecal occult blood test (FOBT), flexible sigmoidoscopy, and colonoscopy. They found that the VHA deployed CDS in the form of clinical reminders; RI used paper encounters for reminders for CRC screenings; and PHS used a template health maintenance list. The study identified six common barriers to CRC screening, including (1) facilities receiving and documenting "Outside" Exam Results, (2) CRC CDS were at times not accurate, (3) some compliance issues were identified, (4) poor electronic health record (EHR) or CDS usability, (5) an occasional lack of coordination between primary care and gastrointestinal (GI) providers, and (6) issues relative to acute vs. preventive care service areas. The study concluded that challenges remain for all stages of CRC screening and follow-up, such as the design of EHR and CDS, provider receipt of the results, and greater coordination between units and providers. Further study was indicated to examine the applicability of these results to institutions with less experience in CDS, as the institutions in this study were identified as benchmark institutions for health IT. Issues of generalizing these results became apparent because of the small sample size. The results were reported largely in terms of system issues or barriers that providers might encounter in the use of CDS, but there was limited emphasis placed upon provider beliefs about CDS and its overall effectiveness in achieving cancer screening objectives.

This study attempted to address one aspect of physician perspective of IT in health care. Ketcham et al. measured how much physician IT can influence disparities in care from the context of Coronary Heart Disease (Ketcham, Lutfey, Gerstenberger, Link, & McKinlay, 2009). Previous studies focused on barriers to implementation of IT but studies have often failed to find that physician IT improves the overall quality of care. Ketcham et al. surveyed physicians working in primary care practices across North and South Carolina between 2006 and 2007. This represented a randomized experiment of 256 physicians measuring the relationships among three health IT functions: (1) feedback, (2) CDS-Patient Risk Estimator, and (3) CDS-Electronic Reminder, and five process-of-care measures (e.g., certainty of diagnosis, the number of tests ordered, and the number of medications). The study found that feedback, disease prevalence, or electronic reminders did not show any statistical significance on effecting diagnostic uncertainty or provider decisions. This study highlighted the need to examine a wider range of IT potential effects on disparities and that much less is known about how IT functions across a broad range of institutions, how decision outcomes vary by type of IT, and by how process outcomes vary by patient or provider characteristics. This study also did not capture how physician IT beliefs impact CDS presence and/or intensity of use.

One study did focus exclusively on HIT as a function of technology acceptance among physicians. In 2007, Yarbrough et al. conducted a Systematic review of physician acceptance of information technology and the technology acceptance model (TAM) (Yarbrough & Smith, 2007). Studies identified a variety of CDS applications, which included computerized physician order entry (CPOE), telemedicine, EMR, Internet-base applications, handheld computers, electronic mental health resources, and medical error reporting systems. The study concluded that factors that influence physicians' acceptance of a new technology included time/practice related issues, organizational issues, personal issues, and system-specific characteristics. There were some identifiable limitations of both the study and the TAM model. Two notable limitations of the TAM model noted in the review were its inability to consider the influence of external variables and barriers to technology, and that context variables must be added to the analysis using TAM to increase its explanatory power. Finally, the studies presented did not close the gap on much needed empirical/quantitative research to identify physician barriers to health IT.

Another study that specifically examined physician barriers of computerized decision support focused on depression. Trivedi et al. conducted a software evaluation of a clinical decision support system for depression (CDSS-D), which was developed by the University of Texas Southwestern (UTSW) Medical Center, Dallas (Trivedi et al., 2009). Fifteen clinicians across five states participated in the study. They accrued over 300 outpatient visits from 168 patients to examine the feasibility and effectiveness of CDSS-D and assessed the associated organizational factors involved in implementation. The study identified computer literacy and hardware/software requirements as initial barriers to CDS implementation. Additionally, the clinicians reported as potential barriers their concerns about the negative impact on workflow and the potential need for records duplication during the transition from paper to electronic systems of medical recordkeeping. The study concluded by presenting the issues into three groups of categories, including: (1) issues that prevented use of the program (e.g., spell check, links to reference material, and editorial ability), (2) issues that discouraged use of the program (e.g., speed and reliability), and (3) issues of program convenience (e.g., IT support). This study highlighted the notion that the adoption of technology is less of a single event and more of a multistage process that involves the routinization of technology after it is implemented and demonstrates that future studies of this evolutionary process are needed.

To better understand the organizational factors of influence for CDS, several studies were identified that looked at the question from both the cancer-specific and non-cancer specific viewpoints. In both cases, the provider perceptions, beliefs, attitudes, and level of engagement proved essential in the adoption, use, and implementation of CDS.

Organizational Determinants/Factors of Clinical Decision Support Presence and Use

After reviewing the literature that explored the relationship between clinical decision support and health outcomes, particularly cancer screening, there was a need to explore some of the contextual factors or determinants that might serve to influence the adoption, use, and/or implementation of clinical decision support. It should be noted that, while this study is focused solely on factors that account for the presence and intensity of use of CDS, the studies on CDS did not always distinguish between those categories and, at times, they may have also included the process of adoption and implementation as focal points. This chapter highlights literature describing all levels of CDS, which include topics of adoption, use, and implementation, and where appropriate, it will identify where the CDS focus area is in the summaries.

Several previous studies referenced organizational factors directly or indirectly as an important element of their overall study (Feifer et al., 2006; Millery & Kukafka, 2010; Saleem et al., 2009; Zapka et al., 2005). Currently, the emphasis is being placed on evaluating studies and/or systematic reviews that sought to understand this relationship formally as the primary intent of the study. Some studies examined the organizational unit as a single entity, while others examined varying perspectives within the organization, which most often included providers/physicians, administrative staff, and occasionally, patient-level factors, all which are components of the organizational setting.

The search terms used in this portion of the literature review included clinical decision support in conjunction with either "organizational determinants," “organizations factors,” or “operations research.” The search was then repeated, combining these same search terms with the added limit of “cancer,” to examine these factors from both the general and cancer-specific perspectives. Several databases also allowed for similar or “like” term searches, and the author conducted these searches when appropriate. This review included both general and specific findings, and where they were specifically related to cancer has been noted. Additionally, another search term was created for consideration in this section: the term “healthcare system” or “health care system” was combined with “cancer screening rates.” It was important to understand how previous studies treated the question of what organizational factors or determinants served to predict the adoption, use, and/or implementation of clinical decision support.

Clinical Decision Support and Health Care Organizational Factors

In 2004, Weiner et al. asked the question: How do integrated delivery systems adopt and implement clinical information systems? They designed a study to examine how five integrated delivery systems adopt and implement clinical information systems. They also examined how organizational factors and IT characteristics affect adoption and implementation (Weiner, Savitz, Bernard, & Pucci, 2004). The study included five integrated delivery systems (IDS)–one from each major region of the U.S., four of which were not-for-profit, and one that represented a government/state-owned facility. These five IDS organizations were each evaluated on a series of organizational characteristics that included size, ownership, number of staffed beds, AHA (American Hospital Association) services provided, insurance products, year formed, and management style/structure. The study also examined the Organizational Learning Culture curve measured via the integration life cycle (to be discussed in the following section on organizational learning). The study reported that IDSs in later stages of the integrated life cycle (i.e., mature and above) would take a more strategic system-level perspective in clinical IT decision-making than would IDSs in earlier stages (i.e., emergence). The organizational factors that promoted CDS adoption included cost savings, clinical performance improvement, and information transfer. The study also found that provider feedback and participation related to IT adoption varied more by IT type and not by organizational characteristics. In some but not all cases, provider feedback and participation in the IT system design and implementation proved to be a significant factor in adoption. The study concluded that IDSs showed high clinical involvement in clinical IT adoption at both the local and system level. Clinical champions or small groups of providers were often drivers in the agenda for clinical information systems. There was also a noted relationship between the stage of integration life cycle and the types of clinical information systems present. The study provided a thorough grounding in the basic study design used for examining the organizational determinants/factors for CDS if others were to follow and test these relationships in other settings. However, additional research is needed to establish the statistical generalizability of the study. Weiner et al. acknowledged there may not have been sufficient sample size and differentiations in the integrated life cycle classifications to be able to observe subtle distinctions.

A comparable study was published one year prior to Weiner et al.'s study, which described advanced clinical information systems in the context in which they had been implemented and were being used. Like Weiner et al., this study also included five participants. This case series analysis included five U.S. hospitals, all of which won the Computer-Based Patient Record Institute Davies' Award. The data for this study was collected from interviews, observations, and document analysis over a two-year period starting June 2000 (Doolan, Bates, & James, 2003). The study found that all five sites implemented computerized results but had varying levels of other computerizing functions. Some of the organizational factors measured in the study, including leadership, management commitment, and vision, were considered very important to successful implementation. The study also reported an interesting challenge in the effort to balance computerization and maintain health care delivery productivity. The study reported that there was often a trade-off scenario manifesting. Doolan et al. noted trade-offs being made between adding computerized functionality and keeping response speed of system objectives. This would probably fall into the realm of potential barriers and resistance to change. These two items will probably have to be addressed in future studies where they are specifically tested. The Doolan et al. study concluded that the use of computerized decision support seemed to be consistent with previous studies that measured leadership and administrative commitment, but there was no evidence reported here, and little formal evidence has been found in the literature that clearly demonstrates the benefits of CDS within the health care delivery process.

Until now, the author of the current study has been making reference to the fact that health IT (HIT) in general, and CDS in particular, are both often comprised of a multiplicity of components. One of the most comprehensive studies listing the multiplicity of health IT (HIT) level of use by specific subcategories was the Burke et al. study that explored the organizational factors associated with 27 categories of HIT in response to the six care aims articulated by the Institute of Medicine (IOM) (Burke, Menachemi, & Brooks, 2005). In October 2003, this study invited 95 Florida Acute Care Hospitals to respond to a Chief Information Officer's (CIO) survey that addressed HIT use in the areas of safety, effectiveness, patient-centered, timeliness, efficiency, and equity, and to what extent organizational issues (e.g., organizational slack, ownership status, channels of communication, and collaborative memberships) explained the level of HIT use. There were a total of 27 different subcategories of HIT assessed in the study and found that hospitals were utilizing 38% of the available HIT associated with care aims. The mean HIT use for the six specific care aims ranged from 30.8% to a high of 43.2%. The results for organizational factors were mixed and shown to be inconsistent as a predictor of HIT within the six IOM areas in hospitals. Organizational size had been shown to be significant, and it was suggested that this finding could also be extended to financial issues when predicting HIT. The study identified the level of use of HIT within the study sample but did not address whether or not these hospitals were more safe, effective, patient-centered, timely, efficient, or equitable through their HIT use. The study did not rank the relative importance of one HIT application over another. It demonstrated that additional research was needed related to the outcomes associated with HIT use in support of IOM care aims.

Another study that examined a multiplicity of technology was that of Brooks et al., where they conducted an examination of 10 technologies comprising a patient safety index (PSIT) (Brooks, Menachemi, Burke, & Clawson, 2005). Some of the factors included in the PSIT index included a pharmacy information system, computerized patient records, handheld PDAs, computerized practitioner order entry (CPOE), a clinical decision support system, automated alerts, and bar-coded medication management. Just as was the case in the Burke et al. study, Brooks et al. also targeted Chief Information Officers (CIO) within a sample of 199 acute care hospitals (170 urban; 29 rural), where the data was collected between May 2003 and October 2003. The study found a similarity to Burke et al., in that HIT usage was limited at best. Brooks et al. revealed that, on average, those participating hospitals only used three of the 10 PSIT applications. When controlling for organizational factors (e.g., bed size), rural and urban hospitals did not differ with respect to overall PSIT adoption, nor did the utilization differ significantly between nonprofit and for-profit organizations. Some of the limitations discussed were that the study focused on hospitals in only one state, which may not be generalized to other states. In addition, the study, as such, may not explain causal relationships. Lastly, the study did not address PSIT in relation to specific patient outcomes and quality of care issues.

These recent studies suggest that, for some reason or another, the uptake of HIT in the form of clinical decision support and several other technology applications seemed sluggish within health care facilities. While there were several organizational factors identified, the overall uptake, even within health care institutions identified as above average performers for HIT, were still not reaching levels of maximum capability for HIT implementation. To investigate this further, Shortell et al. conducted an empirical assessment of high-performing medical groups (Shortell et al., 2005). The goal of the study was to develop a scorecard approach to differentiate between high-performing versus low-performing medical groups in four domains that included (1) Clinical Quality Performance, (2) Patient Satisfaction, (3) Organizational Learning, and (4) Financial Performance. The primary component of organizational learning that Shortell et al. identified was that of the availability of clinical information technology. Shortell et al. used two different data sources in their study: (1) The National Study of Physician Organization collected data nationwide for 1,104 physician organizations from September 2000 to September 2001 and (2) the scorecard was developed from a national database of 693 medical groups. The study reported that a relatively small number of medical groups were classified as high performers. There was also a combination of external environmental and internal environmental factors involved in differentiating high from low performers. Having a either quality centered culture and/or the capability of reporting of results appeared to be the most consistent and strongest differentiators of high-performing versus low-performing medical groups. While this study did not exclusively focus on clinical information systems as the primary outcome of interest, it was in fact a key measure in the category that accounted for organizational learning (the topic of the next section) and did suggest that both internal and external environmental factors can be used to differentiate between high and low performers for variables, such as clinical information systems. The study did not assess causality, and one limitation of the study's findings pertains to groups of 20 or more doctors and cannot be generalized to small group practices.

One other study that examined the work environment (WE) as a factor of HIT uptake was performed in 2010 by Reinhardt testing for environmental factors that might explain reported caller outcomes of a telephone advice nursing (TAN) service and the respective impact on patient outcomes (Reinhardt, 2010). Data was collected from three HMO's that were listed as TAN sites in the original Advice Study to measure the effectiveness of this sort of telephone advice intervention. There were 96 nurses who participated–six nurses from each site, comprising a subgroup of 18 nurses who volunteered to have their calls recorded, totaling 865 calls. The study found that WE scores were significant for work stress, communication, and autonomy, but not for collegial relationships, or organizational support. None of the WE scores found a significant relationship to patient outcomes. The study concluded that examination of the WE factors on clinical practice in response to a telephone advice technology is important and may open a new domain of practice focused on explaining this relationship. While this study did not examine the traditional forms for computerized decision support, it did examine the relationship between the introduction of a technology application and the environmental factors that might impact both the use and acceptance of this new technology and the corresponding impact this technology might have on clinical outcomes.

One common theme emerging from these previous studies is that: (1) CDS use and uptake may not be as high as desired by health IT policy makers/administrators, (2) there might be some organizational and/or environmental factors that might explain CDS use and acceptance, and (3) there is some difficultly is effectively measuring the corresponding impact of CDS on health outcomes. In 2009, Holden et al. attempted to address these issues in a systematic review of theoretical approaches to health information technology usage behavior for patient safety (Holden & Karsh, 2009). Holden was able to define several groups of theories and their respective principles, which would influence the usage behavior of HIT and included:

- Motivation Theories
  - P1 – HIT use should meet, not jeopardize, user needs
  - P2 – HIT use should be easy (low-effort), not difficult
  - P3 – HIT use should lead to observable outcomes
  - P4 – HIT use outcomes should be positive/useful
- Decision Theories
  - P5 – User self-efficacy will influence HIT use decisions
  - P6 – Feedback following HIT usage behavior will influence future usage behavior
  - P7 – HIT usage behavior is an interaction of multiple environmental and personal factors. There is no one cause and no single solution
  - P8 – HIT usage behavior is based on users' beliefs and the attitudes, norms, and perceptions of control produced by these beliefs
  - P9 - One's social and cultural environment affects the desirability of HIT use
  - P10 – The degree to which HIT use is voluntary, or controllable, will have an effect on HIT usage behavior

- Theories of Technology Acceptance
  - P11 – Successful HIT design depends on the fit between characteristics of HIT and characteristics of the work system
  - P12 – Successful HIT outcomes depend on the fit between elements within the work system, where the HIT is implemented relative to the first theme of the study

The Holden et al. review concluded that the Theory-based model of the multilevel interactive determinants of HIT usage behavior is preferable to the atheoretical research, design, and implementation of HIT, which is characteristic of current practice. The principles that Holden et al. lists could effectively serve as one or more hypotheses to be tested in future research studies that examine the relationship between HIT and organizational factors. Holden et al. did not actually test these hypotheses but listed them as a series of focal areas that others should consider within their adoption and/or implementation of HIT or research on the subject.

One study that explored the overall readiness for change in relation to health IT was discovered. In 2008, Weiner et al. conducted an analysis of 106 peer-reviewed articles on the topic of organizational readiness for change measured in the field of health services research between January 1990 and July 2007 (Weiner, Amick, & Lee, 2008). The review sought to provide a comprehensive assessment of how organizational readiness for change had been defined and measured. The review found that published estimates indicating readiness for change ranged from 20% to

60%, depending on the type of change. Overall, they observed little consistency in the terminology or conceptualization used to describe organizational readiness for change; there was limited evidence of reliability or validity for most currently available instruments used to measure organizational readiness for change, and there were few rigorously conducted empirical studies of the consequences of organizational readiness for change in the context of intended outcomes. This review suggested that a gap exists in connecting the process of empirically measuring organizational readiness for change. Such a gap might be extended to new technology interventions that are designed to increase health information technology adoption and CDS uptake. This review may provide a basis to support the argument that a lack of readiness for organizational change can result in limited success of CDS interventions.

Clinical Decision Support and Knowledge Management: The Learning Organization

This section of the literature is focused on understanding the health care facility as a learning organization within the context of knowledge management. The first section of this literature review highlighted studies that helped to define the field of clinical decision support and its relationship to health outcomes, with an emphasis on cancer screening. The second section highlighted studies that identified the contextual or organizational factors that shaped the adoption, utilization, and/or implementation of clinical decision support. Within section two, the author explored how organizational factors/determinants, referred to in some studies as environmental factors, can serve to explain how or why clinical decision support was used and accepted by the health care facility. Section two also examined the role of providers/physicians and leadership in any clinical decision support intervention or implementation. This section intends to build on the previous two sections by exploring how the use of clinical decision support specifically, and in some cases, health information IT (HIT) in general, can contribute to an overall knowledge management strategy. The goal is to understand how the health care facility organizes its knowledge resources and measures learning as a result of using what Ferrante et al. referred to as enhanced technology (Ferrante et al., 2010). To explore this, "clinical decision support" was paired with one of the following search terms– "knowledge management," "business intelligence," "organizational intelligence," "organizational learning," and "cognitive systems engineering." An additional set of searches was performed by adding the term "cancer" to further identify studies that specifically focused on cancer-related activity in any or all of these areas. Several databases also allowed for similar or "like" term searches and these searches were conducted where appropriate.

The Socio-Technical Aspects of CDS and Cancer Screening

In 2006, a study by Feifer et al. sought to assess the impact of a mediated decision support intervention of primary care patient prostate screening (Feifer et al., 2006). The intervention was aimed at improving adherence to clinical practice guidelines. Feifer et al. conducted a review of multi-method interventions (e.g., practice performance reports, site visits, and network meetings) designed to bring about improvement by addressing personal and organizational factors in association with a previous demonstration project called Accelerating the Translation of Research into Practice (A-Trip). The intervention was called the Practice Partner Research Network (PPRNet) Intervention and was implemented in 1995 in a collaboration between the Department of Family Medicine at the Medical University of South Carolina and its Electronic Medical Record (EMR) vendor. Feifer et al. found that efforts designed to translate medical research into practice and improve medical quality should outline the changes, decide on factors of influence, and select from the menu of methods in its intervention that will alter those influences. Such a menu should draw from four fields of organizational theories: (1) Organizational Change, (2) Organizational Learning–asserts correlation between rate of learning and success, (3) Complex Adaptive Theory–asserts that organizations evolve, and (4) Diffusions of Innovations theory–examined rates of innovation. This review suggested that varying combinations of these methods and theoretical approaches have been employed with mixed success in meeting cancer-screening objectives. The goal of using clinical decision support in support of cancer screening will require multi-method approaches when the aims of change are complex. This study further suggested that the attempt to address cancer-screening rates using clinical decision support within health care facilities may be a rather complex agenda.

One challenge in a multi-method approach is to define the agents of learning. Feifer et al. suggested that organizational learning was one of the four critical areas requiring investigation. This next study attempted to define how members of a health care arena might in fact interact with elements designed to inform them. The first concept of health care cognition was explored by Nemeth et al. in an observational study that sought to understand, as one of their themes, the work domain as a complex, high hazard, time-pressured, interrupt-driven environment (Nemeth, Connor, Klock, & Cook, 2006). The study suggested that cognitive artifacts, such as highly encoded, compact representations of what matters in that particular work domain, and their use may reveal hidden subtleties of the coordinator's work in their health domain. The study concluded that acute healthcare settings are difficult to study. On the one hand, at times, they may require deep domain knowledge on the part of the investigator. They may also require a detailed understanding of many local details and contingencies that both offer opportunities and constrain opportunities, for action. While Nemeth et al. did not specifically define clinical decision support as a cognitive artifact, on a general level, CDS can easily meet the Nemeth et al. criteria of being a highly encoded compact representation of what matters in a clinical domain. This study did not identify a specific set of system factors that might be identified as antecedents to the actual use of these cognitive artifacts but it did pose the argument that there is a level of complexity within the health care environment that might contribute to the general creation and use of cognitive artifacts.

A 1999 evaluation study that examined how collaborative prototyping can improve clinical decision support development within a surgical intensive care unit (ICU) was discovered (Ehrhart, Hanson, Marshall, Marshall, & Medsker, 1999). Ehrhart et al. argued that the decision support systems development strategy of build it, test it, and train them to use it, should be expanded to take into account complex adaptive environments, learning required to improve organizational capability, and creative discovery and collaboration. While these assertions were not specifically tested and the ability to duplicate this approach in another environment is in question, this case suggests the need for research involving this evolving and adaptive approach as a means of enhancing the CDS development process for clinical care.

Several studies built on the Ehrhart et al. study further examine socio-technical aspects of CDS adoption and use. First, in 2004, Goldstein et al. sought to describe the application of a "socio-technical" approach to integration of a decision support system for the treatment of hypertension (ATHENA DSS) into primary care clinics (Goldstein et al., 2004). Goldstein conducted a case review of three VA Medical Centers (VA Palo Alto Health Care System, San Francisco VA Medical Center, and Durham VA Medical Center). They concluded that within these VA medical centers the socio-technical approach led to increased clinician use of the system. The study did not report on the impact this approach had on clinician guideline adherence. They reported on a series of lessons learned in using the socio-technical approach to clinical decision support that included (1) building a collaborative team bridging of the necessary institutions and disciplines, (2) addressing the organizations' interests in a technical design, and (3) maintaining close contact with the local administration. Their study also reported that this approach to implementing new information technology addresses both socio-organizational issues and informatics technical issues. Finally, the study reported that, like previous studies have reported, there was a lack of computerized decision support for chronic disease in primary care, in contrast to the prior success in preventive medicine and other areas.

Dadich et al. conducted a 2010 meta-analysis of 69 systematic reviews to examine methods designed to help clinicians and practitioners adopt evidence-based practices (Dadich et al., 2010). The study concluded that the use of EBP requires a look at more than just the physician-patient interaction and should also include system factors, such as organizational infrastructure, regulatory bodies, and support from funding agencies. The study revealed that gaps exist in the literature related to how to best bring EBP into practice and included a myriad of ways to pursue research in this field. However, there was a lack of research to verify the individual effectiveness of these methods. Future research should examine the effects associated with delivering and sponsoring of the intervention.

In 2011, Kilsdonk et al. conducted a literature review of 29 studies to determine the factors associated with acceptance of clinical decision support systems (CDSS), entitled "Factors known to influence acceptance of clinical decision support systems" (Kilsdonk, Peute, Knijnenburg, & Jaspers, 2011). They asserted that, despite the evidence of CDS improving clinical performance and patient outcomes existing, the failure rate for introducing CDS in clinical practices is still over 50%. Some of the issues identified in the high rate of CDS failure were low ease of use, negative end-user attitudes towards the system, and negative impact on clinical workflows. A similar study highlighted a proposed framework to evaluate health information systems (HIS) that focused on the fit between human, organization, and technology, called HOT-fit (Yusof, Kuljis, Papazafeiropoulou, & Stergioulas, 2008). The studies included in the literature review were then analyzed using the HOT-fit framework, which looks at three domains, including, (1) The Technology Domain that is comprised of system quality, information quality, and service quality, (2) the Human Domain, which is comprised of system use and user satisfaction, and (3) the Organization Domain, which encompasses structure and environment. The review of these articles listed a total of 240 HOT-fit factors, including 116 technological factors, 79 human factors, and 37 organizational factors. The study identified gaps associated with HOT-fit factors not mentioned in CDSS-acceptance literature that included resource utilization, data integrity, level of use, decision making satisfaction, clinical champions, teamwork, population served, external communication, and clinical outcomes. The study concluded that, while these factors can have an impact on the acceptance of CDSS, conclusive evidence is not yet provided as to the affect of these factors on CDSS physician acceptance (Yusof, Kuljis, Papazafeiropoulou, & Stergioulas, 2008). The study assists in the identification of potential antecedents of clinical decision support and provides a helpful platform for setting up future research in this arena. This particular review did not test any associations, so one cannot generalize that these findings will be true in all settings.

Goldstein et al.'s study was the first cited by the author of the current study to specifically address socio-technical issues as one of the primary factors of the study; the second was the 2006 Niland et al. literature review of National Comprehensive Cancer Network (NCCN) Outcomes Research Database System (Niland, Rouse, & Stahl, 2006). Niland et al. conducted an overview of non-technical issues in building a successful health care quality information system (HQIS), including human, organizational, and knowledge management perspectives. Niland et al. listed the Nielsen's five usability attributes, including: (1) Learnability, (2) Efficiency, (3) Memorabilty, (4) Errors, and (5) Satisfaction, as factors that can be used as components of a larger blueprint for health care quality information systems developments. The study concluded that the focus on socio-technical and knowledge management (KM) components of building HQIS are often overlooked or under-appreciated, in preference to an emphasis on more technological aspects. Both the Goldstein et al. and Niland et al. studies identified a gap in research on socio-technical aspects of clinical information systems development that examine human, organizational, and knowledge management perspectives.

Measuring the Change in Knowledge: Defining a Knowledge Metric

Both Niland et al. and Goldstein et al. outlined the need for a multi-factor approach to clinical information systems development. In 2002, Montani et al. presented a diabetes case study arguing for something very similar, referred to as

Multimodal Reasoning (MMR), as an improvement over both (1) Case Based Reasoning (CBR) and (2) Rule Based Reasoning (RBR) (Montani & Bellazzi, 2002). Montani et al. wanted to show how knowledge management can be implemented into practice. This goal, they argued, was achieved by integrating the decision support functionality with the knowledge management task. Montani et al. claimed that heterogeneous information should be secured, distributed, and made available to physicians in the right form, at the right time, in order to support decision making. They further stated that decision support cannot be viewed as an independent tool but should be integrated with the KM task. Their study did not present any concrete measure for total knowledge available within the organization and its corresponding uptake. They did, however, mention that there are both explicit and tacit knowledge elements found in health care settings, but they did not report on a metric used to examine the total knowledge any health care organization can use to manage the KM task over time.

One study that did attempt to measure accumulated knowledge at the facility-level was examined in a literature review by Anderson et al., called Knowledge Management: Organizing Nursing Care Knowledge (Anderson & Willson, 2009). This overview of the Concept of Knowledge Management (KM) wanted to examine the accumulation of nursing knowledge that becomes the “know-how” of clinical experience. The review listed four key domains for KM, which included: (1) Evidence-Based Medicine (EBM) Domain, (2) Clinical Audit Domain, (3) Information Systems Domain, and (4) the Mentorship Domain. They outlined that tacit knowledge or “know-how” is more difficult to measure, because it is inherent in the individual but may be shown to relate to outcomes of quality, efficiency, or safety. This review argued that studies are needed to explore the implicit or tacit knowledge expressed as clinical "know-how" and its relationship to quality, efficiency, and safety in clinical care and how clinical decision support can contribute to this concept of clinical "know how."

In response to the concept of measuring knowledge, two studies challenge whether the correct things are even being measured in response to clinical knowledge. Sintchenko et al. conducted a systematic review of factors that modify the effectiveness of clinical decision support systems on patient outcomes to answer the question of whether or not researchers are measuring the right end-points that affect the impact of computerized decision support on patient outcomes (Sintchenko, Magrabi, & Tipper, 2007). The literature review included articles published between January 1, 1994 and January 31, 2006, totaling 24 studies for review summarizing the evidence associating the use of computerized decision support and improved patient outcomes. Out of 24 studies, eight presented patients with acute illness and 16 presented patients with chronic illness. In this analysis, CDS showed an ability to improve prescribing practices and treatment outcomes for acute illness but was less effective in the primary care of chronic conditions. This lack of effectiveness of CDS in support of chronic conditions was consistent with the findings of the 2004 Goldstein et al. study previously reported in this section. Sintchenko et al. revealed that complex interventions involving CDS may require new metrics of assessment to describe the impact on patient outcomes. Generally speaking, CDS has the ability to improve patient outcomes, but the results are not uniform and may require more targeted studies.

Another study, which challenged the measurement of KM in clinical decision support, was the 2010 Sittig et al. exploratory study surveying users on their clinical knowledge management (CKM) tools and techniques to manage clinical decision support (CDS) content (Sittig et al., 2010). The goal was to define the need for, and use of, high quality collaborative CKM. The study included six geographically diverse health care facilities recognized for their excellence in implementation and use of advanced clinical information systems. These health care facilities were of varying size and delivery structure, from a community hospital to integrated delivery networks. The study examined the (1) characteristics of these six organizations, (2) content of the CKM at each site, and (3) the current practices for CKM. This inventory of practices concluded that CDS and CKM are related and that CDS progress may depend on the understanding, implementation, and use of CKM CDS. This inventory only presented what people/organizations have or did not have, and it did not address what works or does not work, nor what factors served to predict CDS as an outcome or its corresponding impact on clinical outcomes. There may be issues of generalizability of these results to other institutions.

The final theme within this section included two studies that listed two potential metrics for measuring organizational progress in both knowledge and IT adaptability. One study examined the concept of intuition and the other examined network density.

Salas et al.'s 2010 review of literature attempted to (1) identify expertise and intuition, (2) define expertise-based intuition and, (3) identify the type of intuition of most value to organizations. Their study defined intuition as a process of thinking. The input to this process is mostly provided by knowledge stored in long-term memory and is acquired by associative learning. The study suggested that primary factors that influence the use and effectiveness of intuition in decision making for individuals include the: (1) decision maker, (2) decision task, and (3) decision environment. The study concluded that the time has come for a dedicated science of intuition in organizations capable of guiding practice and improving effectiveness. The study also expressed the need for more rigorous studies focused on individual and team level expertise-based intuition. Some studies have been conducted on intuition improvement over time, but they were done in isolation and few, if any, looked comprehensively at the development of intuition. This study was one of a very few that examined the actual intelligence that can be gleaned from CDS use and how it can be defined as Anderson et al. referred to earlier as clinical "know-how."

Another metric of interest found in this section was that of network density as an indicator of individual adaptation to IT-induced change. Bruque et al. conducted a survey of 371 employees working in 133 different branches in a large financial company November 2004 and November 2005 (Bruque, Moyano, & Eisenberg, 2008). This cross-sectional study sought to examine the role that two types of social networks–supportive and informational–play in individual adaptation to IT-induced change in a large firm. The study suggested that network measures of size of the support network and density and strength of the information network successfully predicted employees' adaptation to the new IT system. The study concluded that dense networks were actually more effective for individual adaptation to IT-induced change. The authors also suggested that a dense information network may be more effective if the members use it as a tool to resolve doubts, obtain opinions, and deepen their understanding of the new system. Additionally, the informational network may arise as a means to better understand the new IT-related change, rather than serve merely as a source of routine information. The suggestion was that a longitudinal study design might be beneficial to broaden the number of dimensions analyzed, providing a more complete picture of the adaptation process, as well as how social variables might influence the process. Future studies might want to examine relevant organizational factors, such as leadership, to observe the evolution and adaptation of the network over time as applied in a health care setting.

Summary

This literature review discovered that significant research has been conducted on clinical decision support in relationship to cancer screening rates within facilities, but that there is a lack of consistency in the findings on just how effective it is in predicting cancer outcomes. The identified gap in using clinical decision support to successfully explain facility-level cancer screening rates is one of the challenges of the current dissertation study.

This literature review also discovered the existence of a variety of studies that examined organizational factors/determinants and/or environmental factors for clinical decision support. Some of these studies revealed factors, such as leadership, administrative support, collaboration, and external interactions, which may contribute to CDS adoption, use, and implementation success. Other studies focused on the provider/physician as the primary agent of change in CDS success. However, this review found only one study that explored the relationship between CDS and screening of any kind within the organizational setting of the community health center, and none that examined this from the perspective of cancer screening. This dissertation study will seek to address this knowledge gap by studying the relationship between these organizational factors and cancer screening rates with the community health center setting.

Finally, this literature review discovered a growing emphasis on the socio-technical approach towards CDS adoption, use, and implementation in support of cancer outcomes. Such an approach takes into account the human, organizational, and technical dimensions of activity and also examines the health care facility as a complex adaptive entity. The notion was presented that CDS adoption should be seen more as a process over time and not as a single event. Additionally, the literature suggested that steps should be taken to better assess the overall intelligence of a health care organization in the context of CDS usage and, as such, include an overall knowledge management strategy as a component of an overall development strategy. The current study has added a second aim to this dissertation research, which will attempt to measure the community health center as a complex adaptive agent and employ a knowledge metric used to thereby measure varying levels of performance in the cancer screening task and CDS in relationship to the overall rate of change in knowledge absorption over time, which is referred to as *Delta K*.

The Theoretical Approach: A Combined Statistical and Computational Modeling of Community Health Center CDS and Cancer Screening Practices

The Rationale and Relevance for a Dual Modeling Approach

The National Cancer Institute (NCI) convened a conference in March 2011 entitled, Multilevel Interventions in Health Care: Building the Future Foundation for Future Research. This Las Vegas, Nevada conference convened cancer care professionals from around the globe to discuss ways to improve cancer outcomes by employing this multilevel intervention strategy. The goal of the conference was to engage the audience by (1) better understanding the problem of not reaching national cancer care outcome goals despite massive investments over the years, (2) presenting a series of papers designed to increase the use of multilevel intervention techniques to be published in an upcoming supplement to the *Journal of the National Cancer Institute*, and (3) preparing researchers and health care delivery experts in cancer care to employ multilevel intervention design in their cancer care research and practice. The conceptual design of this research project was presented to this audience in the form of a poster presentation for commentary and feedback (Carney et al., 2011).

What is Multilevel Intervention Research and Why is it Important?

Taplin et al. (Taplin, Clauser, Rodgers, Breslau, & Rayson, 2010) suggested that health care in the United States can be considered a layered health care system. As such, the goal is "to build a research foundation that acknowledges this multilayer world." Taplin goes on to outline three key assumptions about the limitations of the traditional research approach: (1) new technologies take, on average, 17 years to be widely adopted, (2) evidence-based innovations are not readily adopted, and (3) practices inconsistent with evidence persist (Taplin et al., 2010). Richard K. Riegelman makes the formal argument in his book *Public Health 101*, specifically the chapter on Systems Thinking Versus Reductionist Thinking and Cigarette Smoking (Riegelman, 2009). Riegelman explains that the National Cancer Institute and the Institute of Medicine are now encouraging a systems-thinking approach (Riegelman, 2009). He states that “Systems thinking is more easily understood by contrasting it with the traditional approach” (Riegelman, 2009). Table 1 summarizes the three concepts that Riegelman believes best highlight the differences between systems thinking and the traditional approach (Riegelman, 2009).

Table 1: Comparison of Traditional Approach Versus Systems Thinking

Model Characteristics	Traditional Approach	Systems Thinking
One intervention at a time versus multiple simultaneous interventions	• Attempts to look at one factor or intervention at a time	• Asks about the best combination of interventions
Straight-line or linear projections versus measuring complex interactions	• Usually assumes a straight-line or linear relationship • May not look at how one intervention may be affected by connecting it with other interventions	• Examines varying combinations of intervention types and levels

One point-in-time or static analysis versus a changing or dynamic analysis	• Static Models
	  o Examines the relationships at one-point-in time
	  o Does not take into account changes that might occur over time (not the same as a linear experiment that examines a population at varying time points) (e.g., $t_{0,}$ t_1, $t_2 \ldots t_n$), as these are considered multiple point-in-time measures
		• Dynamic Models
		  o Includes a feedback process that can account for changes over time, as well as system inhibitors and facilitators

During the NCI Multilevel Intervention Research Conference, Alexander et al. presented two assumptions on multilevel intervention research that reflect both Taplin's and Riegelman's perspectives. Alexander went on to assert that the two key assumptions of Multilevel Interventions are (Alexander, 2010):

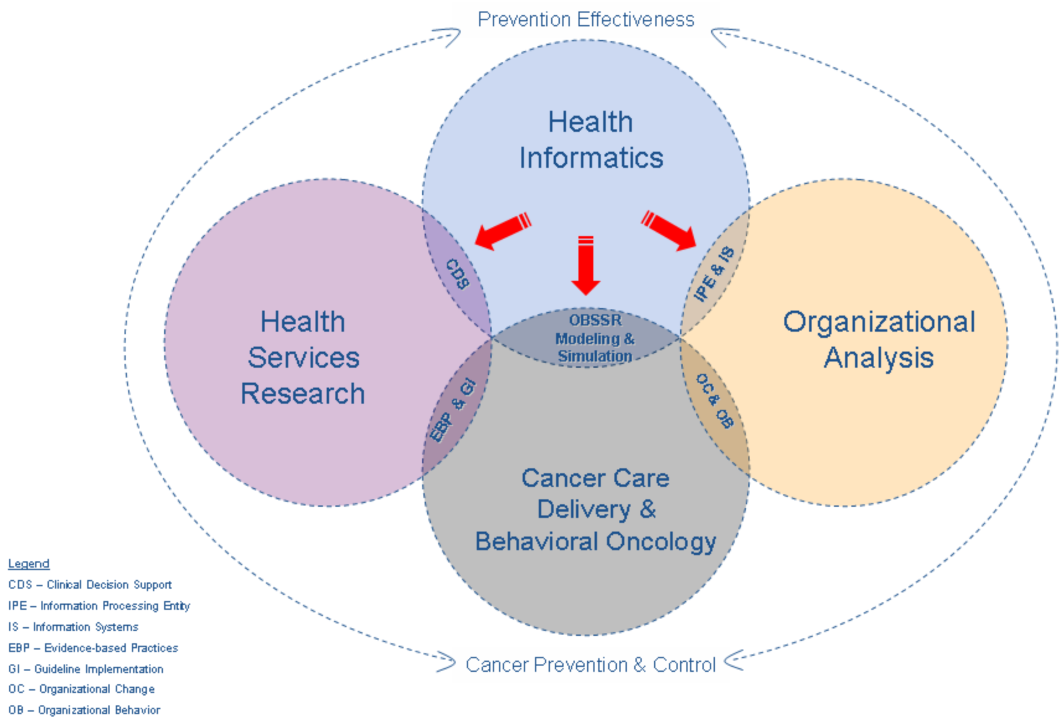
- Individual subjects of Multilevel Interventions (MLIs) are not static–they change systematically in ways unrelated to the intervention and in ways that may increase or decrease the effects of the intervention
- Organizations or environments do not operate in a steady-state mode–they change in ways that may impact the fidelity of the intervention and its effects on patients

Taplin further explained that multilevel intervention research must take into consideration any or all of the layers within what he called the "Care Process within Layers," which includes (from the most basic to the most comprehensive, where each succeeding level contains it predecessor) Individual Patient, Family & Social Supports, Provider/Team, Organizational and/or Practice Setting, Local Community Environment, State Health Policy Environment, and National Health Policy Environment (Taplin et al., 2010). This summary demonstrates that there is an active push at the National Cancer Institute to employ an approach to cancer care delivery and cancer research that successfully examines multiple layers of the cancer care process in a systems-dynamic way. Such an approach recognizes that there are complex adaptive elements to be examined that change over time; that there can be an interaction of agents within the internal organization's components and/or its external environmental factors of the cancer care process, which seek to employ a systems-thinking approach to improve the adoption and diffusion of innovations and evidence-based practices within the cancer care delivery system.

A Model for Multilevel Intervention Research Design

This research project is ultimately aimed at creating a methodological design for multilevel intervention research in cancer care that successfully combines the domains of (1) Health Informatics, (2) Organizational Analysis, (3) Health Services Research, and (4) Cancer Care Delivery & Behavioral Oncology. Figure 1 shows the conceptual design of how these four domains of practice can be combined, along with the fields of practice that become focus areas for systems change and intervention. The red arrows represent the specific target areas that this particular research study will consider for a dual modeling approach, which employs both a statistical modeling (traditional) approach and a computational modeling (systems thinking) approach. This design is meant to highlight how these two modeling approaches can work synergistically to provide a more accurate picture of what might be occurring in a cancer care delivery organization or system over time within community health centers.

Figure 1: Domain Convergence Model for Cancer Prevention and Control



This study will draw from the literature of four distinct domains and their proposed intersections in the construction of the dual-modeling analytical framework. Health Informatics will serve as the chief domain of interest and, as such, intersects the other three domains. Where health Informatics intersects with Health Services Research and the topic areas of Clinical Decisions Support (CDS), its importance to cancer care delivery has been addressed in previous sections of this summary. Where Health Informatics intersects with Organizational Analysis, the field of Organizational Informatics emerges and its emphasis on the Information Processing Entity (IPE) and Information Systems (IS) becomes paramount and will be addressed in the literature review on the topic of Organizational Learning and Socio-Technical Aspects. Where Health Informatics intersects with Cancer Care Delivery & Behavioral Oncology, the current study acknowledges the focus on the National Cancer Institute's Office of Behavioral and Social Science Research (OBSSR), which represents NCI's systems thinking activities hub. This body of literature has been formulated in sections below that address Computational Modeling and Dynamic Network Analysis. Two other areas currently out of scope for this research but which are highly important in the overall cancer prevention and control agenda are: (1) where Health Services Research and Cancer Care Delivery & Behavioral Oncology converge to examine such things as the uptake of Evidence Based Practices (EBP) and the Guideline Implementation and Compliance (GI) for cancer care; and, (2) where Organizational Analysis intersects with Cancer Care Delivery & Behavioral Oncology to examine Organization Change (OC) and Organizational Behavior (OB).

This dual modeling research design is not only timely and consistent with National Cancer Institute objectives, but it is also critically important in the overall attempt by cancer researchers, policy makers, and health care delivery professionals to employ an effective multilevel intervention strategy for cancer prevention and control.

While there will be a dedicated section towards the end of this document that focuses on limitations, it is important to delineate exactly what this research is and what it is not. Health Informatics research can focus on a variety of areas. There are three areas in particular that Health Informatics researchers might examine when studying the convergence of Health Informatics, Health Services Research, Organizational Analysis, and Cancer Care Delivery & Behavioral Oncology. These three areas are: (1) Heath Outcomes (e.g., prevention effectiveness areas of cost-benefit, cost-effectiveness, and cost utility), (2) Technology Adoption and/or Use, and (3) Application Development and Implementation. There are perhaps many other areas not mentioned, but this research agenda seeks to develop a proof of concept for a dual statistical and computational model that can effectively differentiate high performance organizations from low performing organizations as it relates to the presence, intensity-of-use, and impact of CDS and IS on cancer screening related outcomes. As this is a secondary data analysis and not an intervention, this research is not designed to actually change any immediate health outcomes within the study sample of community health centers; instead, it makes recommendations to inform future strategic efforts. This study is not designed to study technology adoption, because there are no time series data to examine the stages of change in technology diffusion, as this survey represents a single point-in-time observation. This is not a study aimed at discussing or explaining CDS or IS application development or implementation strategies, because again, this is not an intervention and none of the survey questions addressed these topic areas. However, this study looks at varying aspects related to technology use in cancer screening, the practices associated with it, and the extent to which one can define the factors associated with the use of CDS and IS, and ultimately demonstrate the levels to which CDS and IS might be associated with facility-level cancer screening outcomes in community health centers. The ultimate ambition of this research is to be able to utilize this methodology in multilevel intervention research in the three areas, namely, health outcomes research, technology adoption and/or use, and application development and/or implementation within the context of comprehensive cancer prevention and control.

A special note on the approach utilized in the presentation of the research methods, results, discussion sections. The author of this combined modeling approach could have either presented the methods, results, and discussion sections for the statistical model (Aim 1) in consecutive order, followed by the computational model sections (Aim 2) respectively. This ordering would essentially result in treating the two modeling exercises as two separate studies. However, the author chose to treat the two models as interdependent parts of a unified analysis, given the focus on the same data source and complimentary outcomes. As such, the sections are presented as follows, a single chapter dedicated to Aim 1 & 2 methods, a chapter dedicated to Aim 1 & 2 results, and finally a chapter on Aim 1 & 2 discussion. While this may prove challenging to follow the goal is highlight the challenges inherent to any dual modeling effort.

On Generating Hypotheses Using Computer Simulations

Organizational informatics research closely examines the link between organizational diagnosis and design and the corresponding information technology and information science, as expressed as a function of some larger, more comprehensive organizational objective (Burton & Obel, 2004; Kling, 1993). This approach is supported by the increasing reliance upon a "systems science" to help better understand complex organizational relationships. According the National Institutes of Health, Office of Behavioral and Social Sciences Research (OBSSR):

> Systems-thinking is an analytical approach that addresses a system and its associated external context as a whole that cannot be analyzed solely through reduction of the system to its component parts. Systems science methodologies provide a way to address complex problems, while taking into account the big picture and context of such problems. These methods enable investigators to examine the dynamic interrelationships of variables at multiple levels of analysis (e.g., from cells to society) simultaneously (often through causal feedback processes), while also studying the impact on the behavior of the system as a whole over time (NetLibrary, 2009).

Several analytical approaches can be utilized to investigate and analyze complex organizational behavior. Kathleen Carley, Director of the Carnegie Mellon University, Center for Computational Analysis of Social and Organizational Systems (CASOC), relies heavily on the use of Computational Modeling as a means of generating hypotheses about organizational dynamics (Carley, 1999; CASOS, 2009). Computational modeling is a set of tools that allow users to create a virtual model of a particular system, such as a hospital or patient care unit, and study its behavior under various conditions (Effken et al., 2003; Ilgen & Hulin, 2000). Computational models are used to ask and answer *what-if* scenario questions that cannot be adequately addressed using traditional statistical techniques (Effken et al., 2005). Such traditional methods may not reveal hidden relationships needed to fully explain some particular organizational behavior or outcome (Effken et al., 2003). According to Judith Effken, to a researcher using computational modeling to evaluate efforts to improve patient care unit safety and outcomes, these types of applications vary greatly. They may be continuous or discrete, static or dynamic, stochastic or deterministic (Effken et al., 2003). Such modeling may incorporate many hypothesis-generating techniques, including but not limited to organizational network analysis.

Effken et al. collected data on 32 patient care units in 12 hospitals in the Arizona area (Effken et al., 2005; Effken et al., 2003). She reported that, after validation steps were taken to gain acceptable levels of correspondence between actual and virtual units, they then used a computational modeling tool called OrgAhead® (another tool developed within CASOS) to generate hypotheses about different kinds of innovations nurse managers might use to achieve improvement in patient safety and quality outcomes (Effken et al., 2005; Effken et al., 2003). The study found that they were able to increase the accuracy in their units by 3.5 points, which for them represented a decrease of about 3.5 errors and a completion ratio of 0.04, which corresponded with a 14% increase in quality (Effken et al., 2005; Effken et al., 2003). Effken concluded that computational modeling assisted her in evaluating a complex and multilevel health care problem (Effken et al., 2005).

Building a Computational Model–Virtual Experiment–Using Dynamic Network Analysis

A network analysis, which represents a type of computational modeling, can take a multiplicity of forms given the wide array of literature and applications of this technique to a variety of disciplines and domains. The fundamental issue for this research study is to (1) define the organizational level predictors of CDS and IS within community health centers, (2) define the corresponding impact of CDS and IS on self-reported cancer screening rates, then (3) determine if novel information can be gleaned from a network analysis that can identify facilitation or inhibition factors that might account for relative performance in cancer screening improvement. The field of network analysis has essentially morphed into several specialized domains of practice that include but are not limited to social networks, organizational networks, neural networks, and more. Valdis Krebs, the designer of *InFlow*® (an organizational network analysis tool), says that "network maps provide a revealing snapshot of a business ecosystem at a particular point in time" (Krebs, 2002; Stephenson, Krebs, & University of California, 1992). A study by Jacqueline Merrill et al. entitled, "Description of a method to support public health information management: Organizational Network Analysis," published in the *Journal of Biomedical Informatics*, highlighted how Organizational Network Analysis (ONA) could provide enhanced insights into understanding critical performance factors (Merrill, Bakken, Rockoff, Gebbie, & Carley, 2007). The primary distinction that ONA provides over the traditional analytic techniques is in the use of structural or relational variables analyzed by using techniques based on graph theory (Merrill et al., 2007). She explains that, networks as an organizational setting are "comprised of nodes that represent agents (human or machine), knowledge, tasks, or resources, and links that show relationships between the nodes. Agents have varying degrees of connectivity with other agents through which information and resources flow. Depending on the scale of analysis, an agent may represent an individual, a project team, a division, or an entire organization" (Merrill et al., 2007). This technique can, according to Merrill, (1) reveal where resources are inadequate for employees to perform their tasks, (2) identify how information travels throughout the health agency, (3) assist in resource allocation planning, and (4) aid in decision making by revealing links between information networks and process performance (Merrill et al., 2007). According to Merrill, Organizational Network Analysis can allow for hypothesis generation and insight into organizational performance by impacting (Merrill-Matzner, 2006):

- Managerial value
- Changes to organizational processes
- Redeployment of resources
- Function changes
- Cross-program support
- Policies affecting use of, access to, or integration of information/communication

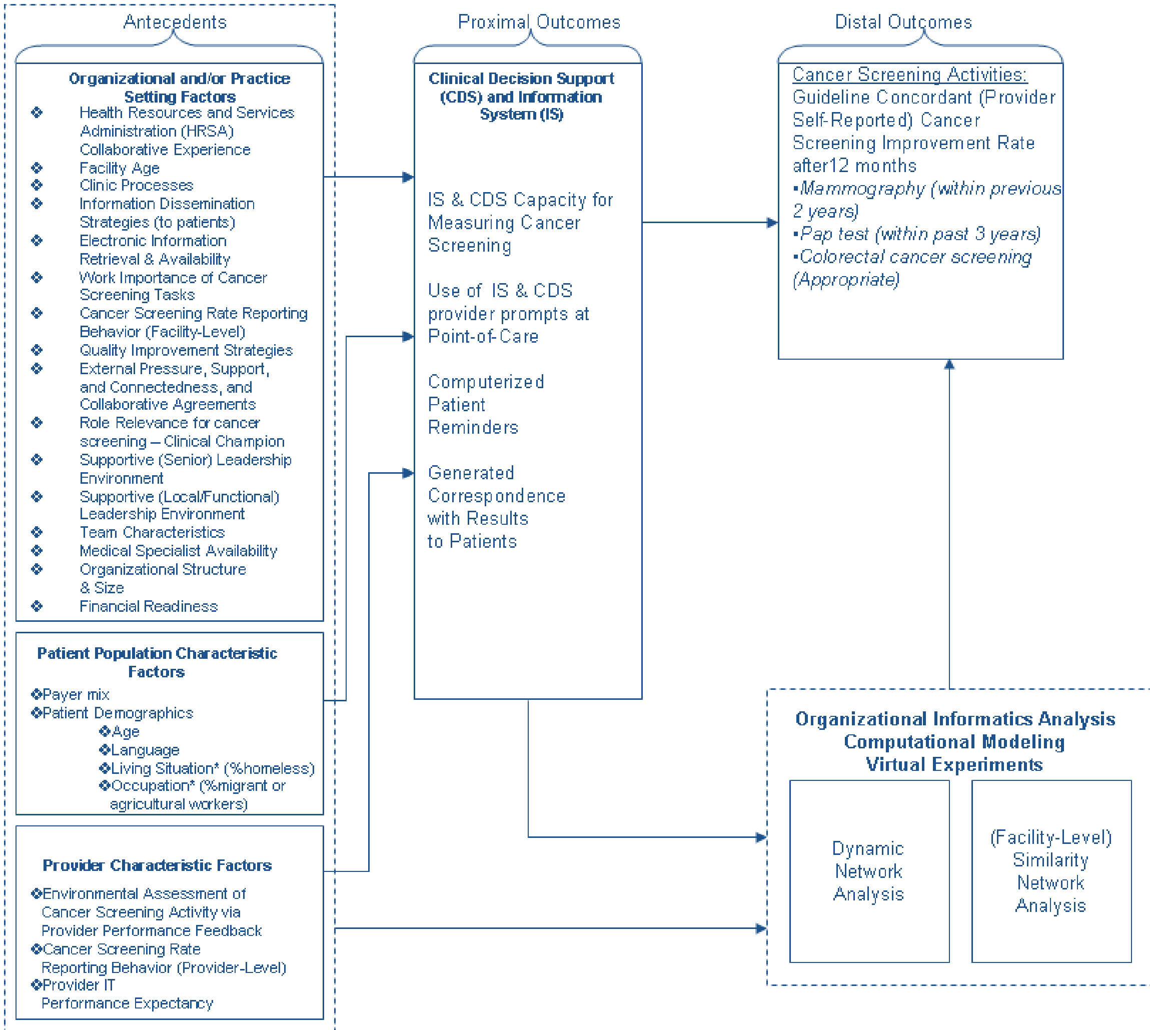
Merrill used a network analysis tool developed by CASOS called Organizational Risk Analyzer–*ORA*. Merrill used 17 of the over 100 network analysis measures of organizational structure and vulnerability that ORA contains (Merrill-Matzner, 2006; Merrill et al., 2007). The ORA measures are constructed from work in social networks, operations research, organizational theory, knowledge management, and task management (CASOS, 2009; Merrill et al., 2007). Merrill's findings were used to describe the structure of information flow in the department's communication networks (Merrill-Matzner, 2006; Merrill et al., 2007).

In 2007, Keith et al. performed a test of network centrality entitled, Coordination Network Analysis: A Research Framework for Studying the Organizational Impacts of Service-Orientation in Business Intelligence (Keith, Demirkan, & Goul, 2007). Keith et al. used three primary constructs in his analysis: (1) individual characteristics (e.g., demographic characteristics), (2) individual resources (e.g., access to software resources, subject-matter expertise, and certifications), and (3) organizational structure (e.g., location, [leadership] hierarchy, and task type). Keith et al. tested each of these constructs against the concept of network centrality. They defined network centrality in terms of individual centrality or the extent to which an individual is connected to others in the network, and group centrality or the variance of individual members of the group (Keith et al., 2007). The goal was to conduct a Coordination Network Analysis (CNA) described as a type of network that exists across organizations to examine the coordination of organizational activities or events that might contribute towards some specific outcome (Keith et al., 2007). This is designed to maximize resource coordination efforts. According to Keith et al., this framework offers researchers a network-based research methodology to examine organizational performance at both the individual and group level analysis (Keith et al., 2007).

The Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University has developed a series of applications to assist in the development of a computational model for use in virtual experiments (CASOS, 2009). The applications vary in their capability and are selected by researchers based on the type of analysis the researchers wish to conduct, and the type of data they may be working with.

These studies inform the proposed researcher by shaping the computational modeling research design contained in Aim 2 of this research and by helping to define the parameters of a virtual experiment. This experiment is designed to generate some novel hypotheses that can facilitate short- or long-term strategic planning associated with either CDS or IS use in, and impact on, cancer screening rates within community health centers. Organizational Network Analysis is a computational modeling technique, seen in Figure 2, as a means of examining potential complex adaptive relationships between the antecedents (organizational, patient, and/or provider) and the CDS and IS components in support of facility-level self-reported cancer screening rates. This is partially achieved through the development of a series of virtual experiments that can test (1) the rate of knowledge absorption of high-performing community health centers versus low-performing community health centers for both cancer screening improvement and CDS use, and (2) comparative or between network analysis (facility-to-facility) using the network diagram visual analysis of varying levels of community health center characteristics.

Figure 2: Conceptual Model



The Rationale for Using the Zapka et al. Framework: A Brief Review of Models of Technology Adoption & Behavioral Science Theories Used in Conceptual Model Development

The Organizational Structure and Process Factors

Health care organizations influence the quality of care they deliver through an array of factors, which directly or indirectly serve as the context in which clinicians practice and patients experience care (Flood, 1994; Zinn & Mor, 1998). This context represents a wide array of attributes, both fixed and mutable, that support interactions between patient and providers; between provider and provider; and within and across teams, medical groups, and facilities (Landon, Wilson, & Cleary, 1998). Thus, each health care setting represents its own organizational array, i.e., the structure and processes that comprise how an organization operates and behaves. Individually or in combination, these structures (e.g., size, staffing) and processes (e.g., practice arrangements, delivery system design) foster or hinder discrete steps in the adoption of organizational change or quality improvement efforts that rely on HIT adoption and/or use. Organizations also mediate environmental factors, enabling facilities to adapt their policies and practices to fit local context and needs.

The authors of *Health Behaviors and Health Education: Theory, Research, and Practice*, make the argument that "Organizational theories can provide insight into how to facilitate the adoption or institutionalization of a particular evidence-based intervention within an organization of help to explain how an organization may actually discourage positive healthy behaviors" (Glanz, Rimer, & Viswanath, 2008). This explains why organizational policies and practices are frequently the target of many health promotion interventions. One major challenge to understanding organizational activity is finding the proper context within which to describe organizational behavior. In 1988, the social ecological model was introduced (McLeroy, Bibeau, Steckler, & Glanz, 1988), proposing that individual, interpersonal, community, organizational, and societal factors should be taken into account when planning and implementing health interventions.

There are two categories of organizational change from within that are central to this research study. The first is Stage Theory of Organizational Change. Glanz et al. summarizes:

> Stage theory suggests that organizations pass through a series of steps or stages as they realize change. Modern stage theory is based on the work of Kurt Lewin (1951) and the work of Roger's Diffusion of Innovations Theory (Rogers, 1983). Stage theory was first applied using a seven-stage model in 1978 by Beyer and Trice. This was later condensed into a four-stage model in 1988 by Kaluzny and Hernandez. This four-stage model progresses through (1) Defining the problem (Awareness Stage), (2) Initiating Action (Adoption Stage), Implementing Change, and (4) Institutionalizing Change" (Glanz et al., 2008).

The other category of organizational change from within is that of Organizational Development Theory. Cummings defines Organizational Development Theory as "a system-wide process of applying behavioral science knowledge to the planned change and development of the strategies, design components, and processes that enable organizations and overall nature of activities, led by a change agent, to enhance the overall performance of the organization" (Cummings & Worley, 2004). Cummings goes on to explain that "Organizational Development Theory addresses these organizational systems, as well as the relationships between organizations and the larger external environment. Organizational Development Theory is a process of continuous diagnosis, action planning, implementation, and evaluation, with the goal of transferring knowledge and skills to organizations to improve their capacity for solving problems and managing future change" (Cummings & Worley, 2004).

These two core concepts in organizational change theory, (1) Stage Theory and (2) Organizational Development Theory, informed this study by highlighting the importance of the development of a structured view of the organization and its multitude of interactive components in trying to explain some particular organizational practice or activity, such as the presence and/or use of CDS and IS within a given community health center, as well as the impact CDS and IS may have on facility-level cancer screening rate improvement.

The Application of the Zapka et al. Framework to This Study

In terms of the current study, the author needed a validated theory-driven model consistent with the tenants of both Stage Theory and Organizational Development Theory to achieve the following tasks: (1) outline the full scale of organizational factors that were examined within community health centers, (2) identify clinical decision support as a component of the organizational environment and a potential contributor to the health outcome of cancer screening, and (3) focus on the multilevel factors (e.g., patient, provider, organizational, etc.) that might account for facility-level cancer screening performance. For this study, the author chose the Zapka et al. framework.

The Zapka et al. framework describes how four distinct levels of influence, with each smaller unit operating as a sub-member of the next higher level, work in tandem to influence screening behavior. These four levels of influence are (in increasing order) patient population level characteristics, provider characteristics, organizational and/or practice settings, and sectors of influence (e.g., federal and state policy). These levels are then modified by proactive team membership, productive encounters, and activated patients to produce improved patient screening outcomes (Zapka, 2008; Zapka et al., 2003). The original Health Disparities Cancer Collaborative (HDCC) organizational survey instrument was used in the assessment of a community health center application of the chronic care model principles in support of cancer screening (see Aim 1 Methods Section for details) (Haggstrom et al., 2008). The questionnaire used by Haggstrom et al. did not directly employ the Zapka et al. framework. This current study used approximations in the matching of HDCC survey constructs to the Zapka et al. framework, hence making this a modified-Zapka et al. framework as seen in Table 2. Table 2 highlights the side-by-side examination of variables from both the Zapka et al. framework and the variables obtained from the HDCC community health center survey. Additionally, while the Zapka et al. framework focused largely on colorectal cancer, the areas of breast and cervical cancer screening rates were added to the research scope, because they were specifically addressed in the Haggstrom and Taplin survey instrument (Haggstrom et al.,2008).

Table 2: Application of Individual Zapka et al. Framework Variables

Factor Level	Original Framework Variables (Zapka et al., 2003)	Community Health Center Variables
Individual Patient Characteristics	• Demographics* • Risk Status** • Insurance Access* • Culture** • Other predisposing, enabling factors**	• Payer mix • Patient Demographics
Provider Characteristics	• Knowledge, skills* • Perceived Barriers, Norms* • Time/Visit** • Competing Service Priorities**	• Environmental Assessment of Cancer Screening Activity via Provider Performance Feedback • Cancer Screening Rate Reporting Behavior (Provider-Level) • Provider IT Performance Expectancy
Organizational and/or Practice Setting Factors	• Leadership* • Organizational Structure* • Delivery System Design, Teams* • Clinical Decision Support* • Clinical Information Systems* • Patient Support, Education, Navigation* • Time Pressures** • Community Linkages*	• Governance: Health Resources and Services Administration (HRSA) Collaborative Experience • Facility Age*** • Clinic Processes • Information Dissemination Strategies (to patients) • Electronic Information Retrieval & Availability • Work Importance of Cancer Screening Tasks • Cancer Screening Rate Reporting Behavior (Facility-Level) • Quality Improvement Strategies • External Pressure, Support, and Connectedness, and Collaborative Agreements • Role Relevance for Cancer Screening – Clinical Champion • Supportive (Senior) Leadership Environment • Supportive (Local/Functional) Leadership Environment • Team Characteristics • Medical Specialist Availability • Organizational Structure & Size • Financial Readiness***

Factor Level	Original Framework Variables (Zapka et al., 2003)	Community Health Center Variables
Sectors of Influence	Federal and State Policy • Entitlements, Reimbursement • Performance Measurement • Regulations Professional Norms • Evidence-based • Provider Guidelines • Corporatization Local Community • Covered Benefits • GI Capacity* • Access • Media, Education • Advocacy	The current study did not employ the category of "Sectors of Influence," however, several of these Zapka measures informed the current study.

*Zapka Factors found as an equivalent for the current study
**Zapka Factors not used in the current study
***Community Health Center Variables not obtained from the Zapka et al. framework

The conceptual model used in this research is centered on the major construct of interest referred to in the Zapka et al. framework as Organizational and/or Practice Setting Factors. This construct will be conceptually defined as the sum total of environmental, medical center, clinical practice, and IT infrastructure and strategy factors influencing colorectal, breast, and cervical cancer screening at community health centers. These items will be measured operationally from the HDCC organizational survey used in the previous Haggstrom et al. study. The construct the author of the current study referred to as Organizational and/or Practice Setting Factors will be comprised of 16 variables plus the added covariate for HDCC membership, which were inspired by the Zapka et al. framework.

The list of antecedents used in the Aim 1 hypotheses testing for both the presence (1a) and intensity-of-use and (1b) of CDS and IS are grouped using the same headings obtained from the Zapka et al. framework: (1) Organizational and/or Practice Settings, (2) Patient Population Characteristics, and (3) Provider Characteristics. The variables in the current model are listed as follows:

Organizational and/or Practice Setting Factors

Delivery System Design is commonly defined by the Zapka et al. framework encompassing service arrangements/contracts, task delegation/teams, quality control/improvement processes, coordination with community resources, and case/demand management (Zapka et al., 2003). These factors most closely align with the following variables obtained from the Haggstrom et al. survey instrument and are expressed in the conceptual model list of antecedents: Team Characteristics; External Pressure, Support, Connectedness, and Collaborative Agreements; Cancer Screening

Rate Reporting Behavior (Facility-level); Role Relevance for Cancer Screening Activity–Clinical Champions; and Medical Specialist Availability, as seen in Figure 2.

Leadership at Multiple Levels is commonly defined by the Zapka et al. framework as encompassing the vision and ability to promote and manage change, performance standards fostering practice norms, and quality control/improvement philosophy (Zapka et al., 2003). These factors most closely align with the following variables obtained from the Haggstrom et al. survey instrument and expressed in the conceptual model list of antecedents: Work Importance of Cancer Screening Tasks; Quality Improvement Strategies; and Supportive Leadership Environment, as seen in Figure 2.

Additionally, the Zapka et al. framework includes a variable for Organizational Structure, of which one dimension Organizational Size is defined here as the total number of employees within the health center. Financial Readiness does not appear in the Zapka et al. framework. However, it is included due to strong evidence to suggest that the availability of financial resources may facilitate the presence of clinical decision support (Hwang, Jeong, & Nandkeolyar, 2008; Iacovou, Benbasat, & Dexter, 1995; Kuan & Chau, 2001) and because previous evidence suggests community health center CDS adoption and use may be associated with funding and affordability (Lardiere, 2010).

Other variables were added the to Organizational and/or Practice Setting after consultation with committee members, including Governance, Facility Age, Clinic Processes, Information Dissemination Strategies to Patients, and Electronic

Information Retrieval Capability. Governance–Health Resources and Services Administration (HRSA) Collaborative Experience is conceptually defined as the overall community health center management strategy and is functionally defined as previous exposure to HRSA-collaborative activities. A separate independent variable is also included to control for whether the health center was an HDCC participant when the survey was administered and if said membership could serve to account for differences in the outcome. This latter designation was used to divide the community health centers into two groups (case vs. control group) and will be discussed further in the Aim 1 methods section. Governance in this study represents a blending of the Zapka variables of Federal and State Policy and Leadership (Zapka et al., 2003). The variable Facility Age is a composite measure of both the time the health center has been exposed to any HRSA Collaborative activities and policies (which the author of this study designated as Facility Age 1) and the number of years the clinic has been funded (designated as Facility Age 2). Information Dissemination Strategies refer to the methods, policies, and practices employed to deliver information on cancer screening tests, importance, eligibility, and procedures provided to patients. Electronic Information Retrieval Capability refers to the ability of the electronic health record (EHR) to carry out core functions related to cancer screening. Where an EHR did not exist, it was assumed that the respondent responded negatively to the question or it was treated as missing data. The Information Dissemination Strategy to Patients closely aligns to the Patient Support Education variable in the Zapka et al. framework, while the Electronic Information Retrieval Capability aligns closely with the Clinical Information Systems variable in the Zapka et al. framework (Zapka et al., 2003). It should be noted that, in order to avoid confounding the results in tests 1a and 1b, the EHR functions that were considered to be closely aligned with the dependent variables for CDS and IS of the Clinical Guidelines and Reminders for Screening, were excluded (e.g., question for use of clinical guidelines and question for use of clinical reminders) as independent measures, thereby reducing the EHR functions to be operationally defined as the delivering mammography results, Pap test results, fecal occult blood test results, etc. These can be interpreted as a component of the Procedure Encounters within the Zapka et al. framework (Zapka et al., 2003).

Finally, a summary measure examining community health center financial readiness to deploy CDS and IS strategies for cancer screening was included in the study. This variable represented the reported level of cash reserves or the ratio between revenue and expenses for the health center. The 44 community health centers within this sample were ranked from 1 to 7, where a score of 1 represented operating expenses exceeding revenues by 25% or more, a score of 2 represented a revenue deficit of 24% to 11%, and a score of 3 represented 10% to 1%, respectively. A score of 4 represented a breakeven. A score of 5 represented revenues exceeding operating expenses of 1% to 10%, a score of 6 represented revenue in excess of 11% to 24%, and a score of 7 represented 25% or greater, respectively.

Patient Population Characteristics

Zapka refers to demographics and several other factors when describing the patient (Zapka, 2008). This study will examine patient age and insurance status as demographic variables due to their importance in determining eligibility for and access to colorectal, breast, and cervical cancer screening (Zapka, 2008).

Provider Characteristics

Zapka defines provider characteristics as encompassing knowledge, skills, perceived barriers, norms, and competing priorities (Zapka, 2008). One variable listed in this category, which has been used in the conceptual model for this study, is that of Provider Performance Expectancy of IT. Another variable, Environmental Assessment of Cancer Screening Rates from Provider Performance Feedback, refers to how the provider views the community health center environment for cancer screening rate management. Finally, the variable Cancer Screening Rate Reporting Behavior (provider-level) was also included. It reflects the practice norms as articulated in the Zapka et al. framework.

The dependent variables used in the Aim 1 tests for hypotheses 1a (presence) and 1b (intensity-of-use) of the study are labeled as CDS and IS, respectively. The CDS and IS composite construct are comprised of four variables that are operationally defined as: (1) CDS and IS Capacity for Measuring Cancer Screening, (2) Use of CDS and IS provider prompts at Point-of-Care, (3) Computerized Patient Reminders, and (4) Generated Correspondence with Results to Patients as previously seen in Figure 2. It should be noted that, in the testing of hypothesis 1a, each of the four CDS and IS variables will be tested individually against each of the three categories of antecedents (e.g., organizational, patient, and provider) from the conceptual model (independent variables) testing for factors associated with the presence of CDS and IS. Correspondingly, CDS and IS component rankings or scores (0 to 4 for the community health center having none, one, two, three, or four CDS/IS components, respectively) will be treating this variable as a composite (single) construct in test 1b against each of the three categories of antecedents from the conceptual model (independent variables) testing for the factors that may determine the intensity-of-use of CDS and IS in community health centers. The author used both the Zapka et al. framework and the Chronic Care Model to conceptually define the CDS and IS measures.

Clinical Decision Support (CDS) is conceptually defined by the Zapka et al. framework and Chronic Care Model as being similar–Guideline development, updating, dissemination, and education of providers. It also involves continuing education and protocols/critical pathways/prompts for providers (Sperl-Hillen et al., 2004; Zapka et al., 2003).

Clinical Information Systems (IS) is defined by the Zapka et al. framework and Chronic Care Model as being similar–encounter reminders, flowcharts, risk lists of screenings due to tracking patients not adhering to screening, follow-up, or other recommendations (Sperl-Hillen et al., 2004; Zapka et al., 2003).

The dependent variables used in the Aim 1 tests for hypothesis 1c of the study are listed as the breast, cervical, and colorectal cancer screening 12-month provider self-reported improvement rate. This measure will be scored as 0 = no improvement, 1 = improvement in one of the three cancer screening areas only (breast cancer or cervical cancer or colorectal cancer screening), 2 = improvement in two of the three areas, and 3 = improvement in all three cancer screening areas.

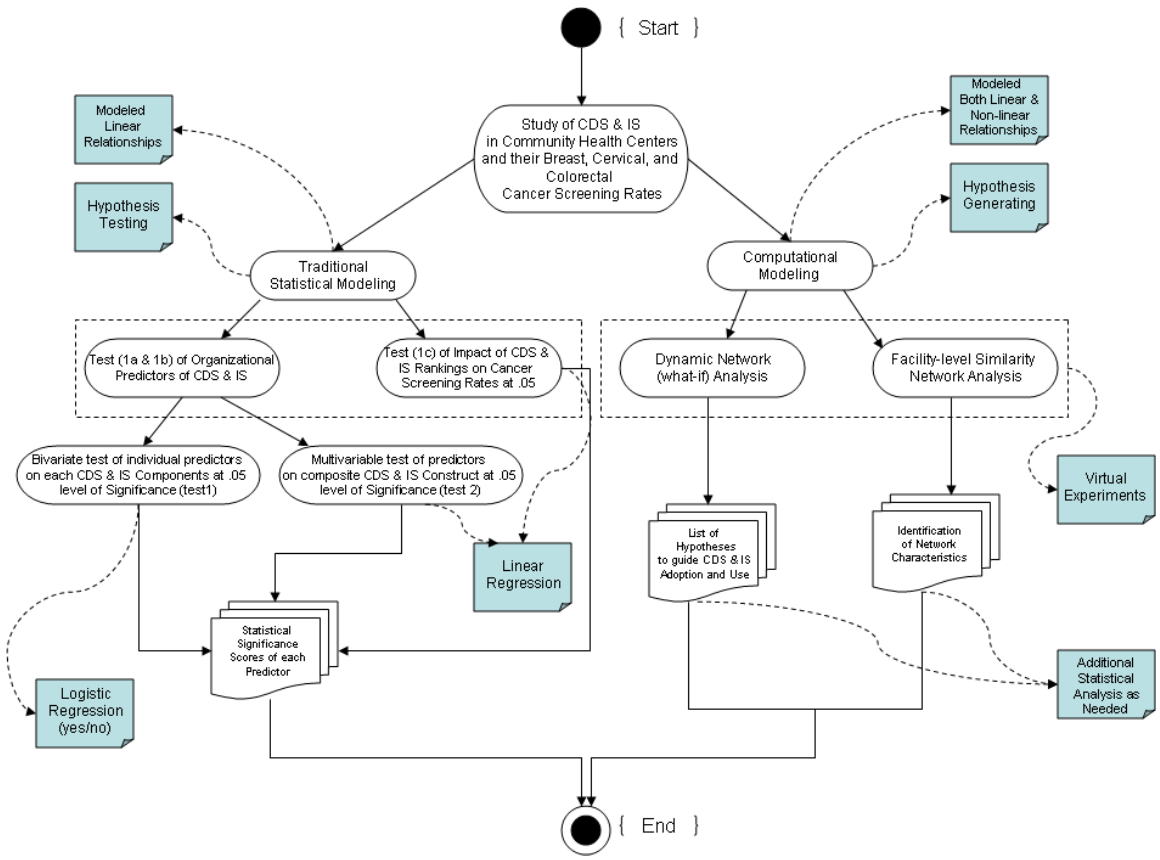
CHAPTER 3: METHODS

Aim 1 Methods–Statistical Model

Overall Study Methods Flowchart

The initial test for the predictors of CDS and IS in community health centers employed a traditional empirical (statistical) modeling approach to measure the level of association among the organizational, provider, and patient level factors and the proximal outcome of CDS and IS, as well as the association between CDS and IS and the distal outcome of cancer screening improvement. This statistical model tested for the presence, intensity-of-use of cancer-screening specific CDS and IS applications, and the corresponding impact of CDS and IS on the 12-month self-reported breast, cervical, and colorectal screening improvement rates in community health centers. These tests were consistent with associations identified by the "Zapka Factors Affecting Improved Cancer Screening in Primary Care," hence forth referred to as the Zapka et al. framework (Zapka, 2008). The next stage of computational modeling served as an exploratory analysis–hypotheses generating activity–in search of the hidden relationships revealed in a series of simulations of community health center performance groupings. These tests utilized the same set of factors associated with CDS and IS and cancer screening practices–which, for purposes of this phase of the analysis, were defined as agents, tasks, knowledge, and beliefs–for input into a simulation or virtual experiment. This research framework is presented in the study flowchart found in Figure 3.

Figure 3: Overall Study Methods Flowchart



Study Design: Aim 1

The research design used in this study is a retrospective cross-sectional cohort. The outcome variable is dichotomous, so as to represent the presence of community health center CDS and IS. The observations occurred in 2005 when the Health Resources and Services Administration (HRSA) Health Disparities Cancer Collaborative (HDCC) was created. The sample includes federally-funded HRSA Community Health Centers (CHCs) as the unit of analysis (n = 44). The sample contained two non-equivalent groups: 22 community health centers that participated in the HDCC and 22 community health centers that did not participate in the HDCC. The data used in this study came from the NCI/HRSA cancer collaborative study (Haggstrom et al., 2008). Because the dependent measure, community health center CDS and IS is dichotomous (Absent/Present), this study used logistic regression to examine associations between selected organizational factors and each of the four CDS and IS variables. A linear regression model was used to examine associations between organizational factors and facility-level composite CDS and IS intensity-of-use score. Additionally, a Spearman's Rank Correlation test was conducted to measure the strength of the relationship between the facility-level rankings for CDS and IS and the Cancer Screening performance rankings within this sample. Multi-collinearity among the set of independent variables was examined. Distributions of study variables were summarized using descriptive statistics appropriate for measurement level. Descriptive statistics were reported at both the facility-level and the performance group rankings level. Table 3 shows the complete list of research questions and hypotheses tested within Aim 1 of this study.

Table 3: Summary of Aim 1 Research Questions and Hypothesis Statements

Research Question by Statistical Model	**Main Hypothesis**
Aim 1: (1a) Presence of CDS/IS 1. What organizational, patient, and provider factors are associated with the **Capacity for Cancer Screening** in community health centers 2. What organizational, patient, and provider factors are associated with the presence of **Use of CDS/IS provider prompts at point-of-care** in community health centers 3. What organizational, patient, and provider factors are associated with the presence of **Computerized Patient Reminders** in community health centers 4. What organizational, patient, and provider factors are associated with the presence of **Computerized Generated Patient Results** in community health centers	Hypothesis 1a: Organizational and/or practice setting, provider characteristics, and patient population characteristics will be associated with the presence of CDS and IS within community health centers.
Aim 1: (1a.1) Presence of CDS/IS controlling for participation in the Health Disparities Cancer Collaboration (HDCC) 1. Controlling for participation the Health Disparities Cancer Collaboration (HDCC), what organizational, patient, and provider factors are associated with the **Capacity for Cancer Screening** in community health centers 2. Controlling for participation the Health Disparities Cancer Collaboration (HDCC), what organizational, patient, and provider factors are associated with the presence **Use of CDS/IS provider prompts at point-of-care** in community health centers 3. Controlling for participation the Health Disparities Cancer Collaboration (HDCC), what organizational, patient, and provider factors are associated with the presence of **Computerized Patient Reminders** in community health centers 4. Controlling for participation the Health Disparities Cancer Collaboration (HDCC), what organizational, patient, and provider factors are associated with the presence of **Computerized Generated Patient Results** in community health centers	Hypothesis 1a.1: Participation in the HRSA Health Disparities Cancer Collaboration (HDCC) will be associated with the presence of CDS and IS within community health centers. • To examine whether or not participation within the Health Disparities Cancer Collaboration (HDCC) impacts on the relationship tested hypothesis 1a
Aim 1: (1b) Intensity of Use of CDS/IS	Hypothesis 1b: Organizational and/or practice setting, provider characteristics, and patient population characteristics (listed in 1a) will be associated with the CDS and IS intensity-of-use scores within community health centers.
Aim 1: (Test 1b.1) Intensity of Use of CDS/IS controlling for participation in the Health	Hypothesis 1b.1: Participation in the HRSA Health Disparities Cancer Collaboration

Disparities Cancer Collaboration (HDCC)	(HDCC) will be associated with the CDS and IS intensity-of-use scores within community health centers. • To examine whether or not participation within the Health Disparities Cancer Collaboration (HDCC) impacts on the relationship tested hypothesis 1b
Aim 1: (1c) Impact of CDS/IS on Cancer Screening (Provider Self-Reported) improvement rates	<u>Hypothesis 1c</u>: Clinical decision support and information systems intensity-of-use scores (0 to 4) will be associated with the colorectal, breast, and cervical cancer screening 12-month (provider self-reported) improvement rate scores (0 to 3) within community health centers.

Study Population and Setting

According to the February 2010 President's Proposal on Health Care Reform, community health centers play a critical role in providing quality care in underserved areas (States, February 22, 2010). There are currently about 1,250 Community Health Centers (CHC) that provide care to 20 million people at more than 7,900 service delivery sites, with an emphasis on preventive and primary care (HRSA, June 2008; States, February 22, 2010). There is at least one CHC in every state within the U.S., the District of Columbia, Puerto Rico, the U.S. Virgin Islands, and the Pacific Basin (HRSA, June 2008). Slightly more than half (52%) of these centers serve rural America, with the remainder serving urban communities (HRSA, June 2008). Over 45% of CHC patients are Medicaid, Medicare, CHIP (Child Health Insurance Protection), or other forms of public insurance, and nearly 40% are uninsured (HRSA, June 2008). Within community health centers, 49% of the patient population is between the age of 25 and 64, 32% is between 5 and 24 years of age, 12% is under 5 years of age, and 7% is age 65 and older (HRSA, June 2008).

Study Sample and Survey Development

The Health Disparities Cancer Collaborative (HDCC) was a quality improvement program designed to increase the cancer control activities of screening and follow-up among underserved populations. It operated from 2003 to 2005 among community health centers supported by HRSA to serve financially, functionally, and culturally vulnerable populations (Harmon & Carlson, 1991; Iglehart, 2008). A sampling of 44 CHCs were chosen to examine the structure of organizations, the level of implementation of the Chronic Care Model components, and contextual factors (e.g., teamwork and leadership) (Sperl-Hillen et al., 2004; Taplin et al., 2008). According to Haggstrom et al., the survey instrument used in the HDCC study was developed in the following manner (complete survey instrument found in Appendix 2):

> Several domains were measured with Likert scales, including information systems, chronic care model implementation, teamwork, and cancer care process improvement; these scales were divided into four response categories: strongly agree, agree, disagree, and strongly disagree. Chronic care model implementation and teamwork scales were assessed using factor analysis by specifying the principal component method of factor extraction, the initial communalities of 1.0, varimax rotation, and scree plots (Haggstrom et al., 2008).

For this study, survey items were reviewed for ability to measure CDS and IS activity and reflect the 16 Organizational and/or Practice Setting Factors, three Provider Characteristics, and two Patient Population Characteristics utilized in this study's theoretical framework. Appendix 1 lists the relevant contributions to the major constructs used in this analysis.

Data Cleaning, Preparation, and Staging

The original data for used in this analysis was obtained in the form of five separate data CSV files, along with their corresponding data code manuals in the form of five separate MS Word documents. The five data files represented response sets from each of the facility representative categories that responded to the survey. The survey respondent categories included: (1) Director (CEO), (2) Chief Financial Officer (CFO), (3) Provider (physicians, nurses), (4) General Staff (e.g., lab, pharmacy, etc.), and (5) Informatics Officer (CIO). The five CSV data files complied responses to the question set from each of the 44 health facilities responding to the survey.

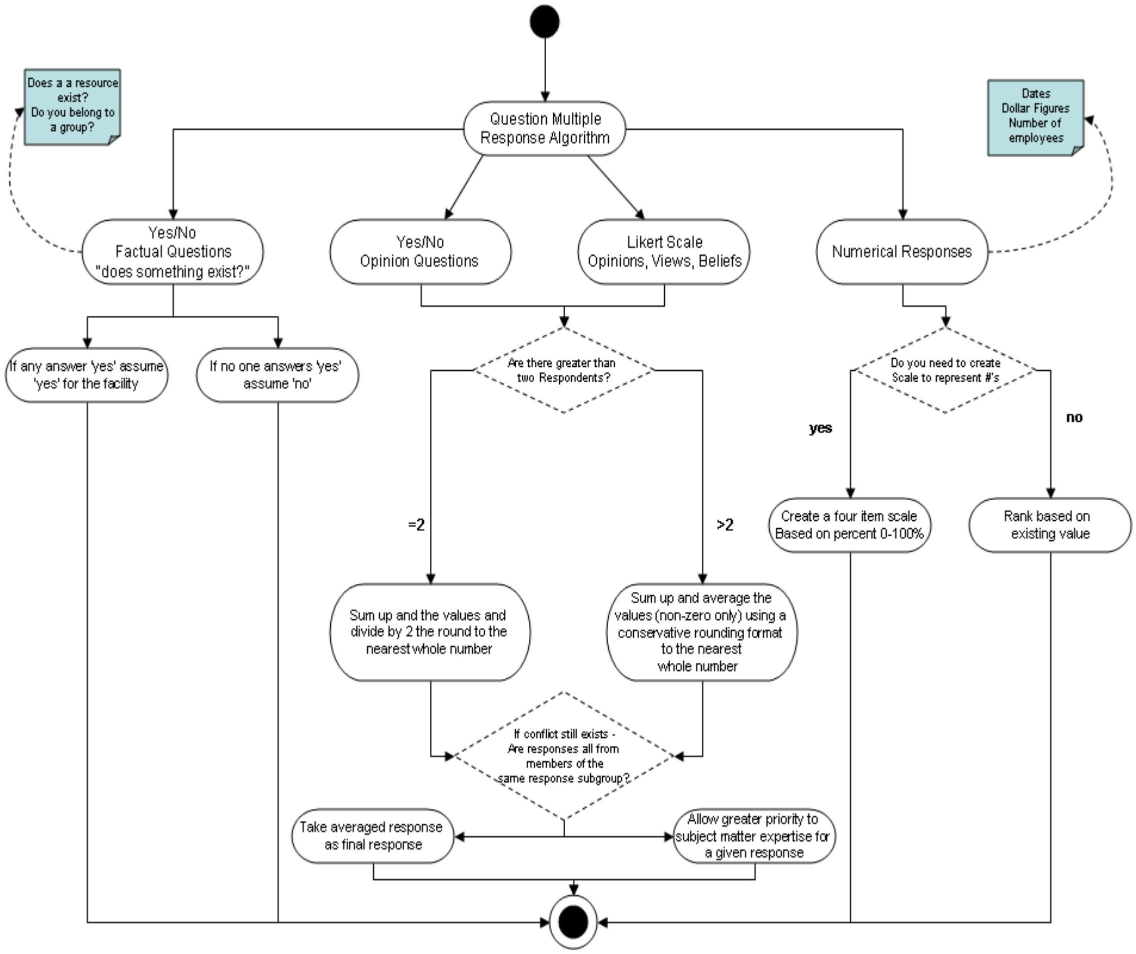
It should be noted that some of the questions were repeated, thereby allowing more than one survey respondent category to address the same question. Additionally, more than one of the same respondent type was allowed to address any and every question within the question set. As such, in the case of the former, there might be a particular question answered from both the perspective of the CEO and the Provider. In the case of the latter, there might be three or four members of a Provider team (nurses and physicians) all answering the questions in the full set of questions intended for Providers. The reconciliation algorithm will be presented later in this section. The goal was to obtain a single score for each variable, henceforth referred to as summary measure, which would represent the consensus for the community health center. The five surveys that each community health center responded to from the original HDCC study consisted of the following questions and categories, as seen in Table 4.

Table 4: Survey Categories and Questions by Survey Respondent

Respondent Type	Questions	Original Category Groupings (Question Number)
CEO – Health Center Director Survey	45 questions	Introduction (1-4) Clinic Processes (5-18) Management Strategies (19-21) Community Outreach (22-24) Information Systems (25-33) Leadership (34-35) Background Information (36-45)
CFO – Financial Officer Survey	35 questions	Governance (1-5) Staffing (6-14) Financial Information (15-21) Revenue Sources (22-24) Patient Demographics (25-28) Background Information (29-35)
Provider – Health Care Provider Survey	53 questions	Introduction (1-3) Clinic Processes (4-15) Information Systems (16-28) Division of Responsibilities (29-32) Leadership (33-36) Teams (37-38) Background Information (39-53)
General Staff – General Staff Survey	37 questions	Introduction (1-4) Clinic Processes (5-18) Information Systems (19-20) Division of Responsibilities (21-24) Leadership (25-28) Teams (29-30) Background Information (31-37)
CIO – Information Systems Personnel Survey	37 questions	Introduction (1-4) Clinic Processes (5-10) Information Systems (11-25) Leadership (26-28) Teams (29-30) Background Information (31-37)

The Consolidation Algorithm was designed to handle multiple responses to a single question from the same facility. The unit of analysis in the research was the facility and, as such, the goal was to obtain representative facility-level responses to each summary measure. This was intended as a minimally intrusive way to reduce varying responses to a single value. There were four different types of questions addressed in the algorithm seen in Figure 4: (1) Yes/No responses based upon a factual statement about the existence of something or not, (2) Yes/No opinionated responses, (3) Likert Scale opinionate responses, and (4) numerical responses.

Figure 4: Management of Multiple Responses and Multiple Respondent Types



Each of the 99 unique survey questions was categorized into one of these four questions types for reconciliation and consolidation. Every attempt was made in this analysis to avoid subjective interpretation of what might be considered the best qualified answer, because the desire was to minimize researcher bias by assuming that one particular designated responder might be more informed than another in terms of addressing a particular question. This is evident in the fact that varying management philosophies might distribute knowledge and expertise differently. A highly distributed organization might rely more on delegation; whereas, a highly concentrated and centralized structure might distribute less expertise throughout the organization. As such, what one subordinate might be expected to know in one facility might vary in another facility, and, at the same time, the amount of knowledge and information that a "hands-on" CEO might have on granular activities in one organization might dramatically differ from a CEO who delegates the bulk of such tasks. Consequently, no attempt was made to assume what any particular responder knew relative to another and, in most, if not all cases, the responses were equally weighted.

The final step in obtaining the facility-level values for each summary measure found in the conceptual model, after applying both the multiple response algorithm, was to then design an algorithm to take the data columns as they were compiled in the master Excel spreadsheet and automatically produce the final value in a separate column for insertion in the summary spreadsheet (see Averaging Algorithm in Appendix 3).

As a result of these treatments, the author of this study was able to obtain a final list of summary measures and their respective values for each measure identified within the conceptual diagram. Additional quality checks were conducted on random values to ensure that the algorithms functioned properly and that the end values corresponded with expectations. Additional quality tests were conducted at random points in the statistical analysis to ensure there were no anomalies in the data that were inconsistent with the original data.

An additional treatment of summary measures was performed on the final master Excel spreadsheet in preparation for the computational modeling exercises that will be discussed in the Aim 2 Methods section. Appendix 4 lists the complete set of HDCC survey summary measures along with their corresponding SAS coded variable name and operational definitions.

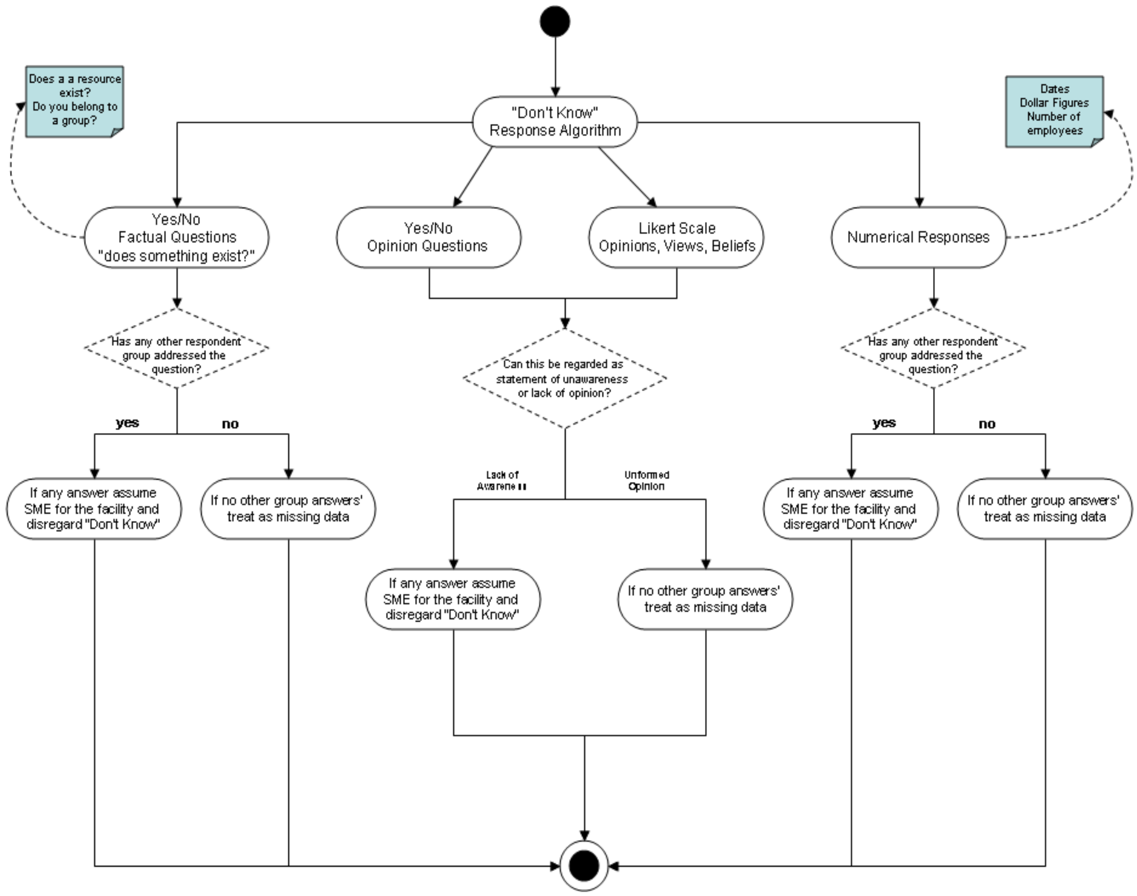
Statistical Analyses

All analyses used health center as the unit of analysis, and employed a 5% Type I error rate for statistical significance. Data were examined for patterns of missing and out-of-range values.

As such, a missing data algorithm, described in Figure 5 below, was created to address all forms of missing data that might be experienced throughout the analysis. It was also assumed that, if the data were randomly missing, ignoring the missing data would not have any effect on the statistical model construction and inference concerning potential predictors. The current study did not have significant occurrences of missing dependent variables, since the level of missing data at the health center level remained low.

One issue discovered in the data was in response to the independent variable Organization Size. Respondents were able to respond to this Organizational and/or Practice Setting question with the number of personnel who work or practice within their community health center. In some cases, responses were discovered with 0 for the number of full-time employees (FTE's) working at the center. The author of the current study could either assume: (1) that all employees of the facility were part-time or temporary employees, or (2) that the zero response represented an anomaly in the response set. The latter reasoning was used–any Organizational Size response of less than 1 was treated as missing data.

Figure 5: Algorithm for the Treatment of Missing Data and “Don’t Know” Responses



Distributions for all study variables were examined using appropriate descriptive statistics. Collaborative participation was included as a covariate in each multivariable organizational and/or practice setting model only when it was identified as a member of the best subset of predictors. Conformance to statistical assumptions was examined for each model, as well as the presence of outlying and influential observations and multi-collinearity. All statistical testing in Aim 1 was conducted using SAS version 9.2.

Hypothesis Testing

Hypothesis 1a: Assessing the level of presence of CDS and IS in Community Health Centers

The dependent variables associated with hypothesis 1a are binary in nature. As a result, a logistic regression approach was used to test this hypothesis. In recognition of the relatively large number of potential predictor variables, a best subsets approach, within Organizational and/or Practice Setting Factors, Patient Characteristics, and Provider Characteristics was used.

Independent Measures for Hypothesis 1a

Sample items for each summary measure and domain area (e.g., organizational and/or practice setting factors, patient characteristics, and provider characteristics) in the conceptual framework (as seen in Figure 2) are shown in Appendix 1.

Dependent Measures for Hypothesis 1a

As previously noted, four separate types of CDS and IS were focused on as dependent variables: The first dependent variable being the Capacity for CDS. Respondents indicated (yes/no) whether their health center's computer system had the capacity to measure cancer-screening activities. Cancer Screening Activity was operationally defined in the survey to include providing timely notification of screening results, timely completion of additional diagnostic testing after abnormal screening results, a timely beginning of treatment, and documenting discussions about cancer screening (Haggstrom et al., 2008).

A second and third dependent variable measured (yes/no) whether provider prompts were used at the point-of-care and whether (yes/no) computerized patient reminders were in use at their health center, respectively. A fourth dependent variable measured (yes/no) whether their facility could generate correspondence through the information system that reports screening results to patients. Consistent with the Chronic Care Model, the first three of the four components of the dependent variable were labeled as clinical decision support (CDS) activity, and the fourth of these dependent variables was considered information systems (IS) activity. Hence, use of the composite acronym CDS and IS (or its equivalent CDS/IS) was used throughout this study.

Modeling Approach for Hypothesis 1a

The four CDS and IS component dependent variables (Capacity for CDS, Use of Clinical Reminders, Availability of Provider Prompts, and Access to Electronic Results Notification) are binary in nature (Absent/Present). A logistic regression approach, modeling Presence of each component dependent variable, was used to address Hypothesis 1a. Specifically, a best subset of independent variables, based on the Score χ^2 statistic, was explored within each category of conceptual model independent variables (e.g., organizational and/or practice setting factors, patient characteristics, and provider characteristics). This method inserted a "Best" or "Select Best" statement in the SAS syntax for test 1a to obtain a "best subset" of predictors that was then utilized in the final run of each test and reported in the Results section. By using the Chi Square or score statistic, the best model from each grouping was selected based on having the highest Chi Square or score statistic available and the fewest number of predictor variables possible. The cutoff was the model where it was shown that by adding any additional variables, there was no corresponding increase in statistical significance of the model and, as such, added no more predictive power than the less parsimonious model (Kutner et al., 2004). Comparative tests on competing Chi Square p-values were conducted using SAS where there was any ambiguity in the decision criteria.

Table 5 summarizes lists the independent measures, dependent measures, and modeling approach for hypothesis 1a in assessing the presence of CDS and IS in community health centers.

Table 5: Summary of Hypothesis 1a Measures and Approach

	Independent Variables	Dependent Variables	Statistical Modeling Approach
Model 1a (Presence of CDS/IS)	Organizational and/or Practice Setting Factors, Provider Characteristics, and Patient Population Characteristics	CDS/IS Components (<u>Tested individually against IVs</u>) (1) Capacity for CDS (2) Use of Clinical Reminders (3) Availability of Provider Prompts (4) Access to Electronic Results Notification	Logistic Regression • Defining the association between predictor variables and outcome variables • All Subsets Logistic Regression to identify the best set of predictors based on score chi-squared statistic

Hypothesis 1b: Assessing the Intensity-of-Use of CDS and IS in Community Health Centers

A multivariable linear regression model was employed to determine whether the composite CDS and IS facility-level score, interpreted as community health center intensity-of-use, was associated with conceptual model antecedents of organizational, patient, and/or provider factors.

Independent Measures for Hypothesis 1b

Sample items for each summary measure and domain area (e.g., organizational and/or practice setting factors, patient characteristics, and provider characteristics) in the conceptual framework (as seen in Figure 2) are shown in Appendix 1.

Dependent Measures for Hypothesis 1b

Hypothesis 1b tested the composite scoring of CDS and IS for each community health center (0 to 4) against the same set of independent measures (organizational and/or practice setting factors, patient characteristics, and/or provider characteristics) from Hypothesis 1a.

Modeling Approach for Hypothesis 1b

A score of 0 or 1 was assigned to each of the four CDS and IS component dependent variables for each facility. Each community center was then given a composite score for overall CDS and IS of 0 to 4 for having none, one, two, three, or all four CDS and IS present in their health center. A multivariable analysis approach, modeling the CDS and IS intensity-of-use was used to address Hypothesis 1b. Specifically, a best subset of independent variables, based on the

Adjusted R^2, was explored within each category of conceptual model independent variables (e.g., organizational and/or practice setting factors, patient characteristics, and provider characteristics). This method inserted a “Best” or “Select Best” statement in the SAS syntax for test 1b to obtain a “best subset” of predictors that was then utilized in the final run of each test and reported in the Results section. By using the Adjusted R-Squared, the best model from each grouping was selected based on having the highest Adjusted R-Squared available and the fewest number of predictor variables possible. The cutoff was the model where it was shown that by adding any additional variables, there was no corresponding increase in statistical significance of the model and, as such, added no more predictive power than the less parsimonious model (Kutner et al., 2004).

Table 6 summarizes lists the independent measures, dependent measures, and modeling approach for hypothesis 1b in assessing the intensity-of-use of CDS and IS in community health centers.

Table 6: Summary of Hypothesis 1b Measures and Approach

	Independent Variables	Dependent Variables	Statistical Modeling Approach
Model 1b (Intensity of Use of CDS/IS)	Organizational and/or Practice Setting Factors, Provider Characteristics, and Patient Population Characteristics	CDS/IS Facility-Level Ranking (0 to 4) 0 = No CDS/IS Component Present 1 = One CDS/IS Component Present 2 = Two CDS/IS Components Present 3 = Three CDS/IS Components Present 4 = All CDS/IS Components Present	Multivariable Analysis – Linear Regression Model Approach Best subsets to identify the best set of predictors based on Adjusted R Squared

Additional Modeling and Analytical Issues for Hypothesis 1a and 1b

In Phillip Good's 2011 book, *Analyzing the Large Number of Variables in Biomedical and Satellite Imagery*, he describes very large data arrays for which the number of observations per subject may be much larger than the number of subjects observed in a problem that arises in several different categories of research (Good, 2011). This can also be the case in organizational studies, where only one or a few organizations (where the organization represents the unit of analysis) may participate in the study, yet look at hundreds of variables. Such a research design violates the integrity argument raised by Good, Kutner, and Peng, who, in particular, point out that–specifically for logistic regression, but consistent with linear regression as well–one should have a 10 to 1 ratio of observations to predictors, and a minimal sample size of 100 (Good, 2011; Kutner, Nachtsheim, & Neter, 2004; Peng, Lee, & Ingersoll, 2002).

There are 17 Organizational and/or Practice Setting variables (16 plus the one added covariate for HDCC membership), 2 Patient Characteristics (made up of 4 Demographic variables and 4 Payer Mix variables, respectively, for a total of eight Patient Characteristics), as well as 3 Provider Characteristics. Without any reduction steps, this brought the total number of predictor variables for tests 1a and 1b to 28 predictor variables respectively. Given the ideal of a 10 to 1 minimum observation-to-predictor ratio, the model would require at least 280 observations. This analysis had only 44 observations. This first attempt at reducing the model was designed to split the independent variables by groupings and separately test each group against the dependent variables. As such, instead of testing the entire set of predictors against each CDS and IS component in test 1a, and the entire set of predictors against the composite CDS and IS score in test 1b, the tests were performed separately for each of the three groups of predictors: (1) Organizational and/or Practice Setting, (2) Patient Characteristics, and (3) Provider Characteristics, in both tests 1a and 1b separately against their respective dependent variables. The results were reported accordingly.

An examination for multi-collinearity represented a second stage of model reduction, where either variables that were highly collinear and/or variables that might cause considerable problems in the analysis, were considered for removal from the analysis. The test for multi-collinearity was conducted in a manner consistent with the model components above, where the test was performed first on all Organizational and/or Practice Setting variables only, then on all Patient Characteristics alone, and finally on all Provider Characteristics alone. The primary interest was to examine whether any of the predictors for which community health center CEO, CFO, CIO, General Staff, and Providers responded to were so highly collinear that one or more could be removed without having an impact on the predictive power of the model. The presence of multi-collinearity among the independent variables was evaluated using (a) Variance Inflation Factor (VIF) and (b) bi-variate correlations with other independent variables. Criteria for the presence of multi-collinearity included (a) VIF > 10 and (b) a bi-variate correlation >.90. Variables approaching those values were evaluated on a case-by-case basis.

Model Fitting and Diagnostics proceeded in two stages. First, three separate models were constructed to assess the relationship between each of the organizational and/or practice characteristics, provider characteristics, and patient population characteristics, and the four dependent variables. The estimated effect size and standard errors for covariates with a significant relationship for any of the four outcome measures was reported. The second stage of model fitting was to fit the multiple predictor models. For each of the four individual dependent variables, the one composite dependent variable, statistically significant covariates, and their interactions, as well as the covariates considered critical for conceptual reasons, were included in a multiple regression model. If a covariate was no longer significant, it was removed from the model using standard model selection techniques. They were then compared against published data. Assumptions were assessed using appropriate diagnostics. Graphical examinations of residuals were performed. Appendix 7 lists the diagnostic tests for both the Logistic Procedure and the Linear Procedure and their relative importance to this analysis by test.

Hypothesis 1c: Assess the Impact of CDS and IS on Cancer Screening Rates in Community Health Centers

As previously noted, each health center was ranked based on the number of CDS and IS components the facility had in use at the time of the survey, ranging from 0 to 4 for having none, one, two, three, or all four of the CDS and IS components, respectively. The facilities were also be ranked based on their performance for the 12-month cancer screening provider self-reported improvement rates from 0 to 3, where 0 represented self-reported improvement in none of the areas of breast, cervical, and colorectal cancer; 1 represented self-reported improvement in only one of those areas;

on up to self-reported improved in all three areas. The computational modeling exercise made use of these same rankings to form a performance matrix based on the CDS and IS score relative to the Cancer Screening Improvement (CSI) Rate Score and grouped them into high performers vs. low performers. This will be discussed in detail in the Aim 2 Methods section.

Independent Measures for Hypothesis 1c

Facility-level CDS and IS intensity-of-use composite score/ranking (0 to 4) as described in hypothesis 1b.

Dependent Measures for Hypothesis 1c

Facility-level 12-month cancer screening improvement composite score/ranking (0 to 3), represents improvement in no area, one area (breast, cervical, or colorectal cancer screening), two areas, or all three areas.

Modeling Approach for Hypothesis 1c

Spearman's Rho Coefficient was employed to test association for CDS and IS intensity-of-use and 12-month cancer screening improvement rates. The range for cancer screening improvement spanned from 0 to 3, signifying improvement in none of the three areas, improvement in only of the three areas, improvement in two of the three areas, and improvement in all three areas, respectively.

Table 7 summarizes lists the independent measures, dependent measures, and modeling approach for hypothesis 1c in assessing the strength of the relationship between CDS and IS intensity-of-use scores and cancer screening improvement rate scores within community health centers.

Table 7: Summary of Hypothesis 1c Measures and Approach

	Independent Variables	Dependent Variables	Statistical Modeling Approach
Model 1c (Impact of CDS/IS on (Provider Self-Reported) Cancer Screening Improvement Rates)	CDS/IS Facility-Level Ranking (0 to 4) 0 = No CDS/IS Component Present 1 = One CDS/IS Component Present 2 = Two CDS/IS Components Present 3 = Three CDS/IS Components Present 4 = All CDS/IS Components Present	12-month cancer screening improvement ranking (0 to 3) 0 = No (provider self-reported) cancer screening rate improvement 1 = (provider self-reported) cancer screening rate improvement in one area 2 = (provider self-reported) cancer screening rate improvement in two areas 3 = (provider self-reported) cancer screening rate improvement in three areas	Correlation to test • The strength of relationship between CDS/IS and cancer screening self-reported rates • For each unit increase in CDS/IS use, what is the corresponding unit increase in cancer screening? • Spearman's R Correlation Coefficient (+/- reveals direction and strength of the relationship)

There were no model-reduction techniques employed in the final statistical testing of the impact of CDS and IS on the 12-month cancer screening (self-reported) improvement rates (1c). This tested the strength of the relationship between the two categories of rankings and there were no issues regarding the minimum observation-to-provider ratio.

Power for Aim 1

The study entails a series of regression models involving both logistic and linear regression approaches. As such, power analyses relate to the detectable effect of a predictor variable in each of these models. Available sample size for this study was 44 community health centers for each modeling approach. Power estimates were calculated using PASS 11 (Hintze, 2011).

Logistic Regression.

- Assuming a non-directional 0.05 significance level for the CDS and IS Capacity for Measuring Cancer Screening, 44 observations, 4 covariates correlated .50, and a baseline P(CDS/IS Presence) = .40, an odds ratio of 0.068 provides a power of .80. The variable of interest for this analysis was the binary measure for HRSA Collaborative Participation with a sample proportion of .50.
- Assuming a non-directional 0.05 significance level for both Provider Prompts at Point-of-Care and Computerized Patient Reminders, 44 observations, 4 covariates correlated .50, and a baseline P(CDS/IS Presence) = .73, an odds ratio of 0.063 provides a power of .80, where the variable of interest for this analysis was the binary measure for HRSA Collaborative Participation with a sample proportion of .50.
- Assuming a non-directional 0.05 significance level for the Computerized Generated Correspondence of Results to Patients, 44 observations, 4 covariates correlated .50, and a baseline P(CDS/IS Presence) = .78, an odds ratio of 0.050 provides a power of .80, where the variable of interest

for this analysis was the binary measure for HRSA Collaborative Participation with a sample proportion of .50.

Linear Regression.

Assuming a 0.05 significance level and a maximum of six predictor variables modeling a single ordinal outcome measuring the intensity-of-use of CDS and IS for use in cancer screening within the health centers, an effect size (R^2) of .27 results in a power of 80%.

Spearman's Rank Correlation. Assuming a 0.05 significance level and 44 observations, a bivariate correlation of .41 will result in a power of .80 for testing the bivariate association between CDS and IS intensity-of-use on cancer screening performance within health centers.

Aim 2 Methods–Computational Model

Study Overview

The goal of Aim 2 was to develop a computational model of community health center *agents*, *tasks*, *knowledge*, and *beliefs* associated with cancer screening and CDS and IS using a network evolution tool called CONSTRUCT™[2], which can ultimately inform both community health center CDS and IS use, adoption, and/or implementation in support of cancer screening intervention strategies. As previously mentioned in the section dedicated to multilevel intervention research, strategies for both health outcomes improvement and/or health information technology adoption, which rely solely on the traditional model, have proven to be less than optimum in meeting national performance benchmarks for areas such as cancer screening and CDS adoption and use. The intent of this study is to introduce a second aim that uses a computational model that can account for organizational dynamics involved in community health center cancer screening practices, with special emphasis on those practices related to CDS and IS not captured in the Aim 1 statistical analysis.

In Aim 1, the unit of analysis was the individual community health center or facility-level. In Aim 2, the unit analysis has been aggregated to the performance group level, as derived from the combined facility-level rankings for CDS and IS and cancer screening (as obtained from Aim 1 test 1c), respectively. While this portion of

[2] "Construct, developed by CASOS, is a multi-agent model of network evolution. Social, knowledge and belief networks co-evolve. Groups and organizations are treated as complex systems, thus capturing the variability in human and organizational factors. In Construct, individuals and groups interact, communicate, learn, and make decisions in a continuous cycle." http://www.casos.cs.cmu.edu/projects/construct/

the research has consistently been called a hypothesis generation exercise in order to be consistent with Carley's discourse, *On Generating Hypotheses Using Computer Simulations* (Carley, 1999), it is important to note that there was actually an underlying hypothesis being tested within this Construct^{TM} simulation (virtual experiment):

- Higher Performing Firms (community health center performance groups) will have a steeper slope curve (representing superior Task Performance and superior Knowledge Absorption) than that of Lower Performing Firms (community health center performance groups) for Cancer Screening.

This computational model will seek to:

Aim 2b): Design a series of agent profiles (e.g., Firm view–Administrative, Firm view–Clinical Care, Outside Collaborators, IT Systems, and Cancer Screening Tests) and their associated Task Performance Elements as measured by a change in **Task Knowledge Impacting Performance** over a 10-year (520-week) period in a comparison of community health center performance groups.

Aim 2b): Design a series of agents profiles (e.g., Firm view–Administrative, Firm view–Clinical Care, Outside Collaborators, IT Systems, and Cancer Screening Tests) and their associated Opportunities for Knowledge Exchange (based upon Homophily or the notion that similar components of a network are more likely to interact at a higher rate than those with less similar components of a network [McPherson, Smith-Lovin, &

Cook, 2001]) as measured by a change in **Knowledge Absorption (also referred to as Homophily Knowledge)** over a 10-year (520-week) period in a comparison of community health center performance groups.

The key factor determining the feasibility of this portion of the analysis of community health center CDS and IS and cancer screening practices would be to convert a traditional organizational survey representing a point-in-time assessment of health center practices into a sufficient data source for a computational model relying on network theory.

Since the primary focus of this research is examining the cancer screening practices of community health centers with respect to CDS and IS, the computational modeling of both task knowledge and knowledge absorption will focus primarily on the behavior of the cancer screening test agent and the tasks associated with the agent. However, overall performance level network characteristics will be examined using all five-agent classifications to obtain a more inclusive look at health center characteristics over time.

Study Design

Aim 2 made use of the same community health center sample data used in Aim 1 of this study. The summary measure scores in the statistical modeling exercise were averaged at the facility-level for each of the 44 community health centers. Two summary measures that account for facility-level CDS and IS rankings and facility-level cancer screening improvement rankings were used to create a composite measure of overall facility-level performance. These performance rankings were the focus on in the building the Aim 2 study design. Additionally, because this was a single point-in-time survey representing community health center practices from 2003 to 2005, the Aim 2 computational model or simulation had to rely upon a virtual representation of each community health center performance level based on statistical means and standard deviation scores for each summary measure by performance level, because no real data about community health center practices beyond 2006 existed within this dataset.

This computational model would utilize the same three categories of antecedents from the modified Zapka et al. framework including: (1) Organizational and/or Practice Setting Factors, (2) Provider Characteristics, and (3) Patient Population Characteristics, along with the variables for clinical decision support and cancer screening (self-reported) improvement rates. As such, the research challenge in this portion of the analysis was to determine the extent to which a computational model could effectively compliment a traditional modeling exercise and provide meaningful information about organizational performance over time. The intent was to provide an enhanced picture of CDS and IS use in combination with cancer screening activities, which would account for complex relationships in a dynamic adaptive organizational setting that a traditional statistical modeling of point-in-time survey instrument may fail to reveal. These factors of CDS and IS for use in cancer screening at the community health center level were tested in a virtual experiment using a dynamic network analysis tool called Construct™. Such an analysis would make use of Construct™ for the primary analysis and ORA, a network visualizer tool developed by the Carnegie Mellon University, Computational Analysis of Social and Organizational Systems (CASOS), in a visual analysis of the all five agent classification and the additional examination of the Construct^{TM} results, as needed (CASOS, 2009). This exploratory analysis was designed to generate a series of new and novel hypotheses for use in future studies about the behavior of this organizational environment under different scenarios related to CDS and IS use and facility-level screening rates expressed as a series of graphs, tables, charts, and network diagrams (Carley, 1999) that could drive further research efforts.

The primary outcome of this analysis was to measure the extent to which these groups of agents could demonstrate some measure of organizational learning (Anderson & Willson, 2009; Niland et al., 2006; Salas, Rosen, & DiazGranados, 2010; Sintchenko et al., 2007; Sittig et al., 2010) relative to the cancer screening task and some measure of organizational maturity in the cancer screening practices as seen through a series of visualized network characteristics (Bruque et al., 2008). Organizational learning of community health centers was measured as a function of both (1) cancer screening task-related knowledge on a specified subset of tasks associated with the agent (expressed as "Task Knowledge that Impacts Performance") and (2) knowledge sharing opportunities (Knowledge Absorption, also referred to as Homophily Knowledge). Each agent, along with his or her corresponding assigned tasks and knowledge elements, is discussed below.

It should be worth mentioning that this portion of the analysis was limited to only the variables contained with the original HDCC data set of summary measures used in Aim 1 of this study. No new variables were introduced into this portion of the analysis. The measure of impact was the extent to which a simulated 10-year performance period could successfully mimic the performance levels exhibited within this point-in-time survey (as obtained from the combined facility-level rankings for CDS and IS and cancer screening improvement). In other words, could firms that initially ranked as high performers consistently outperform those ranked as low performers over a 10-year period in both knowledge and task performance categories? The goal is to essentially be able to inform long-term strategic planning efforts that might rely solely on some form of a point-in-time static data source about organizational practices. If successful, this methodology could provide an incredibly useful systems thinking approach to inform multilevel interventions aimed at achieving both CDS and IS goals, as well as facility-level cancer screening goals over a specified period into the future, taking into account complex adaptive organizational environments. The nine steps in building this simulation, from conceptualization to analyzing model output, have been outlined in greater detail below.

Strengths and Limitations Aim 2 Study Design

One strength of this study design was that it allowed for multiple scenarios to be tested under varying conditions. In fact, the number of combinations seems relatively limitless. In an attempt to generate new hypotheses about a given phenomena, a trial and error approach might be a major part of the experiment. The corresponding limitation is that this same trial and error approach could lead to endless analysis and fail to produce any meaningful results. This may cause one to challenge the actual value of a hypothesis generation exercise as a compliment to a statistical modeling hypothesis testing study. Carley et al. stressed the value of not just hypothesis testing, normally associated what traditional (statistical) models, but also a more dynamic form of hypothesis generation that can come from computational models and simulations (Carley, 1999). Carley explains that the aim of computational research is to build new concepts, theories, and knowledge about complex systems, such as organizations, groups, teams, or command and control architectures (Carley, 1999). The core question Carley asked was whether or not there can be some underlying simple, but non-linear process that might underlie team or group behavior (Carley, 1999). This sort of question encourages the use of commonly collected point-in-time survey data about individual, team, group, and organizational behaviors to examine this possibility. This pursuit alone constitutes growth potential in the understanding and predictability of organizational behaviors based on large amounts of similarly collected strategic and organizational survey data that might reveal so much more than the original intent. Thus, the inherent strength of this analysis can be found in the almost boundless possibilities for exploratory analysis that may inform technology use and eventually adoption and implementation studies in conjunction with facility-level cancer screening improvement interventions.

In this study design, the number of variable combinations was limited in scope to essentially examining the cancer screening test agent category. This concentrated focused can be described as a limiting factor of the overall potential of this type of analysis to explain the entire scope of community health center behaviors, but it can also serve as a foundation for much more streamlined and targeted interventions.

Modeling Community Health Center Cancer Screening Activity

Step-by-Step Overview for Building the Community Health Center Simulation

Step one was more or less an information gathering exercise conducted in the form of literature reviews and informal telephone interviews. The goal was to simply define what could be done and not done with the secondary data obtained from the HDCC survey instrument. One informal interview was conducted in 2009 with Judith Effken, in which she highlighted some of the details of a combined statistical and computational analysis of nursing quality improvement data done in partnership with Dr. Kathleen Carley of CASOS (Effken et al., 2005; Effken et al., 2003). Based on conversations with Dr. Effken, insights into how to transform typical health services delivery and clinical outcome data elements into a machine-type language commonly used in CASOS tools were obtained. In Dr. Effken's particular case, this referred specifically to the tool OrgAhead (Effken, personal communication, 2009).

Another informal telephone conversation was conducted with Dr. Kathleen Carley of Carnegie Mellon University, CASOS (CASOS, 2009). Based on conversations with Dr. Carley, helpful information on the basics of computational modeling, the suite of tools she and her team developed at CASOS, and insights into the types of things one can and cannot do with the kind of data available for use in this study, were obtained (Carley, personal communication, 2009). Perhaps the greatest insight Dr. Carley provided came in the form of an outline that would ultimately limit this portion of the study to what she referred to as a "between" analysis (Carley, personal communication, 2009). Carley described differences amid "within" network analysis and "between" network analysis. The former would require detailed information about contact patterns (e.g., those involving person-to-person, person-to-machine, or machine-to-machine) within a health care organizational unit (Carley, personal communication, 2009). There might also be a need to have a granular view of process and function within the health care organizational unit. Carley explained that the latter "between" analysis was more of a firm-to-firm view of similarities and differences among firms in a given network (Carley, personal communication, 2009). The "between" analysis might also have some higher level aggregate views of process and function but may often lack the fine detail that a "within" analysis would provide (Carley, personal communication, 2009). As a result of the interviews with Dr. Carley and Dr. Effken, both which indicated that, at the very minimum, given the level of granularity within the HDCC survey on the sample of 44 community health centers, that activities would have to be limited to a "between" or "similarity" analysis computational modeling exercise.

Step two commenced once it was determined how to treat the data set in the Aim 1 statistical analysis, as expressed in the conceptual model in Figure 2. The statistical analysis in Aim 1 provided some key statistical associations among several of the 37 summary measures. Several identified relationships were examined in tests for the presence and intensity-of-use of CDS and IS, as well as the strength of relationship for CDS and IS rankings with that of cancer screening improvement rankings. The results of these statistical tests of statistical significance, the test for multicollinearity among the variables in relation to the proximal outcomes of CDS and IS, and the distal outcome of facility-level cancer screening improvement, all informed Aim 2. Additionally, the statistical analysis provided some meaningful information to assist in the building of core assumptions and establishing inclusion/exclusion criteria for one or more of the 37 summary measures (which represent all independent and dependent variables used in the Aim 1 analysis, excluding the binary HDCC participant/non-participant independent variable) obtained from the HDCC survey.

Four critical determinations were made at the very start of the computational research model design: (1) the variable "payer-mix–Self-Pay" would be excluded from this analysis, as it was from the Aim 1 portion of the analysis for the same reasons as described in the summary of multi-collinearity tests of it providing essentially the same information as the variable for "Commercial Pay" insurance type; (2) the variables "Organizational Size and Structure" and "Total Budget" would be combined to represent a measure of the overall community health center size and resources. While these two determinations were retained in the Aim 1 portion of the analysis, in Aim 2, it was deemed redundant to use both, as these variables were shown to be moderately correlated to one another; (3) Aim 2 only used the variable representing HDCC Experience and excluded the variable for HDCC Participant/Non-Participant from this portion of the analysis, as HDCC Experience proved to be a much more robust measure of overall governance strategy; and, (4) this computational model would not rely upon statistical significance as a pruning technique, as first envisioned. It was originally envisioned that testing within the computational modeling exercise would only include those relationships that demonstrated statistical significance in Aim 1. The rationale was that it would be a practical strategy to reducing the overall size and complexity of the simulation. However, after a further review of the literature, it became apparent that one of the strengths of computational modeling was that it was not limited to only assessing previously tested statistical relationships. According to Carley et al., virtual experiments aimed at hypothesis generation actually allowed for the testing of hypothesized relationships yet to be tested or shown not to be statistically significant in previous linear models (Carley, 1999).

Relative to this study, such a broadened approach as described by Carley et al., allowed for the (1) reexamination of the Aim 1 Spearman's Rho test on the strength of relationship between the facility-level scores for CDS and IS (0 to 4), and the facility-level score for 12-month cancer screening (self-reported) improvement rates (0 to 3), as well as (2) testing of the independent variables of Organizational and/or Practice Setting Factors, Patient Characteristics, and Provider Characteristics directly on the distal outcome of cancer screening rates. In the former, the test for cancer screening impact could be examined computational regardless of Aim 1 statistical significance, and in the latter case, tests originally considered out of scope for the statistical analysis could now be considered informative in a hypothesis generation exercise.

<u>Step three</u> included defining a list of agents, tasks, knowledge elements, and beliefs for use in the study, as well as potential outcome measures, and determining how Construct™ output could actually be used in hypothesis generation. The computational modeling approach consisted of building a series of *what-if* scenarios

around the drivers of cancer screening within the community health center. However, it was first necessary to define these drivers of cancer screening in community health centers. The drivers of health center activity are referred to as agents. According to Hirshman et al., agents in a simulated environment can have knowledge, beliefs, store many types of information, perform tasks, take action, have influence, be expressed by an array of attributes, and have interactive tendencies (Hirshman et al., 2009). With this understanding, it became necessary to define a list of agents, tasks, beliefs, and knowledge elements in terms of the HDCC organizational survey data, along with its corresponding list of views or perspectives that ultimately would determine how the health center would be examined.

In defining the views or perspectives of how the community health center would be examined, five agent types were defined that would serve as the primary way to assess the simulation, output, and impact of the study. To some degree, these perspectives mirrored the five survey respondent groupings used in the original HDCC survey, where each health center was given five separate sets of questions targeting the roles of CEO/Health Center Director, Chief Financial Officer, Provider, General Staff, and CIO/Information Systems. In defining the views and/or perspectives, the general staff and financial officer views were collapsed into a single health center administrative view. The provider and information systems perspectives were directly mapped to their corresponding agent classification. An agent classification for outside collaboration was added, because there were several survey items that addressed such collaboration (e.g., the use of outside agreements, the use of medical specialists via contracting, collaborative agreements, and sharing of best practices among community health centers). Finally, because the main clinical focus of this research cancer screening, and all of the survey measures were focused on the idea of increasing cancer screening rates, an agent classification for the cancer screening test itself was included in the analysis (see agent definitions below and Appendix 11). From this it was determined that community health center activity could be classified by these agent classifications or functions. The five agent groupings or perspectives from which community health center practices would be examined included: (1) firm view–Administrative, (2) firm view–Clinical Care, (3) Outside Collaborators, (4) IT Systems, and (5) Cancer Screening Tests. The assumptions and support for the building of agent, knowledge, and task definitions are as follows and the full list is included in Table 8 below:

Agent Definitions

Construct™ ready definition for each of the five classifications of agents described above (e.g., Administrative, Patient Care, IT Systems, Outside Collaborators, and Cancer Screening Tests) had to be created. These agent definitions were based on a set of critical assumptions used in support of building proper definitions that included:

- The assumption that there was one IT System actor, which was sufficient to represent all available technology capabilities (e.g., CDS and IS)
- The assumption that one outside collaborator agent was sufficient to represent all official outside collaborations
- The assumption that there were three types of cancer screening tests, including (1) colorectal, (2) cervical, and (3) breast

- The assumption that the total number of people = 100x the normalized value for financial budget (this is how organizational size and budget were mathematically combined)
- The assumption that the agent Patient Care was to be 60% and the agent Administrative Staff was to be 40% of the community health center (firm) personnel type (these arbitrary percentages were chosen based on the proportion of survey responder types labeled as Administrative vs. Clinical. This was not intended to suggest any actual representation of community health center personnel distributions)

It should be made clear that each definition of an agent was comprised of the logic that was used to determine the start value for the agent and his or her end value within the array. The agents were set up so that Construct™ would be able to read the value for each agent in the array then move directly on to the next agent classification in array for input into the simulation. As such, the start of one agent value may be defined in terms of where the previous agent ends. The detailed agent definitions are seen in Appendix 11.

Knowledge Definitions

Knowledge definitions were based on the key assumption that all tasks were roughly equivalent in complexity, meaning that each task had the same number of what Construct™ developers refer to as "bits" informing it throughout the simulation. This concept of knowledge bits essentially suggests that throughout the simulation, agents can have either 0% saturation of knowledge (or 0 bits) up to 100% saturation of knowledge (or all bits available in the simulation) (Hirshman et al., 2009). There is a direct relationship between the number of knowledge bits and the level of task complexity in this simulation. The greater the level of task complexity, the larger the knowledge complement (or number of knowledge bits) associated with that representation of knowledge. This assumes that it will take more in the way of knowledge bits to saturate or carry out a complex task than it would to implement a more simplified/less complex task (Hirshman et al., 2009). For this Construct™ virtual experiment, the task complexity was made uniform for each representation of knowledge. Each expression of task complexity used in the simulation would consist of the same maximum potential of 50 knowledge bits. The path of equivalence was chosen because there was no way to assess, at the beginning of the simulation, the relative importance of the variables used in the analysis, and as such, the decision was made to make all of them the same size. As such, the definition for knowledge will reveal the start and end values of the index of 50 bits assigned to each knowledge element, described in detail below in Table 8, as a function of both task knowledge and homophily knowledge. Appendix 11 lists the system-wide schema for all knowledge.

Task Definitions

The task definitions associated with each agent's knowledge consisted of assigning an index number for Construct™ to read it into the array and provide a start and end point for each task included in the simulation. The total list of tasks used in this analysis is referenced in Table 8 and Appendix 11.

Table 8: Facility-Level Cancer Screening Performance Agents, Tasks, and Knowledge Elements and Their Assumptions

Agent Categories	Task Knowledge Impacting Performance is Informed by:	Knowledge Absorption (Homophily Knowledge) is Informed by:	Rationale and/or Assumptions
Firm View–Patient Care	• Clinic Processes • Work Importance of Cancer Screening Tasks • CDS and IS Practices • Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions) • Information Dissemination Strategies • Provider IT Performance Expectancy • Electronic Information Retrieval and Availability	• Supportive Senior Leadership Environment • Supportive Local (Functional) Leadership Environment • Team Characteristics	• Human Agent (assumed 60% of firm staff) • % is arbitrary and not meant to represent any single firm within the sample • Patient Care Agents are always active in their ability to interact with other agents in the network • Leadership and Team interactions are viewed as opportunities for firm mission, goals, objectives, culture, and performance to be distributed throughout the firm

Agent Categories	Task Knowledge Impacting Performance is Informed by:	Knowledge Absorption (Homophily Knowledge) is Informed by:	Rationale and/or Assumptions
Firm View–Administrative Care	• Cancer Screening Rate Reporting Behavior (Provider Level) • Cancer Screening Rate Reporting Behavior (Facility Level) • Payer Mix (Insurance Type) o Uninsured Population o Medicare Population o Medicaid Population o Commercial Insurance Population • Financial Readiness (Cash Reserves) • Organizational Structure and Size • Information Dissemination Strategies • Patient Demographics o Patient Age o Patient Language	• Supportive Senior Leadership Environment • Supportive Local (Functional) Leadership Environment • Team Characteristics	• Human Agent (assumed 40% of firm staff) • % is arbitrary and not meant to represent any single firm within the sample • Administrative Agents are always active in their ability to interact with other agents in the network • Leadership and Team interactions are viewed as opportunities for firm mission, goals, objectives, culture, and performance to be distributed throughout the firm

Agent Categories	Task Knowledge Impacting Performance is Informed by:	Knowledge Absorption (Homophily Knowledge) is Informed by:	Rationale and/or Assumptions
IT Systems	• Cancer Screening Rate Reporting Behavior (Provider level) • Cancer Screening Rate Reporting Behavior (Facility Level) • Clinic Processes • Work Importance of Cancer Screening Tests • Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)	• CDS and IS Practices (IT Systems have all of this information)	• Non-human Agent • Specifically referencing IT in support of Cancer Screening • Assumes tie between cancer screening performance and demand for IT Systems Support Systems IT Systems Activity is informed by: • Provider IT Performance Expectancy • Electronic Information Retrieval & Availability The % of this task knowledge that they have is based on: • EHR Functions and Capabilities

Agent Categories	Task Knowledge Impacting Performance is Informed by:	Knowledge Absorption (Homophily Knowledge) is Informed by:	Rationale and/or Assumptions
Outside Collaborators	• Cancer Screening Rate Reporting Behavior (Provider Level) • Cancer Screening Rate Reporting Behavior (Facility Level) • Clinic Processes • Work Importance of Cancer Screening Tests • Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)	• No Explicit Homophily Knowledge sought out for expertise (within the simulation)	• Assumes one-way communication of industry best practices to the firm • Scores represent the level of access and pace of infusion of this outside expertise Outside Collaborator Activity is informed by: • External Factors (e.g., Pressure, Support, Connectedness, and Collaborative Agreements) • Environmental Assessment of Cancer Screening Activities • Medical Specialist Availability

Cancer Screening Test	• Clinic Processes
	• Delivery System Design for Cancer Screening
	• IS & CDS Practices
	• Information Dissemination Strategies
		• Work Importance of Cancer Screening Tests
		• Cancer Screening Rate Reporting Behavior Provider Level
		• Cancer Screening Rate Reporting Behavior Facility Level
		• Patient Demographics
		    o Patient Age
		    o Patient Language
			• Non-human Agent
			
			• Agent is active all the time
			
			• Agent can be interacted with only by Patient Care Agents
			
			• Agent cannot initiate interaction

The next challenge consisted of grouping these summary measures and their association with the respective agents, tasks, knowledge, or belief category for use in the simulation. This classification was largely determined by a subjective assessment that included: (1) defining the respondent group that addressed the specific survey item(s) included in the summary measure (e.g., CEO, CFO, CIO, General Staff, and Provider), (2) examining the wording of the question (specific references to the agents) and/or their logical affiliation to the activities of the agent (e.g., things the agent does, things the agent believes, things the agent needs to know in performing a given task, knowledge the agent has, etc.). For example, questions about cash reserves were assigned to the administrative agent, questions about cancer screening importance were assigned to patient care agents, while questions about external agreements were assigned to the outside collaborators' agent. The doctoral committee represented the final arbiters for any ambiguous variable assignments.

The mapping of each summary measure to one of the four categories used in this Construct™ analysis (e.g., agent, task, knowledge, or belief) was primarily based on the logic of the question(s) making up that particular summary measure. Thus, each of the 37 summary measures was assigned the Construct™ designation of either:

- Agent–which is a statement about something "I" am (from the perspective of one or more of the five agents and/or survey respondents)
- Task–which is a statement about something "I" do (from the perspective of one or more of the five agents and/or survey respondents)

- Knowledge–which is a statement about something "I" have or know (from the perspective of one or more of the five agents and/or survey respondents)
- Belief–which is a statement about something "I" feel to be either true/false, agree/disagree with (from the perspective of one or more of the five agents and/or survey respondents)

Several things should be highlighted at this point. As described briefly above, it was possible to use any or all of the summary measures in a seemingly endless variety of "what-if" scenarios or combinations for hypothesis generation. This study did not employ the use of all 37 summary measures but only those measures thought feasible in the testing for the desired outcomes in some meaningful way, with the minimum amount of ambiguity in applicability of the measure. Other combinations of summary measures not used within this analysis were considered material for future studies.

Additionally, as mentioned above, Construct™ outcomes of this analysis can be understood in two categories: (1) task performance and (2) knowledge absorption. Both task performance and knowledge absorption of the agents in the simulation are measured in terms of the chief outcome of interest, which is facility-level cancer screening rates. CDS and IS are seen as critical but will only be spoken of in the context of their being a driver of overall cancer screening performance in this portion of the analysis, not as an outcome as it was treated in the Aim 1 statistical model.

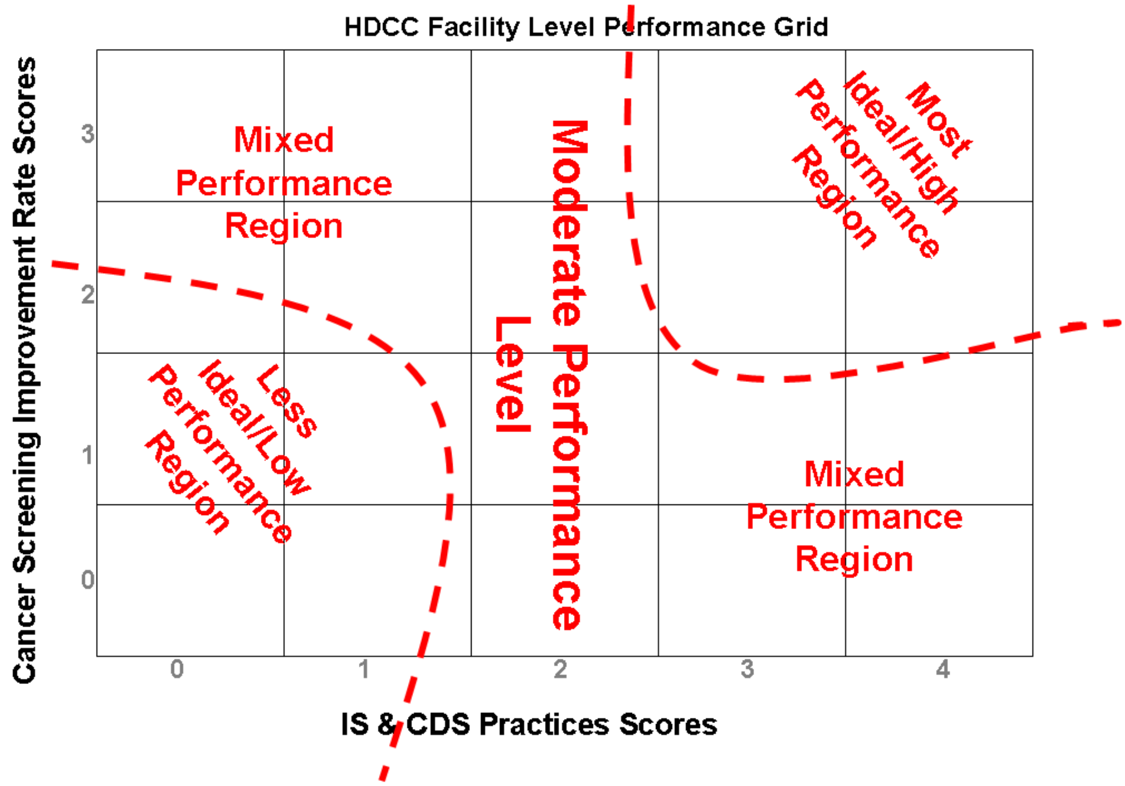
Step four involved the major step of preparing the dataset for entry into the Construct™ modeling tool by normalizing the dataset to ensure that all the data collected on the 37 summary measures raw scores were bound between 0 and 1 (see normalization algorithm Appendix 8). The new normalized data set was then saved as a CSV file (referred to in step six below) and used as the primary data source throughout the Construct™ virtual experiment.

Step five consisted of building a Virtual Health Center for use in Construct™. This encompassed the use of the normalized data and the building of a data array of possibilities (and their corresponding probabilities) for each firm's behavior (by performance level) throughout the simulation. These probabilities were calculated using the original firm-level response scores for each summary measure.

The Virtual Health Center serves as a means of converting a static view of community health center data on community health center practices between 2003 and 2005–where such a view represents a beginning state–into a dynamic organizational complex where progression or network evolution in learning and performance can be assessed over time. A similar virtual organizational representation was developed by Stanford University researchers for use in their Virtual Design Team project, "The 'Virtual Design Team': Simulating How Organizational Structure and Information Processing Tools Affect Team Performance" (Levitt, Cohen, Kunz, Nass, Christiansen, & Jin, 1994; Kunz, Christiansen, Cohen, Jin, & Levitt, 1998; Levitt et al., 1999). These Stanford researchers used what they called a "systematic" design of organizational structures and relied upon abstracted descriptions of tasks and activities that comprise them when building their simulation model (Kunz et al., 1998). The Virtual Design Team is leading the effort to employ use of this technique to model (mimic) the behavior of full-scale organizations (Kunz et al., 1998). This “mimicked” view of an organization represents what these Stanford researchers refer to as the Virtual Health Center. The “mimicked” view of community health centers used in this analysis was based on a performance view of the firm using descriptive statistics (e.g., means and standard deviations) of the summary measure scores for each performance category. This performance view represents the community health center groupings based on the distribution of its responses highlighting its performance on two axes: (1) facility-level score for CDS and IS (0 to 4) and (2) facility-level 12-month cancer screening (self-reported) improvement scores (0 to 3). These are the same two rankings used in the Spearman’s Rho test 1c in Aim 1. Here, each health center was assigned to one of six performance categories (assuming that the higher the score in each category, the better the performance for that category). Table 9 highlights the categories and respective groupings for the entire set of 44 community health centers.

- High/High (HH) — Most Ideal Performers (Top right)
- Medium/High (MH) — Moderate Performers (Top center)
- Medium/Low (ML) — Moderate Performers (Bottom center)
- High/Low (HL) — Mixed Performers (Top left)
- Low/High (LH) — Mixed Performers (Bottom right)
- Low/Low (LL) — Less Ideal Performers (Bottom left)

Table 9: The Performance View of Community Health Centers



Step six consisted of constructing the XML-based Construct Input Deck for Construct^{TM}. The Construct^{TM} Input Deck can be thought of as a modular document containing several core sections (Hirshman et al., 2009). These core Construct^{TM} sections include: (1) Construct^{TM} Variables, (2) Construct^{TM} Parameters, (3) Construct^{TM} Nodes (entities simulated in Construct^{TM} and grouped into node-classes), and (4) Construct^{TM} Networks (listing the specific set of networks used in the simulation). To assist in building the Construct^{TM} Input Deck used in this virtual experiment, a Construct^{TM} code generator worksheet was completed. This Construct^{TM} code generator Excel spreadsheet was designed to serve in lieu of a traditional graphical user interface (GUI) input form and allowed a user familiar with the specific data to structurally organize the Construct^{TM} Input Deck. The code generator was comprised of four sections and, once completed, each section would apply a series of concatenation formulas to user inputs to automatically generate the XML code used to complete the core sections of the Construct^{TM} Input Deck. Prior to completing the code generator, a series of preliminary steps was taken to: (1) create a glossary of the variables used in the simulation (see Appendix 9), (2) successfully load their values into Construct^{TM} (see XML loading statements in Appendix 10), write up agent definitions, write up knowledge definitions, and write up task definitions (see XML structured definitions in Appendix 11).

Selection of Networks

The simulation models in this Construct^{TM} analysis represent a small subset of the over 30 combinations of network agents, tasks, knowledge, groups, and beliefs possible within the tool. Table 10 shows the combination matrix—originally constructed by Carley et al. at CASOS and modified for this study—of the types of networks commonly found in Construct^{TM}. The shaded areas represent targeted areas for use in this study based upon the HDCC survey data. Carley refers to this matrix as a meta-matrix and the corresponding combinations as meta-networks (Carley, 1999 et al; Zacharias, MacMillan, Van Hemel, & National Research Council, 2008). It is important to emphasize that, while these five to six meta-networks are being identified as networks included in this analysis, the results will not be explained by each of these networks individually, but rather by outcome measure for knowledge absorption over the simulated period. As such, there will not be separate outcomes for each meta-network but on the facility (or in this case, the performance-level) as a whole for the cancer screening test agent. There will, however, be a visual examination of the Agent by Knowledge (A x K) Networks in the network visualizer ORA, on all five agents used in the simulation to see if the author of the current study can provide further insights into whatever the facility-level results reveal about the overall facility-level performance related to cancer screening.

Table 10: Matrix of Meta-Networks

	Agents	Knowledge	Beliefs	Tasks	Groups	Dummy (Attributes)
Agents	Interaction Sphere Network	Knowledge Network	Belief Network	Task Assignment Network	Agent Group Network	Agent Type Network
Knowledge		Information Network (What informs what)	Belief Weight Network	Binary Task Requirement Network	Knowledge Group Network	
Beliefs			Association Network			
Tasks				Precedence Network		
Groups						
Dummy (Attributes)						Agent by Time Network

Recreated from CASOS Lecture Material (Carley et al., 1999)

Step seven used the performance matrix, referred to in Step five, to assign the 44 HDCC facilities to one of the performance levels and ran each of the performance levels as separate conditions. These simulations were run for each of the chosen meta-networks, with one of these representing the over-time network. The over-time network examined a particular set of states (scenarios) over a 520-week/10-year period. The baseline was determined as time year 1 (yr1) at the start of the simulation; then the subsequent simulation would show how the organizational unit changed in behavior and learning (as defined by Construct™) over the 10-year period. It should be noted that, wherever there was not sufficient distinctions in the intermediary years, the results were only reported in terms of comparisons of start (year 1) and end (year 10) values in both task knowledge and knowledge absorption between conditions (performance levels). However, if necessary, the results could also be reported in intervals of yr1, yr3, yr5, yr7, and yr10 or any other set of intervals. These results would be analyzed graphically through a series of comparisons of performance level curves (slope).

Step eight consisted of conducting a visual analysis of the Construct™ output using the CASOS network visualizer ORA (Organizational Risk Analyzer) (Carley, Reminga, Storrick, De Reno, & Carnegie-Mellon Univ Pittsburgh Pa Inst Of Software Research, 2009). This visual assessment examined the network characteristics (e.g., network density, network cohesion, and connected versus unconnected nodes) to assess overall network maturity in the context of all five agent classifications. It should be noted that, while the graphical results highlighting both task performance and knowledge absorption are intended to reveal the average performance level curve over the course of 25 simulated runs for each individual performance level, this network visualization analysis portion was based on a representative sample from the set of 25 simulated runs that were chosen from a random number generator.

Step nine consisted of presenting the results as a series of network diagrams, graphs, tables, charts, and where appropriate, summary statistics on the findings.

The Rationale for Using Construct™ in Simulating Community Health Center Cancer Screening Practices

Selecting the Construct™ for This Analysis

CASOS developed a series of computational modeling applications utilizing network theory (Carley et al., 1998; Carley, 1999; Carley & Carnegie-Mellon Univ Pittsburgh Pa Inst Of Software Research; Carley, Diesner, Reminga, Tsvetovat, & Written, 2007; CASOS, 2009). The application referred to as Construct™ is a multi-agent network model for the co-evolution of agents and socio-cultural environments (Schreiber, Singh, Carley, & Carnegie-Mellon Univ Pittsburgh Pa Inst Of Software Research, 2004). According to Carley et al., "Construct™ is designed to capture dynamic behaviors in organizations with different cultural and technological configurations, as well as model groups and organizations as complex systems" (Schreiber et al., 2004). Carley further explained that "Construct™ seems best suited to capture the variability in human, technological, and organizational factors due to its ability to manipulate heterogeneity in information processing, capabilities, knowledge, and resources revealed organizational settings" (Schreiber et al., 2004). This can be extended to include the community health center data obtained in the NCI/HRSA HDCC organizational survey results (Haggstrom et al., 2008). Using Construct™, a 10-year perspective of the network evolution of community health centers grouped by performance level was developed based on both CDS and IS rankings and cancer screening rate rankings. This study identified the key agents, tasks, knowledge, and beliefs for use in a series of *what-if* analyses.

The Principles of CONSTRUCT™ for Use in Simulations

According to Carley, there are three models used by Construct™ in the performance of a simulation (Hirshman, Carley, Kowalchuck, & Carnegie-Mellon Univ Pittsburgh Pa School Of Computer, 2009; Schreiber et al., 2004). Construct relies on the use of (1) the standard interaction model, (2) the standard influence model, and (3) the standard belief model (Hirshman et al., 2009; Schreiber et al., 2004). This simulation relied heavily on the standard interaction model because of the assumption that summary measures, such as senior leadership, clinical leadership, and team activities, account for opportunities for health center values, beliefs, and attitudes to modify agent behavior and exchange knowledge on health center cancer screening performance, strategies, and priority areas. The standard influence model was also used extensively, because of the assumption that summary measures related to provider perceptions, cancer screening reporting behaviors, delivery system design, outside collaboration, and quality improvement strategies, etc., can shape how much the agent can be influenced by others within the health center environment. The belief model was used in limited fashion because of the assumption that the summary measures did not reveal enough detail on the derivation of beliefs and, as such, the precise calculations of belief weights and their respective alterations would not be possible. According the Hirshman et al., these three types of Construct™ models are defined as such:

- *Standard Interaction Model*–The standard interaction model uses homophily and expertise to guide interaction among the agents.

- *Standard Influence Mode*–The standard influence model uses influence and influenceability (how susceptible is a particular agent to influence) to determine how an agent's belief is influenced by those around him or her.
- *Standard Belief Model*–The standard belief model updates an agent's belief based on both the beliefs of others (the influence calculated by the influence model), the belief weights associated with facts that the agent knows, and the agent's knowledge in the previous time period. Thus, in this model, the agent is influenced by both what he or she knows, what has previously been believed, and what others believe.

In this study, the principles of homophily, or the degree to which community health center agents were drawn together by a particular domain of expertise, activity, or set of organizational practices, was critically important as a driver of interaction in this simulated network. Additionally, the principle of influenceability was critical in shaping the behavior of the agents over time within the simulated community health center environment. The HDCC survey summary measures provided limited knowledge of the derivation of belief weights and, as such, the standard belief model was used only where there was sufficient justification within the data to do so.

CHAPTER 4: RESULTS

Aim 1 Results–Statistical Model

HDCC Sample Means and Standard Deviations for Summary Measures

Table 11 summarizes the descriptive statistics for this community health center sample by each of the summary measures used in the analysis. In this sample, 22 community health centers served as HDCC participants and 22 were not. CDS and IS represented the chief proximal outcome as presented in the conceptual model (as seen in Figure 2). A CDS and IS summary score was created for each health center between 0 and 4 as a measurement of how many of the four components each community health center had at the time of the survey data collection. It was also discovered that within this sample of community health centers, 40% had indicated some capacity for measuring cancer screening (13 of the 22 or 59% of HDCC participants and 5 of the 20 or 25% of non-participants, respectively); 73% made use of provider prompts at the point-of-care (19 of the 22 or 86% of HDCC participants and 8 of the 19 or 42% of non-participants, respectively); 73% had computerized clinical reminders (18 of the 22 or 82% of HDCC participants and 9 of the 19 or 47% of non-participants, respectively); and 78% had the capability to generate results to patients (19 of the 22 or 86% of HDCC participants and 10 of the 19 or 53% of non-participants, respectively).

Improvements in provider self-reported breast, cervical, and colorectal cancer screening rates represented the primary distal outcome of the analysis. Within this sample of 44 community health centers, 88% stated they experienced improvement in one or more of the three cancer screening target areas, with 12% reporting no improvement (3 HDCC participants and 2 non-participants), 5% in only one area (1 HDCC participant and 1 non-participant), 17% in two areas (4 HDCC participants and 3 non-participants), and 66% in three areas, respectively (14 HDCC participants and 14 non-participants).

The assumption that the community health center was an under-resourced setting (URS), as presented in the 2010 review on HIT and quality of health care (Millery & Kukafka, 2010), was explored using a summary measure of the level of cash reserves as an indicator of health center financial readiness for CDS and IS within this sample. Six of 37 (or 16%) health centers reporting revenue and expense information reported operating at a deficit of revenue to expense ratio. These results suggest that either this sample of 44 community health centers used in this study may not accurately represent the larger population of community health centers as an URS or this measure for financial readiness was not exactly comparable to the measures used by Millery et al.

Table 11: HDCC Descriptive Statistics for All Summary Measures

Summary Measures	N valid	Missing	Mean	Median	SD	Minimum	Maximum
HRSA Collaborative Experience	44	0	2.66	2.50	1.12	0	3
Facility Age 1– Number of Years Receiving BPHC Funding	36	8	23.44	22.50	10.58	7	50
Facility Age 2– Number of Years in Any HRSA Collaborative	34	10	19.56	19.00	10.43	3	36
Clinic Processes	44	0	2.59	3.00	1.09	0	4
Information Dissemination Strategies	44	0	15.98	17.00	5.04	0	23
Electronic Information Retrieval & Availability	44	0	0.59	1.00	0.62	0	3
Electronic Health Record (EHR) Functions Capabilities	44	0	5.95	8.00	2.96	0	8
Work Importance of Cancer Screening Tasks	44	0	23.36	24.00	5.33	0	28
Cancer Screening Rate Reporting Behavior (Facility-Level)	44	0	3.80	4.00	2.10	0	6

Summary Measures	N valid	Missing	Mean	Median	SD	Minimum	Maximum
Quality Improvement Strategies	44	0	30.82	33.00	10.19	0	43
External Pressure, Support, Connectedness, and Collaborative Agreements	44	0	1.82	1.00	2.13	0	8
Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)	44	0	64.80	71.50	21.85	0	100
Supportive Senior Leadership Environment	44	0	24.93	26.50	6.59	0	36
Supportive Local (Functional) Leadership Environment	44	0	12.61	14.00	3.92	0	16
Team Characteristics	44	0	33.70	37.00	10.16	0	44
Medical Specialist Availability	44	0	6.77	10.00	4.44	0	10
Organizational Structure & Size	44	0	48.11	29.50	55.36	12*	251
Financial Readiness (1) (Total Budget)	37	7	$11,562,912	$8,415,847	$9,833,266	$1,981,721	$45,614,473
Financial	37	7	4.54	5.00	1.02	1	6

Summary Measures	N valid	Missing	Mean	Median	SD	Minimum	Maximum
Readiness (2) (Cash Reserves)							
Payer Mix1–% Uninsured	37	7	37.38	40.00	17.79	5	77
Payer Mix2a–% Medicare	37	7	14.11	9.00	15.40	2	84
Payer Mix2b–% Medicaid	37	7	48.68	49.00	23.53	5	88
Payer Mix2c–% Commercial Insurance	37	7	9.86	8.00	8.74	1	35
Payer Mix2d–% Self-Pay	36	8	27.36	22.00	20.65	2	79
Patient Demographics (Language)	37	7	22.14	12.00	23.99	1	95
Patient Demographics (Occupation Migrant Worker)	34	10	1.85	0.00	4.53	0	21
Patient Demographics (Living Homeless)	30	14	1.97	1.00	2.77	0	10
Patient Demographics (Age)	35	9	1.46	1.00	0.70	1	3
Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback	44	0	54.32	58.00	14.20	0	68
Cancer Screening Rate Reporting Behavior (Provider-Level)	44	0	5.05	6.00	1.84	0	6

Summary Measures	**N valid**	**Missing**	**Mean**	**Median**	**SD**	**Minimum**	**Maximum**
Provider IT Performance Expectancy	44	0	25.07	26.00	7.00	0	38
CDS & IS Capacity for Measuring Cancer Screening (CDS1)	42	2	0.40	0.00	0.50	0	1
Use of CDS & IS Provider Prompts at Point-of-Care (CDS2)	41	3	0.73	1.00	0.45	0	1
Computerized Patient Reminders (CDS3)	41	3	0.73	1.00	0.45	0	1
Generated Correspondence with Results to Patients (CDS4)	41	3	0.78	1.00	0.42	0	1
CDS & IS Practices (Composite CDS Score)	44	0	2.48	3.00	1.41	0	4
Cancer Screening Improvement Rates	42	2	2.38	3.00	1.03	0	3

*Note: For Organizational Size, the smallest number of personnel was 12, and any “0” responses were treated as missing data.

Examination for Multi-Collinearity

The variables Organizational Structure & Size and Total Budget approached the criteria for collinearity (r = .84, VIF of 9.86 and 8.72), but did not appear together in the best subset models, thus, collinearity was not an issue. The same was true in the case of the variables Facility Age1 (number of years receiving BPCH funding) and Facility Age2 (number of years in any HRSA collaborative) showing (r = .83, VIF of 7.88 and 6.56). Because of their moderately high correlations, the organizational structure, size, and total budget were treated as a single composite variable in the Aim 2 computational modeling exercise. There were no other areas of concern with regard to multi-collinearity.

The Evaluation of Patient Characteristics measures revealed one set of variables that were collinear. Specifically, since four of the payer-mix variables were expressed as percentages and they added up to 100%, they were highly correlated. To offset this effect, one of the four variables was excluded from the models examined. Self-Pay was excluded because there was more interest in the effects of different types of insurance within both the Aim 1 and Aim 2 portions of the study.

Hypothesis 1a: Presence of CDS and IS

Logistic Procedure–Test to Obtain the Best Subset of Summary Measures

Table 10 summarizes the variables retained within the best subsets logistic regression analyses for the presence of CDS and IS. The best subset model was chosen based on a non-statistically significant increase in Chi Squared value when additional predictors were added to the model. Appendix 5 shows selected best subsets for (a) organizational and/or practice setting factors, (b) patient characteristics, and (c) provider characteristics independent variables for each of the CDS and IS dependent variables.

Table 12: Summary of the Best Subset of Predictors for Logistic Regression Model of the Presence of Clinical Decision Support (CDS) and Information Systems (IS)

Dependent Variable	Category of Predictors	Best Set of Independent Predictors
CDS & IS Capacity for Measuring Cancer Screening	Organizational and/or Practice Setting Factors	Participant in the HRSA Collaborative HRSA Collaborative Experience Work Importance of Cancer Screening Tasks Supportive Local (Functional) Leadership Environment
	Patient Characteristics	Payer Mix1–% Uninsured Patient Demographics (Age)
	Provider Characteristics	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback Provider IT Performance Expectancy
Use of CDS & IS Provider Prompts at Point-of-Care	Organizational and/or Practice Setting Factors	Participant in the HRSA Collaborative Electronic Information Retrieval & Availability
	Patient Characteristics	Payer Mix1–% Uninsured Payer Mix2b–% Medicaid
	Provider Characteristics	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback Provider IT Performance Expectancy
Computerized Patient Reminders	Organizational and/or Practice Setting Factors	Participant in the HRSA Collaborative Medical Specialist Availability
	Patient Characteristics	Payer Mix1–% Uninsured Payer Mix2c–% Commercial Insurance
	Provider Characteristics	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback Cancer Screening Rate Reporting Behavior (Provider Level)

Dependent Variable	Category of Predictors	Best Set of Independent Predictors
Generated Correspondence with Results to Patients	Organizational and/or Practice Setting Factors	Participant in the HRSA Collaborative Electronic Health Record (EHR) Functions Capabilities
	Patient Characteristics	Payer Mix1–% Uninsured Payer Mix2b–% Medicaid
	Provider Characteristics	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback Provider IT Performance Expectancy

Organizational Factors/Determinants of CDS and IS in Community Health Centers

Overall, both organizational level factors and provider characteristics were associated with the presence of CDS and IS used in support of cancer screening within community health centers. No patient level factors were statistically significantly associated with the presence of CDS and IS, based on this sample. Table 13-16 presents the best predictor subsets for each of the four individual aspects of CDS and IS used in the logistic regression model, which included: (1) capacity for measuring cancer screening, (2) provider prompts at point-of-care, (3) computerized clinical reminders, and (4) generated correspondence of results to patients.

Table 13: Best Subsets Factors Associated with the Presence of CDS & IS Capacity for Measuring Cancer Screening Dependent Variable in Community Health Centers

Category of Predictors	Conceptual Model Construct	Estimate	Pr >Chi	Odds Ratio Point Estimate	95% Wald Confidence Limits		Goodness-of-Fit Test^		
							$\chi 2$	DF	Pr > $\chi 2$
Organizational and/or Practice Setting Factors	Overall Model–Testing Global Null Beta=0^^	N/A	0.0004*	N/A	N/A	N/A	1.87	7	0.97
	Participant in the HRSA Collaborative	-1.14	0.36	0.32	0.03	3.63			
	HRSA Collaborative Experience	3.09	0.01*	22.05	2.05	236.87			
	Work Importance of Cancer Screening Tasks	-0.84	0.049*	0.43	0.19	1.00			
	Supportive Local (Functional) Leadership Environment	0.28	0.22	1.32	0.84	2.07			
Patient Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.57	N/A	N/A	N/A	6.17	6	0.40
	Payer Mix–% Uninsured	0.00141	0.94	1.00	0.96	1.04			
	Patient Demographics (Age)	0.53	0.30	1.70	0.62	4.64			
Provider Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.0004*	N/A	N/A	N/A	5.08	8	0.75
	Environmental Assessment of Cancer Screening and Follow-up	-0.01	0.81	0.99	0.89	1.10			

Category of Predictors	Conceptual Model Construct	Estimate	Pr >Chi	Odds Ratio Point Estimate	95% Wald Confidence Limits		Goodness-of-Fit Test^		
							$\chi 2$	DF	Pr > $\chi 2$
	Activity via Provider Performance Feedback								
	Provider IT Performance Expectancy	-0.37	0.01*	0.69	0.53	0.90			

*Statistically significant

**Test of global null not statistically significant, indicating that those individual p vales should not be interpreted

^Hosmer and Lemesshow Goodness-of-Fit Test

^^Global Null Test–Likelihood Ratio

Table 14: Best Subsets Factors Associated with the <u>Presence of Provider Prompts at Point-of-Care</u> Dependent Variable in Community Health Centers

Category of Predictors	Conceptual Model Construct	Estimate	Pr >Chi	Odds Ratio Point Estimate	95% Wald Confidence Limits		Goodness-of-Fit Test^		
							$\chi2$	DF	Pr > $\chi2$
Organizational and/or Practice Setting Factors	Overall Model–Testing Global Null Beta=0^^	N/A	0.06	N/A	N/A	N/A	2.08	2	0.35
	Participant in the HRSA Collaborative	1.79	0.04**	5.97	1.12	31.95			
	Electronic Information Retrieval & Availability	0.83	0.31	2.29	0.47	11.10			
Patient Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.22	N/A	N/A	N/A	3.61	7	0.82
	Payer Mix–% Uninsured	-0.04	0.13	0.96	0.91	1.01			
	Payer Mix–% Medicaid	-0.02	0.24	0.98	0.94	1.02			
Provider Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.0012*	N/A	N/A	N/A	8.68	8	0.37
	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback	-0.08	0.29	0.92	0.80	1.07			
	Provider IT Performance Expectancy	-0.34	0.02*	0.72	0.54	0.95			

*Statistically significant
**Test of global null not statistically significant, indicating that those individual p vales should not be interpreted
^Hosmer and Lemesshow Goodness-of-Fit Test
^^Global Null Test–Likelihood Ratio

Table 15: Best Subsets Factors Associated with the <u>Presence of Computerized Patient Reminders</u> Dependent Variable in Community Health Centers

Category of Predictors	Conceptual Model Construct	Estimate	Pr >Chi	Odds Ratio Point Estimate	95% Wald Confidence Limits		Goodness-of-Fit Test^		
							$\chi 2$	DF	Pr > $\chi 2$
Organizational and/or Practice Setting Factors	Overall Model–Testing Global Null Beta=0^^	N/A	0.31	N/A	N/A	N/A	1.94	4	0.75
	Participant in the HRSA Collaborative	0.90	0.23	2.45	0.58	10.41			
	Medical Specialist Availability	0.06	0.46	1.06	0.90	1.26			
Patient Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.10	N/A	N/A	N/A	6.20	7	0.52
	Payer Mix–% Uninsured	0.03	0.20	1.03	0.98	1.08			
	Payer Mix–% Commercial Insurance	-0.06	0.22	0.95	0.87	1.03			
Provider Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.30	N/A	N/A	N/A	8.36	7	0.30
	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback	-0.02	0.66	0.98	0.89	1.08			
	Cancer Screening Rate Reporting Behavior (Provider-Level)	0.36	0.21	1.43	0.82	2.50			

*Statistically significant
**Test of global null not statistically significant, indicating that those individual p vales should not be interpreted
^Hosmer and Lemesshow Goodness-of-Fit Test
^^Global Null Test–Likelihood Ratio

Table 16: Best Subsets Factors Associated with the Presence of CDS & IS Generated Correspondence with Results to Patients Dependent Variable in Community Health Centers

Category of Predictors	Conceptual Model Construct	Estimate	Pr >Chi	Odds Ratio Point Estimate	95% Wald Confidence Limits		Goodness-of-Fit Test^		
							$\chi 2$	DF	Pr > $\chi 2$
Organizational and/or Practice Setting Factors	Overall Model–Testing Global Null Beta=0^^	N/A	0.08	N/A	N/A	N/A	4.69	4	0.32
	Participant in the HRSA Collaborative	0.80	0.34	2.24	0.43	11.53			
	Electronic Health Record (EHR) Functions Capabilities	0.25	0.08	1.29	0.97	1.70			
Patient Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.30	N/A	N/A	N/A	5.88	7	0.55
	Payer Mix–% Uninsured	-0.0048	0.85	1.00	0.95	1.05			
	Payer Mix–% Medicaid	-0.03	0.15	0.97	0.93	1.01			
Provider Characteristics	Overall Model–Testing Global Null Beta=0^^	N/A	0.12	N/A	N/A	N/A	4.59	8	0.80
	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback	0.06	0.36	1.06	0.94	1.19			
	Provider IT Performance Expectancy	-0.24	0.05	0.79	0.62	1.00			

*Statistically significant
**Test of global null not statistically significant, indicating that those individual p vales should not be interpreted
^Hosmer and Lemesshow Goodness-of-Fit Test
^^Global Null Test–Likelihood Ratio

Capacity for Measuring Cancer Screening

Separate best subsets of predictors for CDS and IS capacity to measure cancer screening within (1) Organizational and/or Practice Setting Factors, (2) Patient Characteristics, and (3) Provider Characteristics predictors were identified using logistic regression. The logistic regression equation modeled the presence of CDS and IS capacity (that is, CDS and IS capacity = 1).

Organizational and/or Practice Setting Factors: The best subset of predictors within Organizational and/or Practice Setting Factors included: (a) Participant in the HRSA Collaborative (current HDCC designee status), (b) HRSA Collaborative Experience (prior exposure to collaborative policy and procedures), (c) Work Importance of Cancer Screening Tasks, and (d) Supportive Local (Functional) Leadership Environment. The overall model for Organizational and/or Practice Setting Factors was statistically significant ($p<0.001$), and fit the data ($p=0.997$).

Every unit increase in Community Health Centers HRSA Collaborative Experience resulted in a 22 times higher odds for having CDS and IS Capacity for Cancer Screening ($p<0.05$), even after controlling for other factors in the model. The coefficient for Work Importance of Cancer Screening Tasks was negative and statistically significant at the $p<.05$ level. This indicates that, for a unit increase in level of agreement regarding the importance of cancer screening tasks among providers within community health centers, the odds of having CDS and IS Capacity for Cancer Screening decreased by 0.569. The Supportive Local (Functional) Leadership Environment did not appear to be statistically significant in predicting the CDS and IS Capacity for Cancer Screening. Despite several previous studies, which suggested that leadership is a critical factor in HIT implementation (Doolan et al., 2003; Weiner et al., 2004), this study did not confirm an independent association between the two using this sample of community health centers.

Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Feedback, i.e., which providers received audit and feedback data about their individual or facility-level performance in meeting cancer-screening objectives, was also not associated with CDS and IS Capacity for Cancer Screening. Additionally, when controlling for participation as a quality improvement collaborative member at the time of the survey, there was no demonstrated statistical significance using this sample for CDS and IS Capacity for Cancer Screening.

Patient Characteristics: The best subset of predictors within the set of Patient Characteristics included: (a) Payer Mix–% Uninsured and (b) Patient Demographics (Age). However, though that set of predictors fit the data (p=0.404), the set was not statistically significant (p=0.570), indicating there may be no relationship between patient characteristics and presence of CDS and IS capacity for cancer screening. The overall model for Patient Characteristics was not statistically significant (p=0.570), and fit the data (p=0.404).

No patient characteristics were retained within a best subset of predictors to account for community health center CDS and IS Capacity for Measuring Cancer Screening, including insurance status or age distribution of the health center population. This was a consistent finding in each of the subsequent models tested within this study. No statistically significant patient level factors, as derived from the Zapka et al. framework (Zapka et al., 2003) and expressed within the conceptual model of the current study, were found to be associated with CDS and IS presence or use based on this sample of community health centers.

Provider Characteristics: The best subset of predictors within the set of Provider Characteristics included: (a) Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback and (b) Provider IT Performance Expectancy. The overall model for Provider Characteristics was statistically significant ($p<0.001$), and fit the data ($p=0.749$). The coefficient related to Provider IT Performance Expectancy was negative and statistically significant at the $p<0.05$ level. This finding indicates that, as provider expectations related to the performance of IT that was used to assist in cancer screenings increased, the odds of having CDS and IS Capacity for Cancer Screening decreased. Specifically, a unit increase in Provider IT Performance Expectancy results in an expected 0.306 lower odds for having CDS and IS Capacity for Cancer Screening, after controlling for Environmental Assessment of Cancer Screening. This study did not differentiate provider IT performance expectancy for each specific cancer screening category but reported a summary score. This summary measure proved to be a statistically significant predictor for several CDS and IS models or outcomes, including: (1) capacity to measure cancer screening, (2) use of provider prompts at point-of-care, and (3) generating correspondence with results to patients.

Provider Prompts at Point-of-Care

Separate best subsets of predictors for Provider Prompts at point-of-care within (1) Organizational and/or Practice Setting Factors, (2) Patient Characteristics, and (3) Provider Characteristics predictors was identified using logistic regression. The logistic regression equation modeled the presence of Provider Prompts at point-of-care (that is, Provider Prompts at point-of-care = 1).

Organizational and/or Practice Setting Factors: The best subset of predictors chosen for this logistic regression model included: (1) Organizational and/or Practice Setting Factors, including (a) Participant in the HRSA Collaborative (current HDCC designee status) and (b) Electronic Information Retrieval & Availability. The coefficient of Participant in the HRSA Collaborative was positive and statistically significant. However, though that set of predictors fit the data (p=0.353), the set was not statistically significant (p=0.0645), indicating there may be no relationship between Organizational and/or Practice Setting Factors and presence of Provider Prompts at point-of-care for cancer screening. The overall model for Organizational and/or Practice Setting Factors was not statistically significant (p=0.0645), and fit the data (p=0.353).

Electronic Information Retrieval & Availability (e.g., access to computer terminal and Internet access) did not appear to be statistically significant in predicting Provider Prompts at Point-of-Care. This non-statistically significant finding may have been the result of the relatively small sample size and inadequate power. Additionally, the placement of these computer terminals and Internet access portals within this health center sample may not be the only factor(s) in increasing the odds of having provider prompts at point-of-care. Holden et al. identified motivation theories and decision theories that might serve as a platform for further investigation into this particular outcome. Questions about the ease of use, extent to which user needs are jeopardized, user self-efficacy related to HIT, and level of feedback of provider HIT usage behavior, might be investigated in addition to addressing questions covered in this survey regarding computer placement (Holden & Karsh, 2009).

Patient Characteristics: The best subset of predictors within the set of Patient Characteristics included: (a) Payer Mix–% Uninsured and (b) Payer Mix–% Medicaid. However, though that set of predictors fit the data (p=0.823), the set was not statistically significant (p=0.215), indicating there may be no relationship between Patient Characteristics and presence of Provider Prompts at point-of-care for cancer screening. The overall model for Patient Characteristics was not statistically significant (p=0.215), and fit the data (p=0.823). Neither insurance status for being uninsured nor having Medicaid insurance were statistically significant. Overall, no patient characteristics among the measures chosen to be the best subset of predictors were found to account for community health center Provider Prompts at Point-of-Care using this sample.

Provider Characteristics: The best subset of predictors within the set of Provider Characteristics included: (a) Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback and (b) Provider IT Performance Expectancy. The overall model for Provider Characteristics was statistically significant (p=0.001), and fit the data (p=0.370).

Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Feedback–a representation of how providers viewed their facility-level performance in meeting cancer-screening objectives–was not statistically significant in predicting provider prompts at the point-of care. Consistent with the previously reported findings for the health center capacity to measure cancer screening, this study did not successfully identify a relationship between this summary measure and provider prompts at point-of-care, which would validate the Holden et al. findings. The coefficient of Provider IT Performance Expectancy using this sample was negative and statistically significant ($p<0.05$). This finding indicates that, as provider expectations related to the performance of IT that was used to assist in cancer screenings increased, the odds of having Provider Prompts at Point-of-Care for Cancer Screening decreased. Specifically, a unit increase in Provider IT Performance Expectancy results in an expected 0.285 lower odds for having CDS and IS Capacity for Cancer Screening, after controlling for Environmental Assessment of Cancer Screening.

Computerized Patient Reminders

Separate best subsets of predictors for (1) Computerized Patient Reminders within Organizational and/or Practice Setting Factors, (2) Patient Characteristics, and (3) Provider Characteristics predictors was identified using logistic regression. The logistic regression equation modeled presence of Computerized Patient Reminders (that is, Computerized Patient Reminders = 1).

<u>Organizational and/or Practice Setting Factors</u>: The best subset of predictors chosen for this logistical regression model included: (1) Organizational and/or Practice Setting Factors, including (a) Participant in the HRSA Collaborative (current HDCC designee status) and (b) Medical Specialist Availability. However, though that

set of predictors fit the data (p=0.747), the set was not statistically significant (p=0.3085), indicating there may be no relationship between Organizational and/or Practice Setting Factors and presence of Computerized Patient Reminders for cancer screening. The overall model for Organizational and/or Practice Setting Factors was not statistically significant (p=0.3085), and fit the data (p=0.747). Neither HDCC membership nor the level of medical specialist availability at the community health center was statistically significant (p>0.05). Overall, no Organizational and/or Practice Setting Factors among the measures chosen as the best subset of predictors were found to account for variability in community health center Computerized Patient Reminders within this sample.

Patient Characteristics: The best subset of predictors within the set of Patient Characteristics included: (a) Payer Mix–% Uninsured and (b) Payer Mix–% Commercial Insurance. However, though that set of predictors fit the data (p=0.517), the set was not statistically significant (p=0.103), indicating there may be no relationship between Patient Characteristics and presence of Computerized Patient Reminders for cancer screening. The overall model for Patient Characteristics was not statistically significant (p=0.103), and fit the data (p=0.517). Neither the proportion of community health center patients uninsured nor the proportion of patients having commercial insurance at the community health center was statistically significant (p>0.05). As a result, there may be no association between Patient Characteristics and Computerized Patient Reminders based on this sample.

Provider Characteristics: The best subset of predictors within the set of Provider Characteristics included: (a) Environmental Assessment of Cancer

Screening and Follow-up Activity via Provider Performance Feedback and (b) Cancer Screening Rate Reporting Behavior (Provider-Level). However, though that set of predictors fit the data ($p=0.302$), the set was not statistically significant ($p=0.301$), indicating there may be no relationship between Provider Characteristics and presence of Computerized Patient Reminders for cancer screening. The overall model for Provider Characteristics was not statistically significant ($p=0.301$), and fit the data ($p=0.302$). Neither the measure for Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback, (i.e., how providers viewed their facility-level performance of meeting cancer screening objectives), nor the provider-level Cancer Screening Rate Reporting Behaviors at the community health center were statistically significant ($p>0.05$). As a result, no Provider Characteristics among the measures chosen as the best subset of predictors were found to account for variability in the community health center Computerized Patient Reminders within this sample. The intent was to examine the potential for these summary measures, in particular, screening rate reporting behaviors, to demonstrate the association to outcomes as a means of duplicating the findings of studies that specifically addressed provider behaviors and computerized patient reminder outcome (Yarbrough & Smith, 2007; Zapka et al., 2005). This study was unable to duplicate these findings, which were demonstrated in previous studies (Ketcham et al., 2009; Saleem et al., 2009; Yarbrough & Smith, 2007).

Generated Correspondence with Results to Patients

Separate best subsets of predictors for health center CDS and IS generated correspondence with patient results within (1) Organizational and/or Practice Setting Factors, (2) Patient Characteristics, and (3) Provider Characteristics predictors, was identified using logistic regression. The logistic regression equation modeled the presence of CDS and IS generated correspondence with patient results (that is, CDS and IS generated correspondence = 1).

<u>Organizational and/or Practice Setting Factors</u>: The best subset within Organizational and/or Practice Setting Factors included: (a) Participant in the HRSA Collaborative (current HDCC designee status) and (b) electronic health record (EHR) functions capabilities. However, though that set of predictors fit the data ($p=.320$), the set was not statistically significant ($p=0.078$), indicating there may be no relationship between Organizational and/or Practice Setting Factors and presence of CDS and IS generated correspondence with patient results for cancer screening. The overall model for Organizational and/or Practice Setting Factors was not statistically significant ($p<0.078$), and fit the data ($p=0.320$). Neither HDCC membership nor the measure for Electronic Health Record (EHR) Functions Capabilities at the community health center was statistically significant ($p>0.05$). Overall, no Organizational and/or Practice Setting Factors among the measures chosen as the best subset of predictors were found to account for variability in community health center CDS and IS generated correspondence with patient results within this sample.

<u>Patient Characteristics</u>: The best subset of predictors within the set of Patient Characteristics included: (a) Payer Mix–% Uninsured and (b) Payer Mix–%

Medicaid. However, though that set of predictors fit the data (p=.554), the set was not statistically significant (p=0.300), indicating there may be no relationship between Patient Characteristics and presence of CDS and IS generated correspondence with patient results for cancer screening. The overall model for Patient Characteristics was not statistically significant (p=0.300), and fit the data (p=0.554). Neither the proportion of community health center patients uninsured nor the proportion of patients with Medicaid at the community health center were statistically significant (p>0.05). As a result, no Patient Characteristics among the measures chosen as the best subset of predictors was found to explain the variance in community health center generated correspondence with results to patients within this sample.

Provider Characteristics: The best subset of predictors within the set of Provider Characteristics included: (a) Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback and (b) Provider IT Performance Expectancy. However, though that set of predictors fit the data (p=.800), the set was not statistically significant (p=0.1215), indicating there may be no relationship between Provider Characteristics and presence of CDS and IS generated correspondence with patient results for cancer screening. The overall model for Provider Characteristics was not statistically significant (p=0.1215), and fit the data (p=0.800). Neither of the summary measures for Provider IT Performance Expectancy Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Feedback (i.e., how providers viewed their facility-level performance of meeting cancer screening objectives) was statistically significant (p>0.05) for explaining the variance in community health center CDS and IS generation of correspondence with results to patients. The implications of this finding, with respect to previous studies related to provider feedback, were consistent with the evaluation of this summary measure in reports of the above findings.

Hypothesis 1b: Intensity of Use of CDS and IS

Linear Regression Procedure–Test to Obtain the Best Subset of Summary Measures

The best subset models were limited to a maximum of four to five predictors to meet the recommended observations per predictor ratio, with the exception of the examination of organizational and/or practice setting factors where the best model had six predictors. Table 17 lists the set of predictors chosen as the best subsets for each category of predictors within this sample, along with their respective adjusted R^2 scores. Appendix 6 shows the results of the best subsets for the dependent variable accounting for the intensity-of-use of CDS and IS (e.g., facility-level CDS and IS rankings 0 to 4) for each category (e.g., organizational and/or practice setting factors, patient characteristics, and provider characteristics) and their respective adjusted R^2 scores. It should be noted that the overall effect size will be reported in terms of the R^2 and not the Adjusted R^2, the Adjusted R^2 was used in the best subsets model building only.

Table 17: Summary Table of Best Subset of Predictors for Linear Regression Model of the Intensity of Clinical Decision Support (CDS) and Information Systems (IS)

Dependent Variable	Category of Predictors	Best Set of Independent Predictors	Model Adjusted R^2
CDS & IS Intensity-of-Use	Organizational and/or Practice Setting Factors	HRSA Collaborative Experience Facility Age 1–Year began receiving BPHC funding Work Importance of Cancer Screening Tasks External Pressure, Support, Connectedness, and Collaborative Agreements Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions) Supportive Local (Functional) Leadership Environment	0.34
	Patient Characteristics	Patient Demographics (Language) Patient Demographics (Age)	0.08
	Provider Characteristics	Cancer Screening Rate Reporting Behavior (Provider Level) Provider IT Performance Expectancy	0.31

Community Health Center Rankings Based on CDS and IS Intensity of Use

Separate best subsets of predictors for CDS and IS Intensity-of-Use within (1) Organizational and/or Practice Setting Factors, (2) Patient Characteristics, and (3) Provider Characteristics predictors, were identified based on adjusted R^2 using an all subsets linear regression approach. Overall, both organizational level factors and provider characteristics were found to be significantly associated with the intensity-of-use of CDS and IS used in support of cancer screening within community health centers. No patient level factors were found to be significantly associated with the intensity-of-use of CDS and IS within this sample. Table 18 presents the best predictor subset from each best subsets linear regression model for the Intensity-of-use for CDS and IS measure.

Table 18: Best Subsets Factors Associated with the Intensity-of-Use of CDS and IS in Community Health Centers

Category of Predictors	Conceptual Model Construct	R^2	Parameter Estimate	Pr > |t|	Standardized Estimate
	Overall Model–Testing Global Null Beta=0^^ (F=3.31; DF=6; p=.013)	0.41	N/A	N/A	N/A
	HRSA Collaborative Experience		0.60	0.02*	0.37
	Facility Age1–Year began receiving BPHC funding		0.03	0.10	0.27
Organizational and/or Practice Setting Factors	Work Importance of Cancer Screening Tasks		-0.30	0.09	-0.27
	External Pressure, Support, Connectedness, and Collaborative Agreements		0.20	0.04*	0.37
	Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)		-0.03	0.09	-0.28
	Supportive Local (Functional) Leadership Environment		0.13	0.22	0.19
	Overall Model–Testing Global Null Beta=0^^ (F=3.10; DF=2; p=.059)	0.16	N/A	N/A	N/A
Patient Characteristics	Patient Demographics (Language)		0.02	0.05	0.35
	Patient Demographics (Age)		0.62	0.04**	0.37

Category of Predictors	Conceptual Model Construct	R^2	Parameter Estimate	Pr > |t|	Standardized Estimate
Provider Characteristics	Overall Model–Testing Global Null Beta=0^^ (F=10.48; DF=2; p<0.001)	0.34	N/A	N/A	N/A
	Cancer Screening Rate Reporting Behavior (Provider Level)		0.46	<.0001*	0.60
	Provider IT Performance Expectancy		-0.03	0.20	-0.17

*Statistically significant

** Test of global null not statistically significant, indicating that those individual p vales should not be interpreted

^^Global Null Test (Pr > F)

Organizational and/or Practice Setting Factors: The best subset of predictors within Organizational and/or Practice Setting Factors explained about 40% of CDS and IS Intensity of use ($p<0.05$), and included: (a) HRSA Collaborative Experience, (b) Facility Age1–Year began receiving BPHC funding, (c) Work Importance of Cancer Screening Tasks, (d) External Pressure, Support, Connectedness, and Collaborative Agreements, (e) Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions), and (f) Supportive Local (Functional) Leadership Environment. The coefficient for HRSA Collaborative Experience and External Pressure, Support, Connectedness, and Collaborative Agreements, were positive and statistically significant ($p<0.05$). This indicated that community health centers with more HRSA Collaborative experience and greater external ties have higher intensity of CDS and IS utilization.

Variables that were not independently associated with CDS and IS Intensity-of-Use included Facility Age as a function of when the health center commenced receiving BPHC funding, Work Importance of Cancer Screening Tasks, the Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions), and Supportive Local (Functional) Leadership Environment.

Patient Characteristics: The best subset of predictors within Patient Characteristics included: (a) Patient Demographics (Language) and (b) Patient Demographics (Age). The R^2 for this set of predictors, .161, and the overall model was not statistically significant ($p>0.05$), indicating there may be no association between patient characteristics and intensity of CDS and IS use.

Provider Characteristics: The best subset of predictors within Provider Characteristics explained about 34% of CDS/IS intensity of use ($p<0.001$), and included: (a) Cancer Screening Rate Reporting Behavior (Provider Level) and (b) Provider IT Performance Expectancy, which influence the CDS and IS Intensity-of-Use. The coefficient on the provider-level Cancer Screening Rate Reporting Behavior was positive and significantly associated ($p<0.05$). This indicates that provider-level Cancer Screening Rate Reporting Behavior was independently positively associated with the CDS and IS Intensity-of-Use. This study's findings were consistent with previous studies that demonstrated an association between provider work or task-specific behaviors and CDS outcomes (Yarbrough & Smith, 2007; Zapka et al., 2005).

The variable Provider IT Performance Expectancy did not show any independent statistically significant association with CDS and IS Intensity-of-Use based on this community health center sample.

Hypothesis 1c: Measuring the Strength of Relationship between CDS/IS Ranking and Cancer Screening Improvement Rankings

Spearman's Rank Procedure

CDS and IS Impact on Cancer Screening Rates in Community Health Centers

Spearman's correlation coefficient measures the strength of association between two ranked variables. A Spearman's Rank Order correlation was used to test the relationship between community health center facility-level scores for having one or more CDS and IS components within their facility (scored 0 to 4) and community health center facility-level scores for 12-month cancer screening (self-reported) improvement rates for colorectal, breast, and/or cervical cancer screenings (scored 0 to 3). The coefficient of -0.103 was not statistically significant (p=0.514), indicating there may be no relationship between the CDS and IS component facility-level scores and self-reported facility-level cancer screening scores based on this community health center sample.

Aim 2 Results–Computational Model

HDCC Sample Means and Standard Deviations for Summary Measures by Performance Grouping

Table 19 summarizes the descriptive statistics for this community health center sample by performance grouping. Each of the 44 community health centers in this sample was assigned to one of the six performance groups based on its respective scores for both composite measure of CDS and IS and the composite measure for cancer screening improvement. The first designation of high, medium, or low represented the CDS and IS score of 0 to 4. The second designation of high, medium, or low represented the cancer screening self-reported 12-month improvement rate score of 0 to 3. These two designations were then combined to create a composite performance level category that was used in the computational modeling exercise. These community health center performance level designations represent the mean and standard deviations of each set of community health center performance groups. The group designation medium/low was excluded from the table, because it was a group of n=1 and contained several categories of missing data. The level of missing data disqualified it from consideration for simulation and, from this point forward, only results for each of the five remaining performance categories or group levels will be presented.

Table 19: Means and SD by HDCC Performance Grouping

	Firm Categories (Based on Cancer Screening and Clinical Decision Support Scores)									
	High/High (HH)		Low/Low (LL)		Medium/High (MH)		Low/High (LH)		High/Low (HL)	
Summary Measures	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
HRSA Collaborative Experience	2.96	1.12	2.33	0.58	2.80	0.84	2.67	0.82	2.00	0.00
Facility Age1– Number of Years receiving BPHC funding	22.86	10.07	13.50	2.12	19.00	10.65	29.25	6.90	34.00	14.42
Facility Age2– Number of Years in any HRSA Collaborative	17.85	10.56	12.00	0.00	18.60	11.04	27.75	6.55	26.67	11.37
Clinic Processes	2.83	0.92	2.33	0.58	2.20	1.30	2.67	0.82	3.33	1.15
Information Dissemination Strategies	17.38	2.89	17.00	4.36	18.00	2.35	16.00	5.80	11.67	4.04
Electronic Information Retrieval & Availability	0.67	0.70	1.00	0.00	0.60	0.55	0.33	0.52	0.33	0.58
Electronic Health Record (EHR) Functions Capabilities	5.08	1.98	1.00	1.73	5.80	0.45	3.33	3.01	6.00	0.00
Work Importance of	24.67	0.76	23.33	0.58	25.20	1.10	24.17	2.93	23.33	1.15

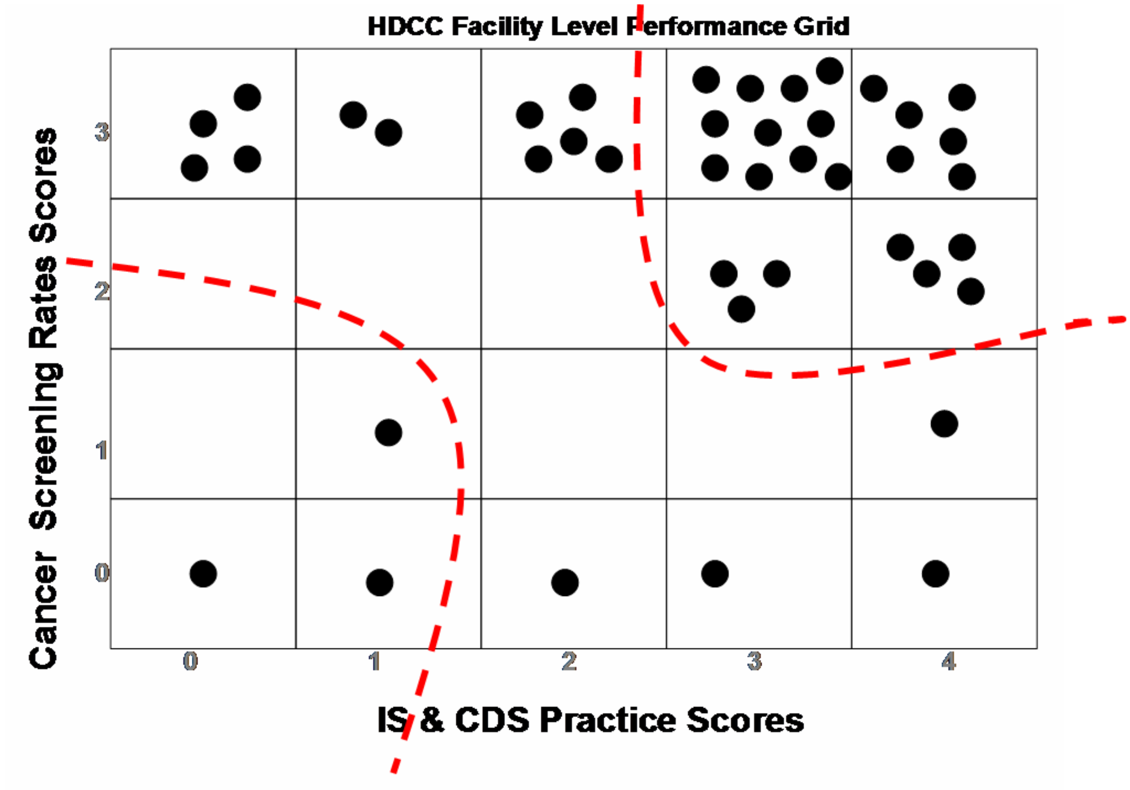
Cancer Screening Tasks										
Cancer Screening Rate Reporting Behavior (Facility-Level)	4.21	1.86	3.33	2.52	5.00	1.22	1.83	1.72	5.67	0.58
Quality Improvement Strategies	31.92	8.67	34.00	2.00	33.80	3.90	32.00	11.01	30.00	1.73
External Pressure, Support, Connectedness, and Collaborative Agreements	31.92	8.67	34.00	2.00	33.80	3.90	32.00	11.01	30.00	1.73
Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)	68.92	9.99	54.33	31.66	73.00	17.35	63.67	32.00	69.33	9.24
Supportive Senior Leadership Environment	25.83	3.75	25.67	3.21	24.60	3.78	29.00	3.69	25.33	3.79
Supportive Local (Functional) Leadership Environment	13.71	1.88	13.33	1.53	13.40	2.30	11.33	5.65	12.00	3.61

Team Characteristics	36.63	3.55	38.33	5.13	36.20	4.09	29.83	14.69	31.00	11.36
Medical Specialist Availability	7.46	4.10	6.67	5.77	5.80	4.38	6.67	5.16	10.00	0.00
Organizational Structure & Size	47.71	47.66	25.67	26.01	102.20	105.45	28.17	24.69	71.67	41.79
Financial Readiness(1) (Total Budget)	$11,115,815	$10,834,573	$14,486,121	$7,797,802	$14,614,705	$10,971,317	$8,386,814	$6,751,285	$13,100,000	$9,100,000
Financial Readiness(2) (Cash Reserves)	4.41	1.18	5.00	0.00	5.00	0.00	4.20	1.10	5.00	0.00
Payer Mix1–% Uninsured	36.41	17.20	12.50	10.61	44.60	16.65	41.20	23.83	42.67	2.52
Payer Mix2a–% Medicare	16.59	18.22	5.50	4.95	7.80	6.22	14.20	13.61	12.00	8.54
Payer Mix2b–% Medicaid	44.77	22.56	74.50	14.85	49.80	34.88	45.60	15.53	63.33	20.43
Payer Mix2c–% Commercial Insurance	10.41	8.26	4.50	3.54	7.80	8.67	11.80	13.57	9.67	8.96
Payer Mix2d–% Self-Pay	28.29	21.43	15.50	6.36	34.60	31.61	28.40	12.46	15.00	5.00
Patient Demographics (Language)	19.14	22.22	6.00	5.66	38.00	15.17	8.80	12.13	50.67	41.79
Patient Demographics (Occupation Migrant Worker)	1.74	4.82	1.00	1.41	2.20	3.90	0.40	0.89	7.50	10.61
Patient Demographics	2.47	3.22	0.00	0.00	1.75	2.22	1.00	1.15	0.50	0.71

(Living Homeless)										
Patient Demographics (Age)	1.62	0.80	1.00	0.00	1.20	0.45	1.25	0.50	1.33	0.58
Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback	57.33	7.18	52.67	9.87	60.20	5.85	60.83	4.17	43.33	7.51
Cancer Screening Rate Reporting Behavior (Provider Level)	5.54	1.06	5.67	0.58	6.00	0.00	3.00	2.37	6.00	0.00
Provider IT Performance Expectancy	25.13	3.94	27.00	4.00	26.80	2.28	31.67	3.83	21.33	1.53
CDS & IS Practices (Composite Score)	3.42	0.50	0.67	0.58	2.00	0.00	0.33	0.52	3.67	0.58
Cancer Screening Improvement Rates	2.71	0.46	0.33	0.58	3.00	0.00	3.00	0.00	0.33	0.58

Note: Medium/Low (ML) has been omitted for consideration within the Aim 2 simulation, because it only had an N of 1 and contained several missing data elements.

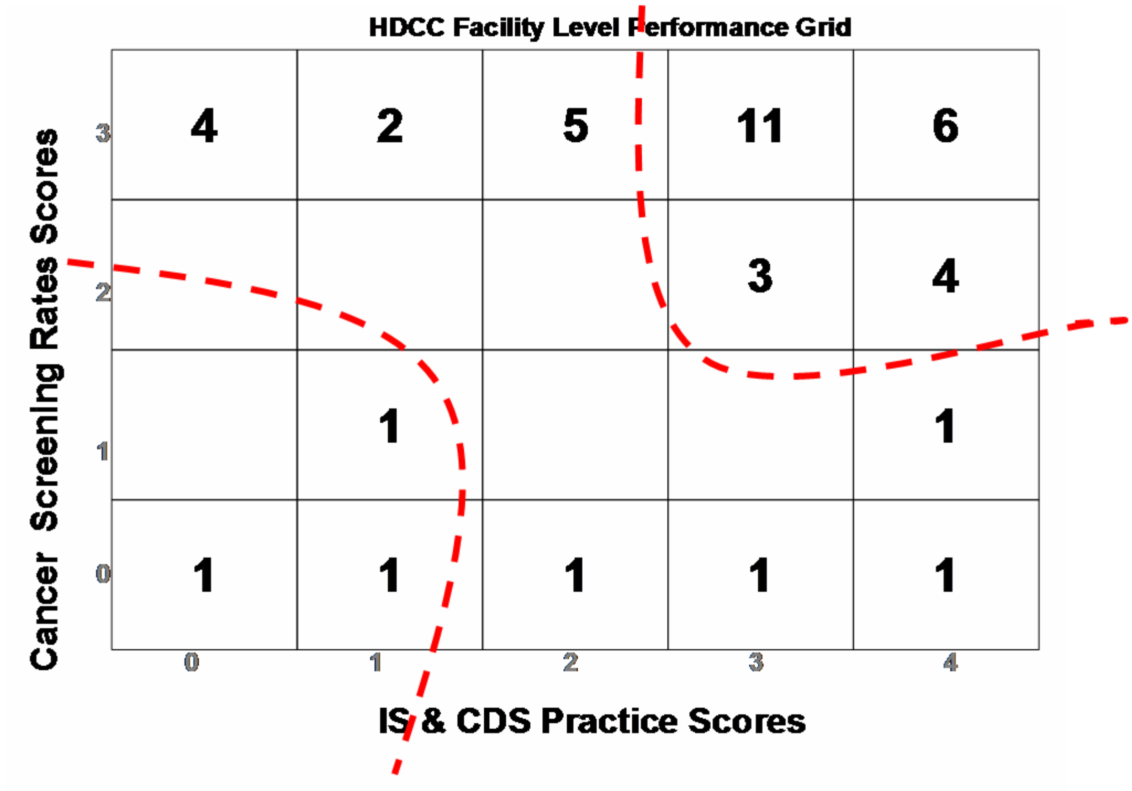
Table 20: HDCC Performance Level Grid–Scatter Plot View



Community Health Center Performance Level Matrix for CDS and IS and 12-Month Cancer (Self-reported) Improvement Rates

• High/High (HH)–24 firms	Most Ideal Performers (Top right)
• Medium/High (MH)–5 firms	Moderate Performers (Top center)
• Medium/Low (ML)–1 firm	Moderate Performers (Bottom center)
• High/Low (HL)–3 firms	Mixed Performers (Top left)
• Low/High (LH)–6 firms	Mixed Performers (Bottom right)
• Low/Low (LL)–3 firms	Less Ideal Performers (Bottom left)

Table 21: HDCC Performance Level Grid–Numerical View



Clinical Decision Support and Knowledge Management: The Learning Organization

Aim 2 of this research study was designed to test the notion of learning or evolving organization from the perspective tasks associated with facility-level cancer screening rates. Nemeth et al. described the health care work domain as a “complex, high hazard, time-pressured, interrupt-driven environment” (Nemeth et al., 2006). As was reported earlier, this research was largely inspired by the work of Haggstrom et al. as a part of the HRSA Cancer Collaborative and that subsequent studies followed from the data collected about community health centers with respect to implementing a variety of chronic care model principles in support of breast, cervical, and colorectal cancer screening (Haggstrom et al., 2008). There were some recognized limiting aspects of being able to take point-in-time data collected about community health center events, beliefs, behaviors, tasks, etc., and project them out over a 10-year period. In particular, addressing such questions as: (1) are these community health centers learning to be or are becoming smarter in the cancer-screening task through their use of clinical decision support?, (2) are there characteristic traits of high-performing community health centers (henceforth in this section known as the firm) versus low-performing community health centers that can be visualized?, and, (3) can it be assumed that a high performing firm (determined at the time of the survey) will remain a high performing firm into the foreseeable future and vice versa for a low performing firm? The Aim 2 experimental design was intended to examine these kinds of issues in a simulated community health center environment that would be informed by the same set of summary measures used in Aim 1; however, instead of using facility-level raw scores used in the test of associations for CDS and IS and cancer screening, Aim 2 would use the means and standard deviations of each performance group to define the parameters of the simulation.

This study built the assumptions of change and evolution of the health care facility and the limited nature of point-in-time assessment or surveys on studies that examined the socio-technical aspects of CDS and cancer screening. Feifer et al. examined multi-method interventions designed to improve adherence to clinical practice guidelines for prostate cancer screening (Feifer et al., 2006). Feifer et al. argued that organizations change over time; organizations learn; there is a correlation between the rate of learning and success; organizations evolve in complex, adaptive ways; and there may be varying rates of innovation from one environment to the next (Feifer et al., 2006). These assertions by Feifer et al. were consistent with the 1999 evaluation of CDS within a surgical intensive care unit, where these authors found that decision support systems development should take into account complex adaptive environments, learning required to improve organizational capability, and creative discovery and collaboration (Ehrhart et al., 1999). Other socio-technical studies suggested that, within VA Medical Centers, the socio-technical approach led to increased clinician use of the systems (Goldstein et al., 2004). Additionally, Niland et al. found that socio-technical and knowledge management components of building health care quality information systems (HQIS) are often overlooked and should be measured against learnability, efficiency, memorability, errors, and satisfaction, as components of a larger blueprint (Niland et al., 2006).

In Aim 2, an experiment was conducted on a virtual representation of community health centers, as captured from the 2005 organizational survey, and defined levels of growth and evolution over a 520-week or 10-year period (1) for the cancer screening agent and all associated tasks[3] that are intended to inform this cancer screening agent (as seen in Figure 6) and (2) for the cancer screening agent and the CDS and IS task only intended to inform this cancer screening agent (as seen in Figure 7).

Ten-Year Performance of Cancer Screening Agent Simulation: Graphical Representation

A series of 25 runs were conducted on each of the five performance level groupings (or conditions) used in the simulation (e.g., high/high-HH, medium/high-MH, high/low-HL, low/high-LH, and low/low-LL). It should be reiterated that the first designation refers to the CDS and IS community health ranking of 0 to 4 and the second designation refers to the cancer screening self-reported improvement rate of 0 to 3. Figure 6 shows the composite means for each set of 25 runs for each of the five conditions tested in this simulation. The x-axis shows the time period of 10 years and the y-axis shows the rate of knowledge absorption of the cancer-screening agent for each condition or performance group. The change in rate of knowledge absorption is referred to as the delta k (Δk).

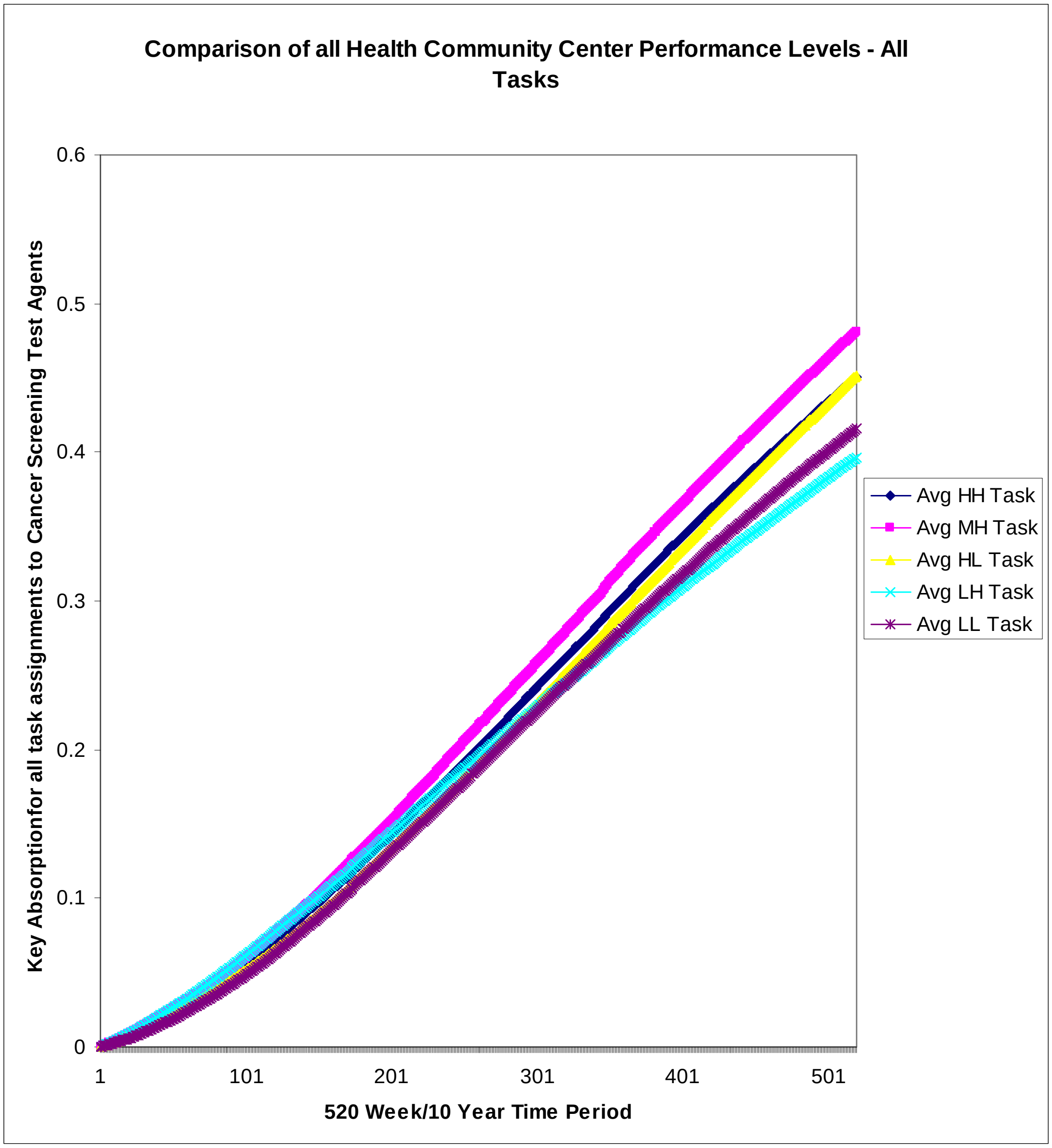
This study demonstrated that, if all performance level firm groupings or conditions at the start of the simulation are assumed to have no knowledge, then firms that show a higher rate of knowledge absorption will have a steeper slope compared

[3] Summary Measures informing the Cancer Screening Agent: Clinic Processes; Delivery System Design for Cancer Screening; IS & CDS Practices; Information Dissemination Strategies; Work Importance of Cancer Screening Tests; Cancer Screening Rate Reporting Behavior Provider-level; Cancer Screening Rate; Reporting Behavior Facility-level; and Patient Demographics.

to those with less knowledge absorption over the same time period. This simulation showed that medium/high firms had the highest rate of knowledge absorption over the 10-year period, followed by high/high and high/low firms, which were virtually even, followed by low/low firms, and finally low/high firms. This study found that there was a clear distinction in the rate of knowledge absorption between community health center performance levels that ranked highest in clinical decision support. In other words, the performance levels where the CDS and IS scores were either medium or high, demonstrated a higher rate of knowledge absorption over the 10-year period compared to those firms that ranked low for CDS and IS. The results for the cancer screening improvement rate performance levels were mixed and not as clearly delineated as was the case for CDS and IS.

Task Knowledge Impacting Performance over a 10-year (520-week) period for **All Community Health Center Performance Levels**: Cancer Screening Test Agents Knowledge Absorption **for All Tasks**

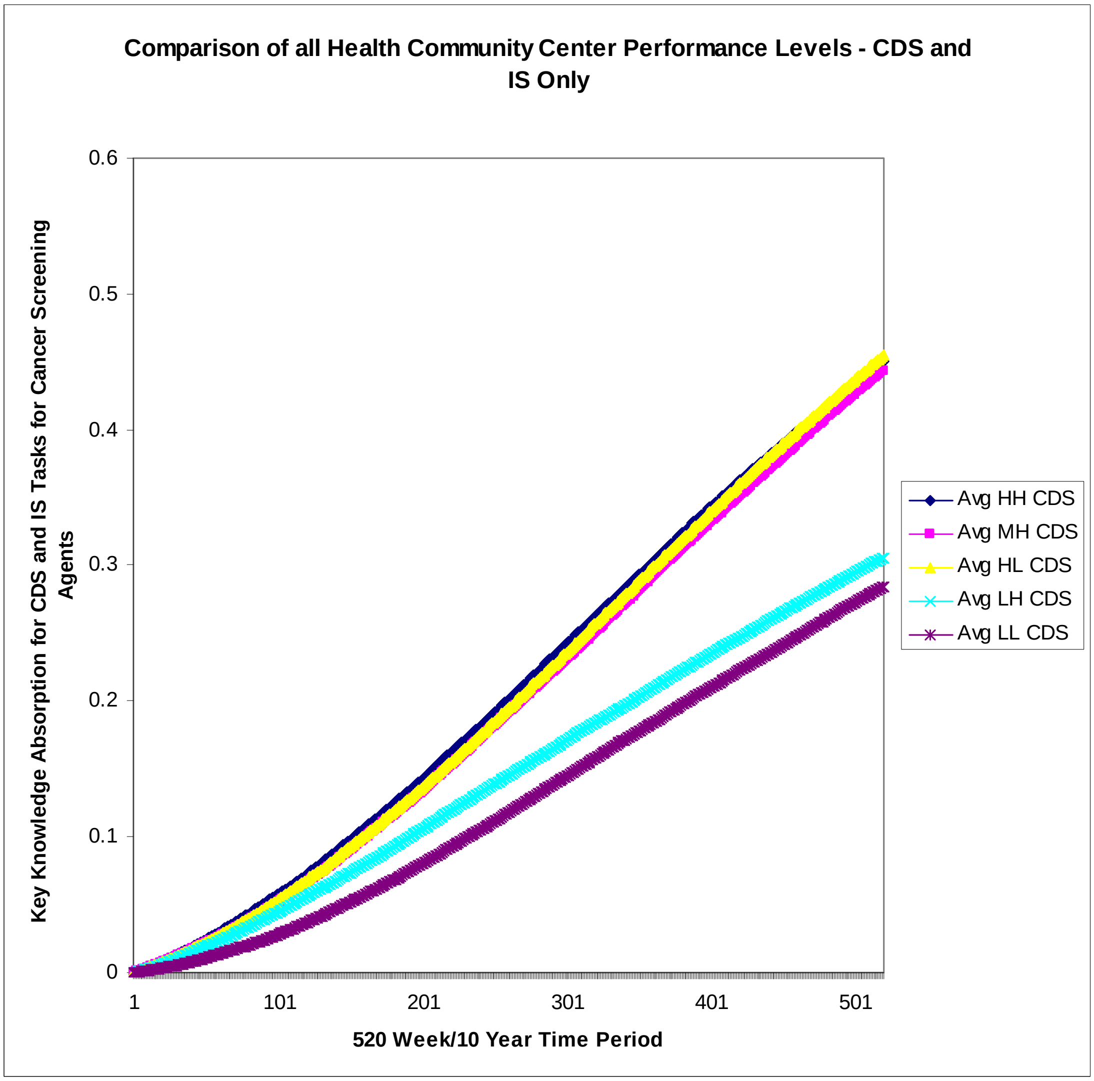
Figure 6: All Firms Comparison by Performance Level for All Tasks



The simulated experiments of 25 runs were then repeated for each performance level or condition, examining the relative knowledge absorption rate. However, this test only focused on the relationship between the cancer screening agent and the CDS and IS task (excluding all other cancer screening agent tasks) over the same 10-year period. This test revealed an even starker contrast between the higher performing firms for CDS and IS and those lower performing firms for CDS and IS (as seen in Figure 7). Here, a far more dramatic contrast was observed between the higher performing firms for CDS and IS, as demonstrated by the steepness in the relative slope for each performance level. Additionally, within each of the two clusters of higher performers versus lower performers, the cancer screening improvement rate performance levels were now shown to be more consistent across all conditions. In other words, not only did the firms that ranked higher for CDS and IS have a steeper slope and, as such, a higher rate of knowledge absorption or Δk, but the observed slope of the higher ranked firms for cancer screening rate improvement also had a steeper slope and high Δk, when the clustering into two distinct performance groups was accounted for. Figure 7 shows two very dramatic performance clustering's for knowledge absorption over time in a group of higher performers (e.g., HH, MH, and HL) versus lower performers (e.g., LL, LH).

<u>Task Knowledge Impacting Performance</u> over a 10-year (520-week) period for **<u>All Community Health Center Performance Levels</u>**: Cancer Screening Test Agents Knowledge Absorption **<u>for CDS and IS Tasks Only</u>**

Figure 7: All Firms Comparison by Performance Level for CDS and IS Task Only



Ten-Year Performance of Agent by Knowledge Simulation: Network Diagram Representation

The next step in the analysis was to investigate the simulation results by using ORA, the network visualizer, to see if additional insight could be gained from beyond the graphical assessments. The intent was to examine some of the network diagram characteristics and their respective measures, in particular, network density to the number of links relative to the total possible number of lines to attempt to explain some earlier simulation findings. Bruque et al. suggested that network measures of size, density, and strength of information ties can serve as predictors of adaptation and change (Bruque et al., 2008). Bruque et al. concluded that a dense information network may be more effective if the members use it as a tool to resolve doubts, obtain opinions, and deepen their understanding of the new system (or for that matter, existing strategies for improvement) (Bruque et al., 2008). For this study, a random sample chosen from each performance level set of 25 simulated runs that provided a visual display of the Agent by Knowledge network was used, because of the focus on the knowledge absorption of the agents over time. Each network diagram by condition or performance level was compared at the beginning (year 1) of the simulated period and at the end (year 10) using the objective measure of network density and the subjective network characteristics of clustering or cliques (where fewer clusters or cliques is considered more ideal), cohesion (where centralized cohesion implies greater collaboration, and connectivity (where fewer unconnected agents and fewer unconnected knowledge elements represent a more ideal state). Based on the assessments made of the graphical results, it was determined that additional insight of firm characteristics might be obtained through comparisons of three primary performance levels: (1) high/high vs. low/low to examine the two greatest extremes in performance, (2) high/high vs. medium/high to examine how these two performance levels compare, and (3) high/high vs. high/low to again determine how these two performance levels compare. The summary of these three comparisons of both the beginning (year 1) and end networks (year 10) is featured in Table 22. The visual comparisons of the high/high beginning and end are seen in Figure 8, comparisons of high/high beginning and end are seen in Figure 9, and comparisons of high/high beginning and end are featured in Figure 10.

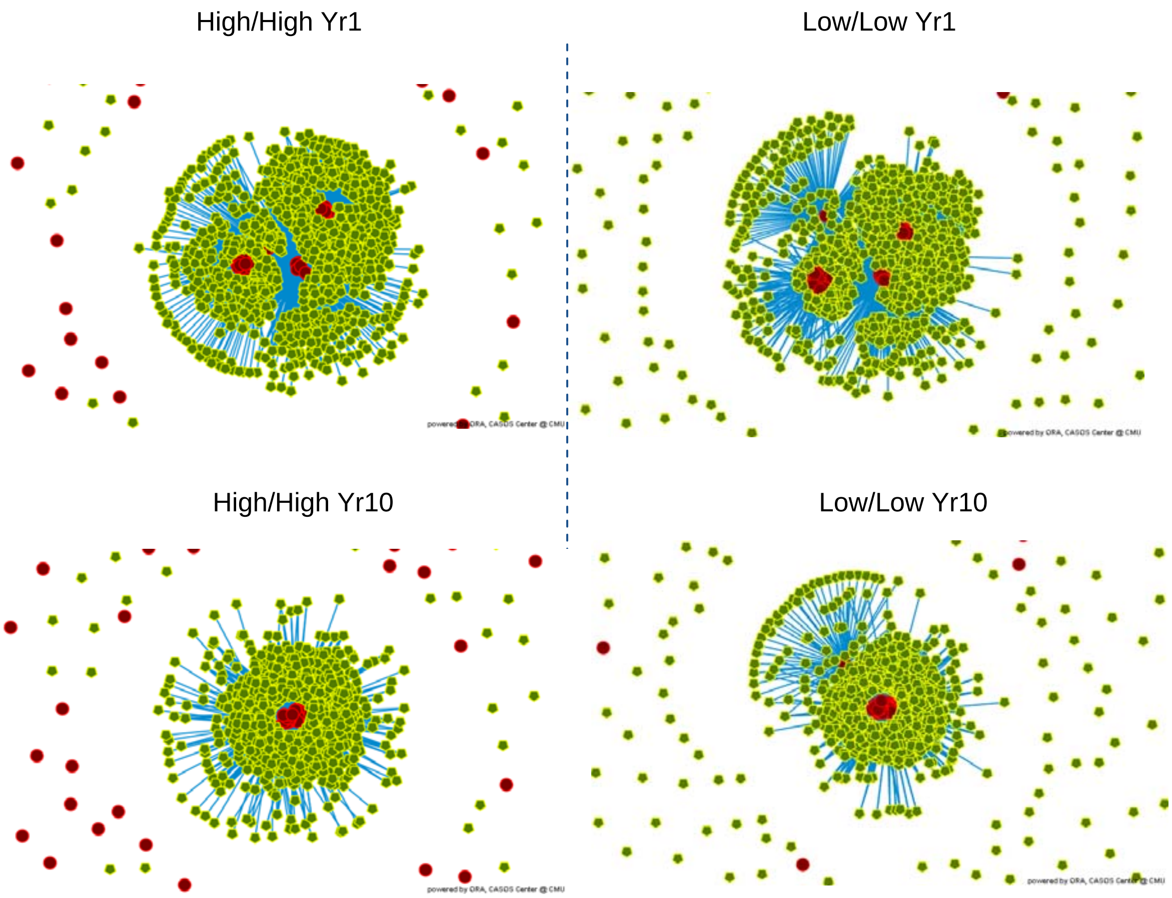
Table 22: Summary of Visual Network Diagrams and Comparison of Key Networks

Agent by Knowledge Network 1	Agent by Knowledge Network 2
High/High–Year 1 • Density 0.154 • Visually, there are four agent clusters surrounded by knowledge elements • Several unconnected agents and knowledge agents about suggesting several unused or poorly used knowledge elements and uninformed or less informed agents • The knowledge elements are not uniformly distributed throughout the network • Several knowledge elements are clustered around two of the larger agent clusters in the network • Overall, the agent clusters represent cliques and limited cooperation	Low/Low–Year 1 • Density 0.174 • Visually, there are four agent clusters surrounded by unconnected knowledge elements • There are many knowledge elements widely dispersed and unconnected throughout the network. Some are concentrated around the agent clusters, some are not and merely bunched up with one or more agent(s) connected to that knowledge element • Overall, this network shows an uneven distribution of knowledge, much unused knowledge, and less cooperative environment as demonstrated by the distinct knowledge groupings
High/High–Year 10 • Density 0.335 • Still seeing some unconnected agents and some unused knowledge on the periphery • The internal structure shows maturity of a central clustering of agents, implying greater cohesion and cooperation • The center cluster of agents surrounded by knowledge elements in a circular fashion implies greater access to knowledge among the agents and greater levels of connectivity • Overall high quality network with some room for improvement on the periphery by tying more agents into the central network	Low/Low–Year 10 • Density 0.473 • Still seeing much knowledge unused on the periphery, with the addition of some agents implying some discontinuity. The internal structure still shows agent clustering but some improvement in knowledge sharing in one agent cluster but not in the other • Appears that the network is still somewhat fragmented and not as cohesive as the author of the current study sees regarding the evolution of the High/High (despite higher density than HH at year 10) • Overall, this network realized some improvement over the 10-year period but still requires more cohesion and cooperation
High/High–Year 1 • Density 0.154 • Same as above	Medium/High–Year 1 • Density 0.229 • Visually, there are four agent clusters surrounded by unconnected knowledge elements • The knowledge elements are not uniformly distributed throughout the network • Several knowledge elements are clustered around two of the larger agent clusters in the network • Overall, the agent clusters represent cliques and limited cooperation

Agent by Knowledge Network 1	Agent by Knowledge Network 2
High/High–Year 10 • Density 0.335 • Same as above	Medium/High–Year 10 • Density 0.519 • Still seeing some unconnected agents and some unused knowledge on the periphery • The internal structure shows maturity of a central clustering of agents, implying greater cohesion and cooperation • The center cluster of agents are surrounded by knowledge elements in a circular fashion, implying greater access to knowledge among the agents and greater levels of connectivity • Overall high quality network with some room for improvement on the periphery by tying more agents into the central network
High/High–Year 1 • Density 0.154 • Same as above	High/Low–Year 1 • Density 0.192 • Visually, there are three agent clusters surrounded by unconnected agents and knowledge elements • Some unconnected agents and knowledge agents about suggesting several unused or poorly used knowledge elements and uninformed or less informed agents • The knowledge elements are not uniformly distributed throughout the network • Several knowledge elements are clustered around two of the larger agent clusters in the network • Overall, the agent clusters represent cliques and limited cooperation
High/High–Year 10 • Density 0.335 • Same as above	High/Low–Year 10 • Density 0.442 • Still seeing some unconnected agents and some unused knowledge on the periphery • The internal structure shows maturity of a central clustering of agents, implying greater cohesion and cooperation • The center cluster of agents surrounded by knowledge elements in a circular fashion implies greater access to knowledge among the agents and greater levels of connectivity • Overall high quality network with some room for improvement on the periphery by tying more agents into the central network but fewer than high/high, indicating a higher quality network

Agent x Knowledge Comparison of High/High vs. Low/Low Firms

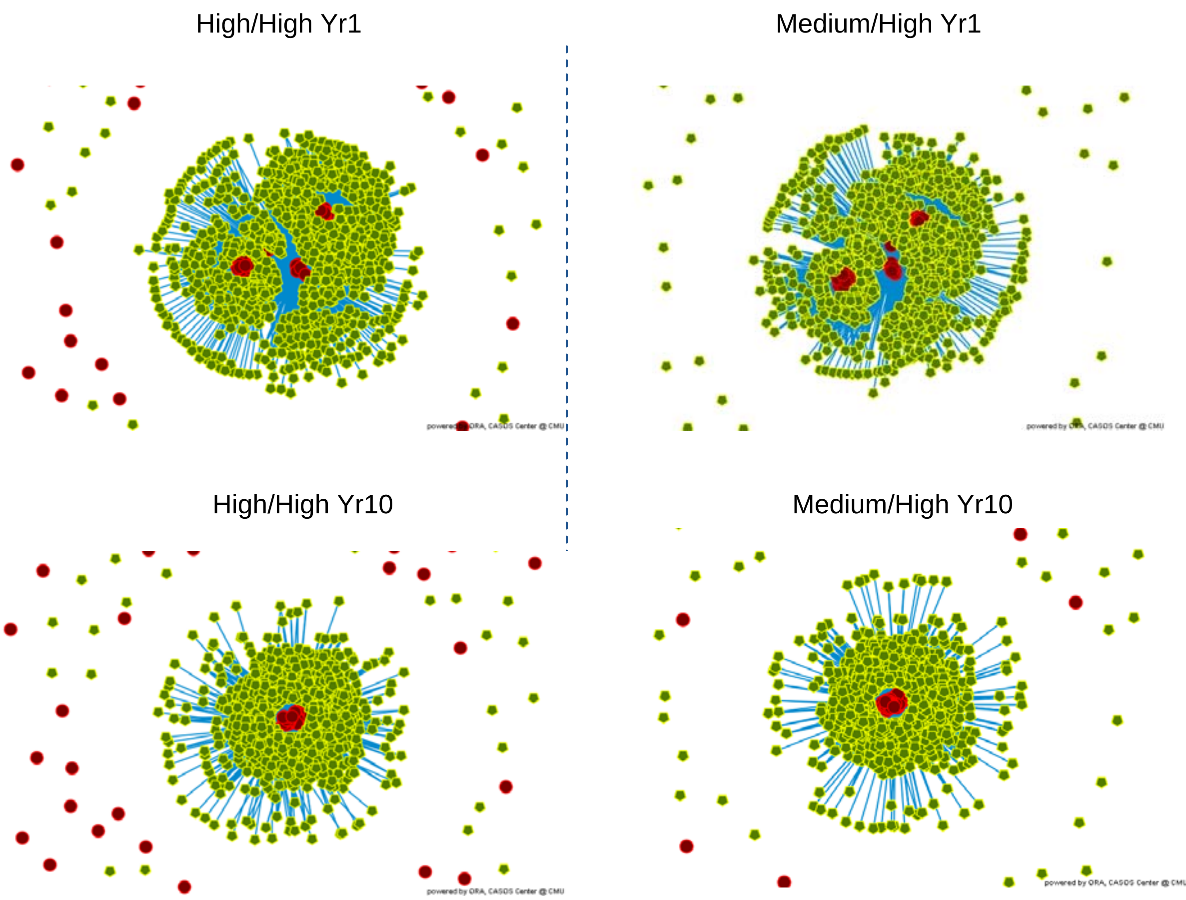
Figure 8: Comparison of High/High vs. Low/Low



<u>Legend</u>:
Agents – Red Figures
Knowledge – Green Figures
Lines – Links (Agent x Knowledge)

Agent x Knowledge Comparison of High/High vs. Medium/High Firms

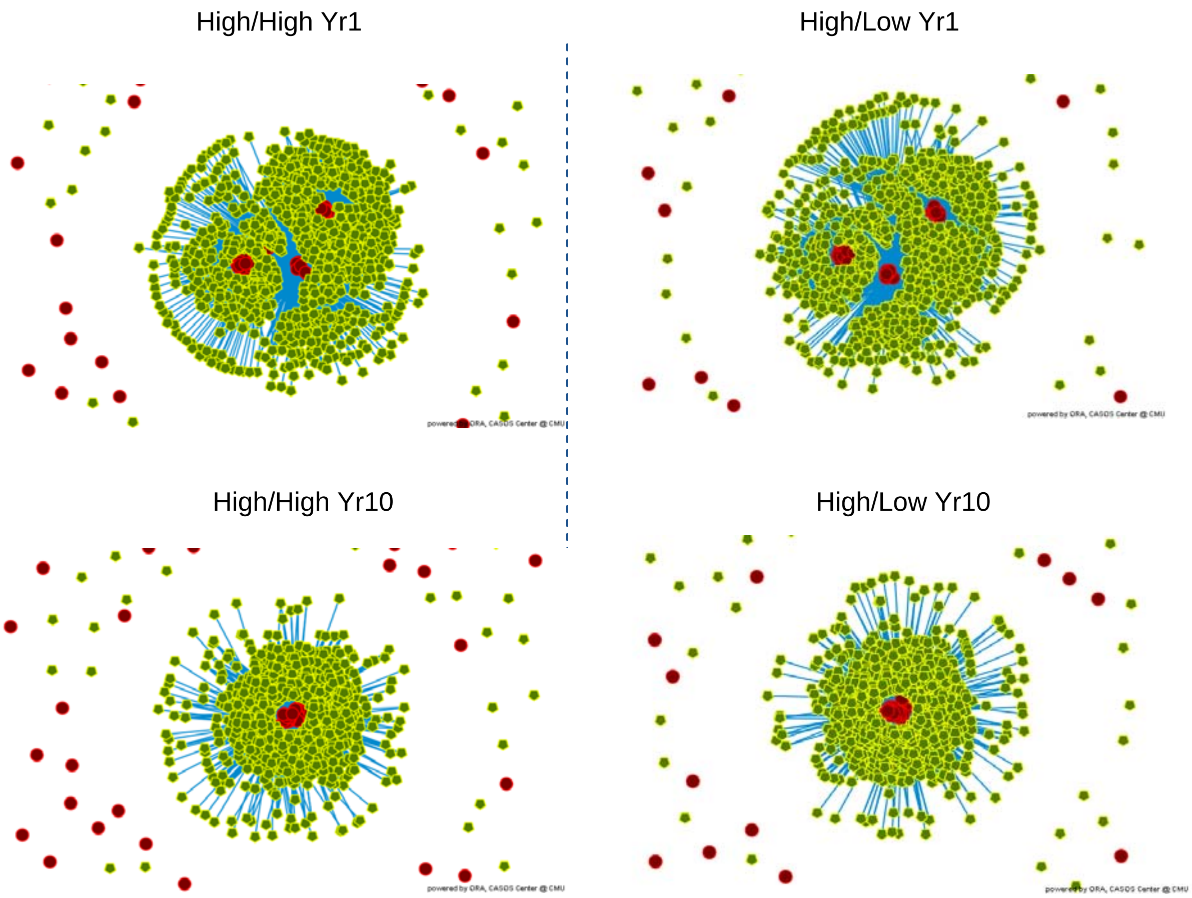
Figure 9: Comparison of High/High vs. Medium/High



<u>Legend</u>:
Agents – Red Figures
Knowledge – Green Figures
Lines – Links (Agent x Knowledge)

Agent x Knowledge Comparison of High/High vs. High/Low Firms

Figure 10: Comparison of High/High vs. High/Low



<u>Legend</u>:
Agents – Red Figures
Knowledge – Green Figures
Lines – Links (Agent x Knowledge)

These network diagram results show how these virtual community health center performance levels evolved over a 10-year period. The network agent classes are designated in red and show clustering that includes each of the five agent classes used in the simulation, which include: (1) firm-administrative staff agents, (2) firm-patient care staff agents, (3) IT Systems agent, (4) outside collaborator agent, and (5) cancer screening task agent. The knowledge elements in the network are represented in green (5-sided) figures, agents in red (round) figures, and connections or links are represented in the blue lines. The results showed several characteristic traits that differentiated one condition from another within the network diagrams. Each of the beginning networks for high/high, low/low, medium/high, and high/low showed individual agent clusters or cliques that were characteristic of like agents showing greater interaction with other like agents. Each of the beginning networks had some degree of unevenly distributed knowledge resources and free-flowing or unconnected agents and knowledge resources. Unconnected agents within a network diagram can represent a lack of connection to the core group or key resources, and unconnected knowledge elements represent unused or outmoded knowledge resources. Each of these unconnected agents and knowledge elements represent less ideal states. Over the evolution of 10 years, the results showed how the networks evolved from a less ideal to a more ideal state, which was reflected in a higher centralized cohesion of agents and knowledge resources, as denoted by a centralized agent cluster surrounded by knowledge resources in a circular fashion. Such a formation implies, as Bruque et al. described, a network that is characteristic of greater sharing, more effective use of knowledge resources, and a greater capacity for information exchange system growth and evolution. These results revealed that, by comparing high/high to low/low, the year 10 representation of high/high represents a far more ideal clustering of agents and knowledge resources. It was noticed that the low/low year 10 network had a higher overall density than the year 10 high/high network, but the network configuration of low/low year 10 was less ideal than that of the high/high year 10 network, because of the more evenly distributed knowledge elements throughout the high/high network.

The graphic results revealed that both medium/high and high/low consistently clustered with high/high as a relatively higher performer of 10-year knowledge absorption for the cancer screening agent on all tasks and only for CDS and IS. As such, a decision was made to further investigate how both medium/high and high/low visually compared to the high/high network both at beginning and end of the simulated period. The results of this visual analysis showed that, in both cases of medium/high and high/low, there were very similar characteristics to that of the high/high network at the beginning of the simulated period. There were varying degrees of free-flowing and unconnected agents and knowledge elements. In year 10, the results showed that both medium/high and high/low had greater density, greater cohesion, greater collaboration, and less unconnected agents and knowledge elements than the high/high network configuration.

CHAPTER 5: DISCUSSION

Aim 1 Discussion–Statistical Model

Overview and Perspectives of Aim 1

The ultimate purpose of Aim 1 of the study was to identify a set of factors that may be associated with the presence and use of clinical decision support and information systems used in support of cancer screening activities. This study was considered important, because (1) clinical decision support has oftentimes been shown to be effective in improving clinical outcomes and (2) the overall uptake of clinical decision support in U.S. health care organizations remains fairly low. This study examined the role of organizational characteristics in the uptake and success of clinical decision support among a sample of HRSA-supported community health centers. The goal of this study was to provide a foundation to support future research and intervention strategies aimed at increasing CDS and IS uptake and use in support of cancer screening through changes in organizational factors and/or provider practices, especially among community health centers serving vulnerable populations.

Aim 1 focused on identifying: (1a) factors associated with the presence of clinical decision support and information systems used to support cancer screening and (1b) factors associated with the level or intensity of use of the same clinical decision support and information systems used to support cancer screenings. A set of Organizational and/or Practice Setting Factors, Patient Characteristics, and Provider Characteristics were identified from a previously developed theoretical framework by Jane Zapka (Zapka et al., 2003). Previous studies have shown that CDS and IS are effective in improving clinical outcomes and health care facility performance

(Kilsdonk et al., 2011; Saleem et al., 2005; Shortell et al., 2005). The current study set out to test not only whether the presence of CDS and IS was independently associated with the stated list of antecedents, but also in (1c) whether CDS and IS intensity-of-use within community health centers was associated with overall facility-level self-reported cancer screening rate improvement, a clinically-based outcome measure for facility-level cancer screening performance.

Capacity for Measuring Cancer Screening

The Organizational and/or Practice Setting model contained a subset of antecedents from the conceptual model that measured (1) whether or not the health center was a HRSA collaborative participant at the time of the survey, (2) the level of experience the health center had with HRSA collaborative activities, (3) the degree of importance providers placed in cancer screening activities, and (4) the level of support health center staff received from the functional (clinical) leadership team. This overall model was statistically significant and provided a set of predictors for overall capacity for measuring cancer screening activities in community health centers. Two of the four predictors, HRSA Collaborative Experience and Work Importance of Cancer Screening Tasks, were shown to be independently associated with the presence of health center capacity for measuring cancer screening. The Patient Characteristics model contained a subset of antecedents that measured (1) payer mix (expressed as the percentage of uninsured patients) and (2) the patient demographics variable for age. This model was not statistically significant and was unable to provide any patient characteristics that could account for the presence of this CDS and IS outcome. The Provider Characteristics model contained a subset of antecedents that measured (1) use of the health center provider performance feedback and (2) provider expectations of the health center information technology (IT) to address cancer screening activities. This overall model was a statistically significant set of predictors for measuring the overall capacity for measuring cancer-screening activities in community health centers. One of the two predictors, Provider IT Performance Expectancy, was shown to be independently associated with this CDS and IS outcome.

Experience with the Health Disparities Cancer Collaborative (HDCC) was associated with a greater capacity for measuring cancer screening through the use of CDS and IS. Furthermore, the level of facility-wide perceptions on the important work of cancer screening tasks was also associated with an increased capacity for community health centers' measuring cancer screening through CDS and IS. These findings add to a growing body of knowledge related to building the CDS and IS capacity of community health centers, in particular, and/or health care facilities, in general, to utilize CDS and IS in measuring and improving overall cancer screening efforts (Doolan et al., 2003; Haggstrom et al., 2008; Taplin et al., 2008; Zapka et al., 2005; Zapka et al., 2003). Many prior studies have examined the actual CDS and IS systems as the single, or one of a set of primary outcomes of interest (Goins et al., 2003; Ferrante et al., 2010; Steele et al., 2005; Saleem et al., 2009; Ketcham et al., 2009; Weiner et al., 2004; Burke et al., 2005). Historically, the creation of CDS and IS capacity for cancer screening has been a significant challenge to community health centers, in part because many community health centers work with underserved populations and function as what Millery et al. referred to as an under-resourced setting with limited capacity (Millery & Kukafka, 2010). To the extent that CDS and IS are associated with improved clinical processes, it will be more difficult to improve cancer screening in these under-resourced settings if they cannot afford to adopt new technologies. CDS and IS capacity may need to be further studied as a precursor to an overall CDS and IS adoption and use a strategy designed to impact cancer screening practices (Ferrante et al., 2010; Goins et al., 2003; Millery & Kukafka, 2010).

This study adds to the established literature by exploring factors associated with the uptake of health information technology. The importance of identifying such factors is highlighted by the slow adoption of electronic health records in U.S. hospitals (Jha et al., 2009). This study also adds to the literature related to whether CDS and IS can improve system performance in a clinical environment (Brooks et al., 2005; Burke et al., 2005; Doolan et al., 2003; Reinhardt, 2010; Weiner et al., 2004). In addition to assessing the presence and use of CDS and IS, this study also examined the capacity of the community health center to actually use these systems to support cancer screening activity (Burke et al., 2005; Doolan et al., 2003; Shortell et al., 2004; Trivedi et al., 2009; Tsiknakis & Kouroubali, 2009; Weiner et al., 2004).

An inverse association was found between the level of importance placed on cancer screening tasks and the capacity to measure and improve cancer screenings through the use of CDS and IS. In other words, as the level of importance the provider placed upon the cancer screening tasks increased, the odds for CDS and IS capacity decreased. One possible explanation for this finding may be that centers that place a high priority on cancer screenings were able to achieve their goals with existing legacy, even paper-based systems, without the need to implement new CDS and IS. Alternatively, centers that had not implemented CDS and IS were more acutely aware of the need to prioritize cancer screening activities but had not yet adopted the information systems needed to achieve their goals. The variables inversely related to CDS and IS capacity (cancer screening task importance and provider IT performance expectancy) represent provider beliefs and expectations of their cancer screening activities and CDS/IS, respectively. In these cases, it does not appear as though provider beliefs and expectations in these domains translate into increased CDS and IS capacity.

Zapka et al. surveyed 761 primary care clinicians regarding their perceptions of screening guidelines, the presence of reminders for screening, as well as a plan and practice commitment to high-quality screening, in order to identify opportunities to improve the uptake of breast and cervical cancer screening guidelines. As part of establishing their methodology for identifying the presence of clinical information systems in health plans, Zapka et al. found that clinicians agreed with a health plan's report of the presence of a clinical information system to promote screening from 65% to 90% of the time for breast cancer screening and 51% to 72% for cervical cancer screening. Zapka et al. demonstrated that clinician reports of the routine presence of clinical information systems were positively associated with clinician perceptions of there being "excellent/very good" plan efforts to maximize member access to cancer screenings (Zapka et al., 2005).

The inverse relationship found in this study between the provider view of IT and the CDS measure for capacity for cancer screenings through the use of CDS and IS could potentially be understood as a change in perceptions that takes place in the informed user. Specifically, as providers are educated about the value and importance of CDS and IS to support cancer screening activities, providers could obtain a new understanding of system deficiencies, resulting in a perception of reduced capacity. In such an instance, the provider who is trained on the value of IT in support of cancer screening can, in turn, have an increase in the Performance IT Expectancy and a corresponding belief that his or her health center IT system lacks the capacity to adequately address their cancer screening needs.

A similar logic may explain the inverse relationship between cancer screening task importance and CDS/IS capacity. Yano et al. examined the influences that primary care organizations had on colorectal cancer screening performance and found a negative association between formalization (more common in larger organizations) and innovation (defined as structures and processes to facilitate CRC screening) (Yano et al., 2007). The Yano et al. findings were also consistent with Rogers' study on the diffusion of innovation theory (Rogers, 1995). Yano asserts that this type of association raises an important issue about the nature of CRC screening, the level of coordination across organizational departments, and the need to achieve a complete diagnostic evaluation (Yano et al., 2007). This dissertation study did not address the general concept of innovation as broadly defined by Rogers (1995) in Aim 1, but it did examine the association between structures and processes as defined by Yano et al. related to cancer screening with CDS/IS as a mediator of cancer screening performance. From this, one can hypothesize that, when it comes to a complex activity, such as CRC screening requiring high levels of coordination, that, as the level of formalization of organizational practices (expressed as changes in delivery model, adoption of new technology, and management strategies) (Institute of Medicine, 2000) increases, the level of innovation in CRC-related structures and processes decreases. Such a relationship may, in turn, account for the findings within this dissertation study, suggesting that, as community health centers underwent increased formalization through HRSA-sponsored collaborative activities, provider perceptions about the capacity of the current CDS/IS system to adequately measure complex interdepartmental cancer screening activity, decreased.

This study builds upon previous studies that have demonstrated how disease-focused quality improvement collaboratives (such as HRSA Collaboratives) are effective in improving health care quality or clinical processes of care (Asch et al., 2005; Chin et al., 2004; Haggstrom et al., 2008; Landon et al., 2007; Taplin et al., 2008). Many of these prior studies focused on community health centers receiving support from HRSA to perform quality improvement collaboratives as their health care (Chin et al., 2004; Landon et al., 2007; Taplin et al., 2008). This suggests that health center interventions for cancer-screening improvement could benefit from the lessons learned and shared best practices/experiences gleaned from previous HRSA collaborative activities.

Provider Prompts at Point-of-Care

The Organizational and/or Practice Setting model contained a subset of antecedents from the conceptual model that included (1) whether or not the health center was a HRSA collaborative participant, whether it focused on the associated work of quality improvement at the time of the survey and (2) the availability of electronic information and information retrieval practices at the health center in support of cancer screening. This overall model was not statistically significant and, thus, was unable to identify any organizational and/or practice setting factors that were associated with the use of provider prompts at the point-of-care in community health centers. The Patient Characteristics model contained a subset of antecedents that included (1) payer mix (expressed as the percentage of uninsured patients) and (2) payer mix (expressed as the percentage of patients on Medicaid). Again, this model was not statistically significant; therefore, it was unable to identify any patient characteristics associated with the presence of this CDS and IS outcome. The Provider Characteristics model contained a subset of antecedents that included (1) an overall assessment of the health center cancer screening environment based upon provider performance feedback and (2) provider expectations of the health center information technology (IT) to address cancer screening activities. This overall model was statistically significant; one of the two predictors, Provider IT Performance Expectancy, was shown to be independently associated with this CDS and IS outcome.

Within the community health center sample, there was an independent inverse association between provider IT performance expectancy and the presence of provider prompts at point-of-care. This was consistent with the findings that examined the association between provider IT performance expectancy and health center CDS and IS capacity for measuring cancer screening. Here, with respect to the use of provider prompts, the same inverse association between provider IT expectations and a CDS and IS outcome measure, was observed. Here, too, previous studies showed that provider or physician acceptance, expressed as beliefs and attitudes towards health information technology, had an influence on HIT adoption, use, and implementation success (Ketcham et al., 2009; Saleem et al., 2009; Trivedi et al., 2009; Yarbrough & Smith, 2007; Zapka et al., 2005). Factors of provider HIT acceptance encompass such constructs as provider beliefs about usefulness of the system to achieve clinical outcomes (Saleem et al., 2009) or beliefs about the effectiveness of health IT to improve overall quality (Ketcham et al., 2009). Yarbrough et al. identified a variety of issues that impacted providers' acceptance of technology, including interruptions of traditional practice patterns, lack of evidence regarding benefits of IT, physician time constraints, ease of use of computer devices, as well as organizational and system-specific issues (Yarbrough & Smith, 2007). Trivedi et al. described the implementation of a computerized decision support system for depression among 15 clinicians. These clinician participants identified workflow disruption as a barrier to implementation, especially when the system required these clinician participants to repeat their clinical tasks more than once. Facilitators to implementation included management and administrative support to assist with workflow impact and allowing clinicians' flexibility and autonomy in the use of the algorithm (Trivedi et al., 2009). The inverse relationship between provider expectations and prompts at the point-of-care observed in this study may, in part, be due to the presence of confounding factors, some of which this study was able to measure (administrative support), and others, which were not (workflow disruption). The day-to-day observational data commonly collected to assess clinical workflow was not a part of this study's design. On a more conceptual level, a previous study by Holden et al. found that, with respect to theories of technology acceptance, successful HIT outcomes depend on the fit between elements within the work system where HIT is implemented (Holden & Karsh, 2009).

A factor that might be important to understanding the availability of electronic information and information retrieval practices at the health center, which supports cancer screening, is the idea of readiness for change of a facility for HIT-related activity as developed by Weiner et al. (Weiner, Amick, & Lee, 2008). Weiner et al. found evidence that a lack of readiness for organizational change—for example, in the case of a facility-level CDS intervention—can result in limited success. This lack of readiness for change can result in (1) a change effort that experiences a false start from which it might or might not recover, (2) a change effort that can stall as resistance grows, or (3) a change effort that can fail outright (Weiner, Amick, & Lee, 2008). Future studies of health information technology adoption within all types of organizational settings are likely and should explicitly measure organizational readiness for change. Weiner et al. used a working definition of organizational readiness as the extent to which organizational members are psychologically and behaviorally prepared to implement organizational change (Weiner, Amick, & Lee, 2008).

In summary, the findings of the current study show that Electronic Information Retrieval & Availability (e.g., access to a computer terminal and Internet access) was not independently associated with Provider Prompts at Point-of-Care. Future studies may be needed to demonstrate how facility placement of computer terminals and Internet access portals may actually serve to support clinical practices at point-of-care within this health setting.

Computerized Patient Reminders

The Organizational and/or Practice Setting model contained a subset of antecedents from the conceptual model that included (1) whether or not the health center was a HRSA collaborative participant at the time of the survey and (2) the level of medical specialist availability for cancer screening practices. This overall model was not statistically significant, and thus, we were unable to infer any relationships between collaborative participation in quality improvement activity or medical specialist availability, and the use of computerized patient reminders. The Patient Characteristics model contained a subset of antecedents that measured payer mix in the following two categories: (1) percent of uninsured patients and (2) percent of patients with commercial insurance. This model was not statistically significant. The Provider Characteristics model contained a subset of antecedents that included (1) an overall assessment of the health center cancer screening environment based upon provider performance feedback and (2) Provider-Level Cancer Screening reporting behaviors. This model was also not statistically significant and unable to provide any patient characteristics that could account for the presence of this CDS and IS outcome. Overall, none of the three models used to test the association between conceptual model antecedents and this outcome for CDS and IS were successful in confirming or identifying new relationships.

The literature suggests that providers can serve as clinical champions or agents of change, although the relationship between overall facility leadership and the implementation of clinical decision support examined in this study were negative (Kilsdonk et al., 2011; Weiner et al., 2004). These findings suggest that there may be factors in addition to the antecedents selected for this study that could influence the implementation and use of these reminders. Other potential technology-related factors include the level of use of mobile and wireless technology, HIPAA-related data privacy and security issues, and IT system integration issues. In addition, provider attitudes toward intrusive technologies may also influence the degree of implementation (Holden & Karsh, 2009; Ketcham et al., 2009; Saleem et al., 2009; Trivedi et al., 2009; Yarbrough & Smith, 2007).

The lack of statistically significant findings may also have been related to the size of the sample of community health centers (44) that were included in the study. In terms of the level of use of computerized patient reminders, 73% of community health centers had employed reminders and only 27% did not. Therefore, this study sample may not have had sufficient variation needed to accurately account for the associations among these variables.

The lack of an association between medical specialist availability and computerized clinical reminders differs from the findings of Saleem et al., who found that lack of coordination between primary care and gastroenterology specialists was one of the barriers to implementation of CRC screening decision support for colorectal cancer (Saleem et al., 2009). The study by Saleem et al. collected ethnographic observations in health care settings using some form of CDS for CRC screening. The observations were subsequently coded into emergent themes guided by sociotechnical systems theory. The study by Saleem et al. was performed at multiple "benchmark" institutions that were early adopters of the implementation of both electronic health records and clinical decision support. The lack of a statistically significant relationship between medical specialist availability and CDS due to "availability" is not the relevant construct. Instead, it may be the quality of the relationships between primary care (the core work force of community health centers) and medical specialists, rather than the mere presence of specialists, that leads to the successful implementation of CDS. The different conclusions between the current study and the research done by Saleem et al. may also be related to methodology. The ethnographic methods used by Saleem et al. may be more sensitive to rare but important observations, while the survey measurement and quantitative models employed in the current study required a different type of evidence and larger sample size in order to draw conclusions about the influence of medical specialist availability upon CDS for cancer screening.

The current study relied largely on the Zapka et al. framework (Zapka et al., 2003), which, in turn, built upon the Chronic Care Model for conceptually defining the measures for clinical decision support and clinical information system outcomes (Haggstrom, 2008; Glasgow, Orleans, & Wagner, 2001). This study used organizational surveys to operationalize organizational measures drawn from the Zapka et al. conceptual framework. It may be that either there are key organizational constructs that were not identified by this conceptual framework or that the organizational survey did not precisely or accurately measure the underlying organizational constructs. Finally, the relatively small sample size of the organizations (community health centers) relative to the number of covariates modeled may also have contributed to the inability to draw definitive conclusions. To summarize, the current study found that no organizational, patient, or provider measures were independently associated with computerized patient reminders.

Generated Correspondence with Results to Patients

The Organizational and/or Practice Setting model contained a subset of antecedents from the conceptual model, which measured (1) whether or not the health center was a HRSA collaborative participant at the time of the survey and (2) the community health center electronic health record functions/capabilities were in support of cancer screening practices. The Patient Characteristics model contained a subset of antecedents that measured payer mix in the following two categories: (1) percent of uninsured patients and (2) percent of patients on Medicaid. The Provider Characteristics model contained a subset of antecedents that measured (1) the health center use of provider performance feedback and (2) provider expectations of the health center information technology (IT) to address cancer screening activities. Overall, none of the three statistical models used to measure the association between conceptual model antecedents and this outcome for CDS and IS detected significant associations.

The current study attempted to identify associations between CDS and IS-generated correspondence—operationally defined as whether or not the health center used its information system to send correspondence or reminders to patients eligible for cancer screenings—and several independent measures, including electronic health record (EHR) capability, provider IT performance expectancy, and provider performance feedback. Shortell et al. identified high performance firms versus low performance firms for HIT using a scorecard method and found that average performers for HIT were still not reaching levels of maximum capability for HIT implementation (Shortell et al., 2005). The current study included this summary measure of EHR capabilities in an attempt to identify an association between the EHR summary measure and the CDS and IS outcomes. The rationale for this measure was that EHR capability could be viewed as an overall measure of HIT implementation within this sample. This study intended to test whether or not EHR capability served as a catalyst for increased ability to generate cancer screening specific electronic correspondence that included patient results. However, this study was unable to detect such a relationship and, in turn, could not claim that increased EHR/HIT capabilities within health care organizations could lead to a greater ability to carry out health care objectives, such as cancer screenings (Brooks et al., 2005; Burke et al., 2005; Shortell et al., 2005). This study did not find any factors associated with the presence of a health center CDS and IS system capacity to generate correspondence results to patients.

There might be other factors beyond the current study's list of independent measures that account for the presence of this CDS and IS outcome. Computer-generated correspondence with patient results capability can serve as a critical decision aid in the cancer screening process to (1) define eligible populations for screening, (2) ensure proper follow-up of diagnostic tests and procedures results, and (3) assist in informing patients of critical information in a timely manner. This capability is essential to any overall strategy for meeting facility-level cancer screening objectives and may require additional study within the community health center setting.

Community Health Center Factors of CDS and IS Intensity of Use

The Organizational and/or Practice Setting model contained a subset of antecedents from the conceptual model that measured (1) the level of experience the health center had with HRSA collaborative activities, (2) the health center age (expressed in terms of how long it has been receiving funding from the Bureau of Primary Health Clinics (BPHC), (3) the degree of importance providers placed in cancer screening activities, (4) the level of external connections the health center has in the form of support structures, collaborative agreements, and external drivers, (5) the cancer screening delivery system design (expressed as roles responsibility, clinical champions, etc.), and (6) the level of support health center staff received from it functional (clinical) leadership team. This overall model was statistically significant and provided a set of predictors for overall CDS and IS intensity-of-use in cancer screening activities in community health centers. Two of the six predictors, HRSA Collaborative Experience and External Pressure, Support, Connectedness, and Collaborative Agreements, were shown to be independently associated with this CDS and IS outcome. The Patient Characteristics model contained a subset of antecedents that measured payer demographics for (1) primary language of the patient population and (2) age. This model was not statistically significant and unable to provide any patient characteristics that could account for the presence of this CDS and IS outcome. The Provider Characteristics model contained a subset of antecedents that measured, (1) Provider-Level Cancer Screening reporting behaviors and (2) provider expectations of the health center information technology (IT) to address cancer-screening activities. This overall model was statistically significant for measuring overall CDS and IS intensity-of-use in cancer screening activities. One of the two predictors, Cancer Screening Rate Reporting Behavior (Provider-level), was shown to be independently associated with this CDS and IS outcome.

Experience with the Health Disparities Cancer Collaborative (HDCC) was associated with greater utilization of CDS and IS. These findings illustrate the potential impact that team-based, collaborative quality improvement activities can have on improving the process of care within health care organizations (Taplin et al., 2008; Balasubramanian et al. 2010; McInnes et al., 2007). External environmental forces, in the form of external pressures (e.g., Board of Director accountability for HRSA Collaborative activities, explicit or implied performance benchmarking as member of HRSA Collaborative), support (e.g., listings of community cancer resources, staff/resources needed to make use of community cancer resources), connectedness, and collaborative agreements (e.g., informal or formal contractual agreements with outside organizations), were associated with increased level of utilization of CDS and IS in support of cancer screening activities. This finding was consistent with previous studies which have found that external environmental factors

(Shortell et al., 2005) and external communication (Kilsdonk et al., 2011) may have an impact on HIT usage. External agreements or contracts may promote CDS and IS use by providing more reliable support from outside organizations that, in turn, reduce the risks taken by community health centers investing in health information technology. This external support and interaction could also lead to a more broad diffusion of technology and innovation, a greater sharing of best practices, and perhaps a greater level of shared accountability among multiple practices.

This study also found that provider-level cancer screening rate-reporting behavior was associated with the intensity-of-use within community health centers. These findings are consistent with previous findings that demonstrated both the provider's work environment and clinical task-related behaviors are associated with CDS level of use (Yarbrough & Smith, 2007; Zapka et al., 2005).

This dissertation study found that audit and feedback, even in the low-resource setting of community health centers (and expressed here as provider-level cancer screening reporting), is more likely to occur when CDS and IS have also been implemented. Some previous literature suggests that provider audit and feedback, on specific clinical tasks and processes, is associated with positive, although incremental, improvements in health care quality (Jamtvedt, Young, Kristoffersen, O'Brien, & Oxman, 2006). "Audit and feedback can be effective in improving professional practice. When it is effective, the effects are generally small to moderate. The relative effectiveness of audit and feedback is likely to be greater when baseline adherence to recommended practice is low and when feedback is delivered more intensively" (Jamtvedt et al., 2006). The HRSA Health Disparities Cancer

Collaborative effort was aimed at increasing adherence to practice guidelines for breast, cervical, and colorectal cancer screening (Taplin et al., 2008). However, the current study did not find, as Jatvedt et al. did, that audit and feedback was associated with improved professional practice (or cancer screening) in these settings. Other literature also finds that audit and feedback is not uniformly effective in improving clinical practice. In one study conducted in a community primary care practice setting, office system changes, including audit and feedback, did not increase breast cancer screening. Providers were allowed to offer feedback on 12- to 18-month facility-level cancer screening performance, but this alone did not prove overly significant in changing breast cancer screening rates (Kinsinger, Harris, Qaqish, Strecher, & Kaluzny, 1998). Given these mixed results, audit and feedback may need to be applied in association with other strategies, such as clinical reminders, provider incentives, outreach, and the cultivation of opinion leaders.

CDS and IS Impact on Cancer Screening Rates in Community Health Centers

The current study did not demonstrate any significant association between facility-level rankings for intensity-of-use of CDS and IS and the rankings of facility-level self-reported cancer screening improvement rate scores within health centers. Previous studies suggested that the use of self-reported screening activities may be inaccurate in assessing overall facility-level screening rates (Gordon, 1993; Montano, 1995). This study's finding was consistent with the mixed results of previous studies that did not always demonstrate a significant relationship between HIT of any kind and health outcomes in general, and cancer screening, in particular (Ferrante et al., 2010; Goins et al., 2003; Millery & Kukafka, 2010; Poon et al., 2010). Goins et al. suggested that multiple strategies, including clinical decision support, should be aimed at multiple health care processes; but at the same time, cautioned that the same strategy for one cancer type might not be transferable to other cancer types (Goins et al., 2003). In the current study, a composite score was used to represent improvement in one or more areas of cancer, including breast, cervical, and colorectal cancer. Future studies might require separation of these outcome variables and that each cancer screening type should be independently tested against the list of predictors. Bates et al. found that the association between IS and quality was stronger for problem list, visit note, and radiology test capabilities than for other electronic health record features. There may also be additional human, organizational, and/or socio-technical factors that confound the relationship between CDS and IS and cancer screening (Kilsdonk et al., 2011) that were not measured in the current study. High-yield targets for future interventions or studies would include human computer interface issues, as well as facility, and/or provider-level incentive programs (Ketcham et al., 2009; Saleem et al., 2009; Yarbrough & Smith, 2007).

One study in the community health center setting did, in fact, find a significant relationship between CDS and screening. In 2005, Steele et al. examined the link between CDS and latent tuberculosis infection screening (LTBI) within community health centers (Steele et al., 2005). Steele et al. observed a significant improvement in adherence with the LTBI screening guideline and concluded that CDS made a positive impact. Despite being performed in the same type of underserved health care setting, the current study did not find the same association between CDS and process improvement, perhaps due to the different types of clinical process being targeted (tuberculosis vs. cancer screening) which also involve different types of patients.

Again, the Spearman's Rank Order test found no statistically significant association between the CDS and IS ranking and the facility-level self-reported cancer screening improvement rate scores. However, these findings were consistent with other studies that did not always demonstrate a significant relationship between HIT (e.g., CDS and IS) and health care processes (e.g., cancer screening).

Application of Aim 1 Findings

This dissertation project makes an important contribution to the field of organizational informatics. The approaches taken here to identify and model organizational characteristics and activities are well-suited for application to other research or projects wherein there is a simultaneous examination of three primary areas that include (1) one or more health information technology capabilities, (2) one or more disease/health care processes or outcomes, and (3) one or more organizational settings. The CDS and IS research questions were divided into three primary areas representing factors of CDS and IS presence, factors of CDS and IS use, and the measure of impact of CDS and IS on cancer screening outcomes. The findings of this study are most generalizable to practices focusing upon (1) clinical decision support for the purpose of improving (2) cancer screening in the primary care practice setting of (3) community health centers.

The community health center setting is unique, based upon several factors, including its focus on primary care, its mission to provide health care to vulnerable populations, and its national network of clinics in both urban and rural areas. The leadership of community health centers trying to promote CDS and IS adoption face several challenges, including limited resources and time (Millery & Kukafka, 2010). Individuals operating in such pressured environments commonly face high cognitive demands (Nemeth et al., 2006). This research seeks to provide a theory-driven foundation for future studies in these settings. This study operationalized the Zapka et al. framework and its corresponding list of organizational, patient, and provider factors, due to its unique multilevel perspective on improving cancer-screening performance.

The framework operationalized and tested here can also potentially assist strategic planning in community health centers by providing a streamlined set of variables that identify specific CDS and IS applications, such as provider prompts at point-of-care and computerized patient reminders. Furthermore, the results of this theory-driven approach provide health center leadership with a streamlined list of organizational, patient, and/or provider factors that are likely to be associated with CDS and IS. Budgetary, time, or other constraints may force a more streamlined approach that seeks to identify a small set, or even at times a single factor for CDS and IS interventions, designed to (1) increase the presence of CDS and IS, (2) increase the level of CDS and IS use in clinical care, and (3) ultimately increase facility-level cancer screening rates. Specifically, this study found that the level of prior HRSA collaborative experience, in combination with the level of significance providers placed on cancer screening work practices, as well as provider expectations of IT performance, were all associated with the community health centers' CDS and IS capacity for measuring cancer screening activity. Provider IT expectancy was also associated with provider prompts at point-of-care. Additionally, this study found that the level HRSA collaborative experience, in combination with the level of community health external connections and the provider-level cancer screening rate reporting behavior, where all tied to CDS and IS utilization.

This study has several important limitations. First, caution should be taken in drawing strong causal inferences based upon cross-sectional survey data. Nonetheless, considerable effort has been taken to place the study findings in the context of the existing literature, and thereby minimize the risk of drawing unsupported conclusions. Furthermore, the organizational surveys were administered after completion of the HRSA quality improvement collaborative, and therefore, the observations can be tightly linked temporally, if not causally, to collaborative performance. Another limitation of the survey instrument was that it did not measure the unique IT design specifications (e.g., operating platform, database architecture, user interfaces, etc.) within health center systems for CDS and IS, nor did it examine issues associated with software development and implementation. Instead, the examination of CDS and IS was focused upon the practical questions of its presence and level of use by providers in clinical practice within the organizational setting.

It is also worth noting that the summary measure of EHR capabilities rarely emerged as significant in the statistical models developed here. Yet, previous literature suggests a strong correlation between EHR and CDS (Mostashari &

Tripathi, 2009; Osheroff et al., 2007). In fact, clinical decision support is often seen as a specialized subset of a larger EHR system targeting some specific clinical objective, in this case, cancer screening (DesRoches et al., 2008). There was one CDS and IS outcome, i.e., the generation of computerized results, where EHR capabilities served as a predictor within the best subset model chosen. However, EHR capabilities were still not found to be statistically significant in this model. Given the strength of prior evidence, it is quite possible that either there are other factors that are more strongly associated with CDS and IS than EHR capabilities, or the summary measure used for EHR capability did not capture the EHR construct in a manner consistent with previous research designs. Specifically, the HDCC survey focused on whether or not the EHR could facilitate a series of cancer screening tasks and did not account for global functions normally associated with EHR that extend far beyond cancer screening. Additionally, this study did not investigate conditions, such as the stage of development of the facility-level EHR or the percentage of health center core processes that were paper vs. electronic, both of which would arguably play a role in overall CDS and IS applications for cancer screening activity.

These finding provide a foundation for future research and/or implementation efforts that can focus on either a single variable or set of variables to examine the potential influence of CDS and IS adoption and/or utilization in a community health center. However, there would be several practical considerations for such activity in any health care setting. First, the implementation of a single predictor-to-outcome relationship in the form of a CDS and IS intervention would require an organizational assessment mechanism of the measure in question, a strategically derived means to change it over time, a way to monitor it over time, and the resources to implement this system of change. For example, consider if one wanted to focus on increasing the health center's capacity for CDS and IS by way of adjusting for the importance of conducting cancer screening tasks among providers. Such an intervention would require that an infrastructure be put in place (assuming one may not exist) that would gain a benchmark measure of current CDS and IS capacity and the current level of importance viewed by staff, who are designing a system of change (assuming they are not at the desired levels), monitoring change over time, and making operational adjustments, where necessary. This hypothetical scenario suggests that, given a small subset of intervening variables discovered to be associated with the outcomes for cancer screening CDS and IS, even focusing on a single predictor-to-outcome relationship could prove to be a major implementation task in an under-resourced setting. This may partially explain the relatively slow uptake of CDS and IS for use in cancer screening, despite the prevailing evidence that suggests its effectiveness in clinical care process improvement as a single intervention.

Aim 1 Observations and Learning

Testing of the organizational predictor variables in this study against their CDS/IS and clinical outcomes was exhaustive, and every attempt was made to maintain the integrity of each response as it was delivered by respondents to the HDCC survey items used here. This study served to inform the researcher on how to manage a large set of predictors intended to explain organizational behavior in a limited set of observations. Limited data regarding organizational characteristics is common, as many organizations are reluctant to share critical strategic data on internal operations and, as such, choose not to participate in studies that could result in negative exposure without assurance of anonymity. Additionally, the findings from an in-house assessment or research study focusing on a single organization often cannot be generalized to a larger population, partially because the conditions in one organizational setting cannot be easily duplicated in another. This organizational heterogeneity informs the rationale for the current push towards complex adaptive tools to measure organizational change, which, in part, serves as justification for the computational model used in Aim 2 of this study. Despite these methodologic challenges, Aim 1 served to highlight a series of steps involving model reduction and model diagnostics, which can serve as a template for other organizational studies related to information technology and cancer control. This study design can be replicated or adopted in any other study that seeks to combine (1) some identified health care organizational cohort, (2) some objective measure of the cancer care continuum in support of cancer prevention and control, and/or (3) any particular form of health information technology application.

Overall Conclusions for Aim 1

This study identified Organizational and/or Practice Setting Factors that showed a relationship to the presence of CDS and IS within community health centers. There was evidence that HDCC experience was associated with the CDS and IS capacity for measuring cancer screening, although there was no association between being a current HDCC participant and CDS/IS capacity. These findings suggest that cumulative collaborative experience, rather than current quality improvement membership status, more directly relates to the likelihood of implementing these types of health information technology.

No Patient Characteristics were found to be related to the presence of CDS and IS, nor were patient characteristics found to have an association with the intensity-of-use of CDS and IS within community health centers. This negative finding regarding patient characteristics is consistent with several other studies that emphasized instead the importance of organizational structure and processes to an overall HIT implementation strategy (Burke et al., 2005; Millery & Kukafka, 2010; Shortell et al., 2005).

Regarding intensity-of-use, measures were found in both the Organizational and/or Practice Setting and Provider Characteristics categories that were associated with this outcome. HDCC experience showed an association with the intensity-of-use of CDS and IS within community health centers, while current HDCC membership/participation did not, again suggesting that cumulative experience rather than current membership status was most important.

The current study did not find an association between the proximal outcome for the intensity-of-use of CDS and IS community health center rankings and that of self-reported cancer screening improvement rankings.

From its multilevel framework, this study successfully identified factors associated with two of the three targeted outcomes. Additional studies are needed to identify if and how CDS and IS can improve 12-month cancer screening rates.

Aim 2 Discussion–Computational Model

Overview and Perspectives of Aim 2

The primary purpose of this portion of the study was to examine how a computational modeling exercise could be paired with results from Aim 1 and add strategic insights, while also identifying future intervention strategies related to these outcomes. It is important to note that everything in this Aim 2 will be discussed in terms of the five performance level groupings (or simulated conditions) of community health centers as the unit of analysis, as opposed to Aim 1, where the unit of analysis was the individual community health center. Each individual community health center was ranked using the same scores from the Spearman's Rho test used in Aim 1c. The combined scores for CDS and IS intensity-of-use comprised the first portion of the composite ranking of high, medium, or low. This element of the ranking system scored each community health center (designated in Aim 2 as firm) from 0 to 4 for having none, one, two, three, or four CDS and IS components, respectively. The second component of the composite performance level was based on the community health center (firm) 12-month self-reporting cancer screening improvement rate score. Each firm would be scored from 0 to 3 for improvement in none of the areas of cancer screening, or in only one, two, or all three areas of colorectal, breast, and cervical cancer screening, respectively, resulting in a second designation of high, medium, and low. Next, there was a combined performance level obtained for each firm as having one combination of high/medium/low for CDS and IS, along with high/medium/low for cancer screening. These values were obtained from the original HDCC dataset. After each of the 44 firms was given a combined score, they were then assigned to one or more of the performance levels in the CDS and IS and Cancer Screening Performance Matrix created solely for this study. For this computational modeling exercise, six designations where used, including high/high (HH) (where CDS and IS represents the first designation, and where the second designation represents the cancer screening ranking), low/low (LL), high/low (HL), low/high (LH), medium/high (MH), and medium/low (ML). The mean and standard deviations for each of the 37 measures was calculated for each of these performance levels and used as input for the virtual experiment. Two important things are worth noting: (1) there were no categories of low/medium (LM) or high/medium (HM) applied within this analysis (matrix) and (2) the condition of medium/low was not included in the final set of simulated models tested, because this grouping was comprised of only one firm (n=1), and it also contained more than the minimum recommended number of missing data elements. With only one firm in the medium/low category, the missing data factor could not be overcome through the use of aggregated scoring, which caused it to be removed from this portion of the analysis.

While careful effort was made to objectively distinguish between relatively high performers and relatively low ones, two limiting factors were recognized in the preparation of the simulation: (1) there may be debate as to where the actual cutoff points from one designation to another may actually lie, and (2) the intent of the original survey was not to categorize community health centers into performance levels but simply to investigate the larger issue of determinants of cancer screening rates. As such, the designations of high/high (HH), low/low (LL), high/low (HL), low/high (LH), medium/high (MH), and medium/low (ML), and the respective assignment of the 44 firms to one of these levels, may only have meaning within the context of this study.

Clinical Decision Support and Knowledge Management: The Learning Organization

This virtual experiment or simulation was intended to best predict the relative change in each community health center performance level group's knowledge absorption over time, which was referred to as the Delta k (Δk). This metric Δk was measured over a 10-year period (520 weekly intervals) in relation to the cancer-screening agent. The simulation included a testing of the cancer screening agent Δk with respect to both the entire set of cancer screening associated tasks and opportunities for knowledge exchange, as well as for the CDS and IS task only, along with its corresponding set of knowledge exchange opportunities. It was hypothesized that higher performing firms would have higher rates of knowledge absorption Δk compared to lower performing firms over the 10-year period, as observed through the steepness (in graphical representation) of the slope. Previous studies identified metrics for organizational learning and described them in terms of such things as clinical "know-how" (Anderson & Willson, 2009), collective intuition (Salas et al., 2010), and overall organizational learning and/or organizational intelligence (Feifer et al., 2006; Niland et al., 2006; SAS Institute, 2004; Wang, Nayda, & Dettinger, 2007).

One set of simulated results focused exclusively on performance with respect to only the cancer-screening agent classification and examined the two perspectives for task-related performance which was graphically observed. The second set of simulated results examined all five agent classifications, which included firm-administrative view, firm-clinical practice view, IT systems, outside collaborators, and the cancer screening test. This second analysis consisted of a visual inspection of the network diagrams to examine how these networks evolved over time relative to their agent by knowledge interactions over a 10-year period.

The findings related to these simulations were consistent with previous studies that argued the following principles: (1) that organizations change over time, (2) there is a correlation between the rate of organizational learning and some measure of performance/success, (3) that HIT used in support of cancer outcomes should take into account the learning required to improve organizational capability, and (4) that the health care facility should be viewed as a complex adaptive environment (Feifer et al., 2006; Niland et al., 2006).

Ten-Year Performance of Cancer Screening Agent Simulation: Graphical Representation

Observing the Δk for each of the five community health center performance levels over a 10-year period for the cancer-screening agent revealed two major clusters or performance levels for knowledge absorption over time. It was apparent that the five conditions were clustered into either a higher set of performers or a lower set. These distinctive higher versus lower performance clustering's were over and above the original designations, given the five conditions of high/high, low/low, medium/high, etc. The original designations were a representation of the CDS and IS and cancer screening improvement score. However, this new clustering into two distinct groups of either higher versus lower performers was solely based on the Δk over the 10-year period. This study found that firms that ranked higher for CDS and IS at the start of the simulation were part of the higher cluster for knowledge absorption rate, while firms marked lower at the start of the simulation were part of the lower cluster for knowledge absorption rate. This was consistent with previous findings that differentiated performance levels for HIT use in support of clinical outcomes into groups of high performing and low performing medical groups (Shortell et al., 2005).

The first of two graphical tests examined task knowledge impacting performance over a 10-year period (520 weekly intervals) of the cancer screening test agent's knowledge absorption with respect to all assigned tasks. The second test examined task knowledge impacting performance over a 10-year period (520-week interval) of the cancer screening test agent's knowledge absorption for only the assigned task of CDS and IS. In both tests, the two lower performing levels of low/low (low for CDS and IS and low for cancer screening, respectively) and low/high were found to be members of the lower Δk performance cluster, while high/high, high/low, and medium/high were consistently members of the upper Δk performance cluster. In test one, the condition that outperformed all the other conditions for 10-year knowledge absorption Δk was medium/high. This was followed by virtually identical 10-year Δk for high/high and high/low. There were some unexplained results observed in both the Δk performance clusters in that the correlation between the original firm rankings and the Δk performance clusters was not as high. In the higher performing cluster, it was apparent that medium/high outperformed high/high, and within the lower performing cluster, the author of the current study observed that low/low outperformed low/high. This would imply that either the distinctions between one level of CDS and IS and/or one level of cancer screening improvement used in the rankings of firms may not be as great as the terms high, medium, and low would imply. Previous studies examining HIT and clinical outcomes found that, while a firm may be identified as a high performer, many are still not reaching the level of maximum capability (Shortell et al., 2005). This suggests that regardless of what a firm is designated as at one point in time, such a designation may not consistently be associated with higher performance. It could also mean that there is a complex adaptive element involved, which suggests that, regardless of the original ranking, firms have the ability to adapt over time to either increase or decrease their performance over the 10-year period. This complex adaptive element can be explained as either the readiness for change and innovation (Weiner et al., 2008) or socio-technical elements combining in a complex manner that account for the unexplained organizational behavior and outcomes (Ehrhart et al., 1999; Feifer et al., 2006; Goldstein et al., 2004; Kilsdonk et al., 2011; Nemeth et al., 2006; Niland et al., 2006).

In the second graphical test the same cancer-screening agent was tested against only the CDS and IS assigned task. Here, there was much more correlation observed between the original performance level rankings for both CDS and IS and the cancer screening scores and the 10-year Δk. There was a far more dramatic separation observed that distinguished the higher and lower clusters from one another. This wider spacing between the two clusters represented many more differences in Δk between the higher and lower performers when the cancer-screening agent was measured in terms of the CDS and IS task only. Within the higher performing cluster for knowledge absorption, there was a much denser clustering of the same three rankings of high/high, high/low, and medium/high at year 10. Within the lower cluster, the same two conditions of low/low and low/high were found to cluster. Within this second test on the CDS and IS task alone, the 10-year Δk was much more highly correlated with the original performance level rankings for CDS and IS and the cancer screening scores. Within the higher cluster, high/high and high/low were almost indistinguishable in their 10-year Δk, and they were followed very closely by medium/high. In the lower cluster, the author of the current study saw low/low with the lowest 10-year Δk, and this was closely followed by low/high with a slightly higher 10-year Δk. Within this test, the correlation between the original CDS and IS ranking and the 10-year Δk was much more distinct than in the test that included all cancer screening test associated tasks. These findings were consistent with the results observed in previous research that asserted there was a correlation between the rate of organizational learning and some measure performance/success (Feifer et al., 2006). The correlation within the two clusters between the original cancer screening scores and the 10-year Δk was much more distinct than in previous tests on all tasks.

These findings were consistent with studies that measured the concept organizational intelligence, intuition, and clinical "know-how," all which represent varying ways to measure organizational learning over time (Anderson & Willson, 2009; Salas et al., 2010). Anderson et al. referred to as clinical "know-how" and its relationship to quality, efficiency, and safety in clinical care (Anderson & Willson, 2009). Anderson found that clinical decision support can contribute to the concept of clinical know-how (Anderson & Willson, 2009). A closely related concept to clinical know-how is that of intuition. Salas et al. suggested that decision task and decision environment are part of an overall understanding of intuition within an organization (Salas et al., 2010). This study used Δk as an overall measure of the *virtual* community health center clinical know-how or intuition as a metric of overall organizational learning over time. Essentially, the intent was to define a concrete measure consistent with clinical know-how and/or organizational intuition that would serve as a proxy for distinguishing higher learning organizations from that of lower learning organizations over a 10-year period. The results show that when community health center cancer screening agent knowledge absorption is measured relative to all of the assigned cancer screening tasks from the simulation (which includes: (1) Clinic Processes, (2) Delivery System Design for Cancer Screening, (3) CDS and IS Practices, and (4) Information Dissemination Strategies) and its associated opportunities for knowledge sharing, learning, and exchange (which include (1) Work Importance of Cancer Screening Tests, (2) Cancer Screening Rate Reporting Behavior Provider-level, (3) Cancer Screening Rate Reporting Behavior Facility-level, and (4) Patient Demographics), it was apparent that community health center performance levels that ranked higher in CDS and IS at the start of the simulation demonstrated a higher rate of knowledge absorption over the 10-year period. The community health centers' performance levels that ranked higher in cancer screening self-reported improvement rates showed mixed results. However, when the test was only conducted on the cancer screening agent against CDS and IS practices, and the same list of associated opportunities for knowledge sharing, learning, and exchange were present, clusters of higher versus lower learning organizations were observed and the results that were seen were more consistent with the performance level rankings from the start of the simulated period. These results are consistent with the notion put forth by Feifer et al. that there is a correlation between the rate of learning, as measured in this simulation as Δk or rate of knowledge absorption, and performance, as measured by the proxy of CDS and IS presence/use, and cancer screening self-reported improvement rates for breast, cervical, and colorectal cancer.

Ten-Year Performance of Agent by Knowledge Simulation: Network Diagram Representation

The next analysis consisted of a series of network diagram visual inspections of the simulation output. This portion of the study would not only examine the 10-year performance of the cancer-screening agent but also included the other four agent classifications of the firms (e.g., administrative staff, patient care staff, outside collaborators, and IT systems). This was meant to provide the most comprehensive look at the firm as a function of overall agent and knowledge interactions. Here, an examination of objective network measures of density, and some of the more subjective measures of clusters/cliques, collaboration, and free-flowing and unconnected agents and knowledge elements used to assist in the understanding of each performance level over the 10-year simulated period, occurred. These findings were consistent with previous studies, which suggested that measures of density, overall network size, and clustering of network elements, can serve as indicators of performance over time and of the ability of the organization to learn, exchange information, and adapt over time (Bruque et al., 2008). All agent five classifications were included, along with all of their respective assigned tasks in the simulation. Here, the focus was on comparative analyses of the network diagrams to examine distinguishing characteristics between the networks that might explain their relative performance over the 10 year simulated period. The first network diagram comparison was made between the two extreme conditions used in the simulation of high/high beginning and low/low beginning and again between high/high end and low/low end. The next set of network diagram comparisons was performed examining the conditions of high/high beginning and end to both high/low and medium/high beginning and end, respectively. This was done because there were some unexplained behaviors observed in the graphical results that these two conditions consistently seemed to perform well against high/high for both 10-year knowledge absorption Δk. Visual inspection of the network diagrams helped to explain the fact that these two performance levels competed well against high/high, because their networks were as mature, or even more mature, over time, and they demonstrated a close to or even greater level of cohesion, cooperation, and knowledge absorption over the 10-year period.

The results of the visual inspections of these network diagrams strongly suggest that this simulation model works really well when demonstrating network evolution as gleaned from a single point-in-time survey, but that there may need to be some additional tuning of the performance categories to ensure that the performance levels are easily distinguishable in the simulation. The tests showed that high/low and medium/high firms demonstrated high levels of organizational maturity (as expressed by network characteristics) over time, high/high remained a high performer, and low/high and low/low consistently remained low performers. This could also help to add insight into the lack of statistical correlation within the Spearman's Rho test in that there may be something inherent in the data that does not agree with (1) the original rankings used in the Spearman's Rho and/or subsequent performance levels assigned to each firm based on those rankings. This could also suggest that there is always room for change and adaptability within any simulation and this model was simply accurate in pointing that out. The changes could reflect that high/high started out as such but later got out-performed by medium/high and high/low in their respective tests. Such a measure of adaptability might suggest that varying combinations of task performance for knowledge absorption Δk outperforms other combinations of task performance for knowledge absorption Δk over time. This model was not able to test every set of task combinations and, as a result, future research is needed.

This study demonstrated that a health care facility, as defined by 37 summary measures obtained from an organizational survey of cancer screening behaviors, tasks, agents, and knowledge resources, could be described as a learning organization expressed as a function of knowledge absorption (Bruque et al., 2008; Nemeth et al., 2006; Niland et al., 2006; Salas et al., 2010). This study also employed the use of visual analytics, using a series of network diagrams to provide insight into how the health care organizational environment performance levels can be understood as a function of network density, collaboration, and cohesion, which facilitates knowledge sharing, information exchange, and increased diffusions of innovation (Bruque et al., 2008). Finally, these results revealed an association between high performance firms for CDS and IS with cancer screening agents for both testing against all assigned tasks and CDS and IS only (Feifer et al., 2006). And, with respect to high performance level firms for cancer screening self-reported improvement rates for breast, cervical, and colorectal, the cancer screening agent simulation demonstrated an association between knowledge absorption over time for the CDS and IS task only and mixed results for all assigned tasks (Feifer et al., 2006).

Such an analysis reinforces previous studies, which suggested high performing firms will show greater learning, intuition, or knowledge absorption as in overall clinical knowledge management practices and views the health care organization as a complex adaptive entity (Anderson & Willson, 2009; Niland et al., 2006; Salas et al., 2010; Sittig et al., 2010).

Computational (Simulation) Model Validation

A natural progression from any computational modeling exercise is to proceed from the existing data to that of making inferences about the real world. A preliminary step in being able to address issues of learning, adaptation, and the evolution of social and organizational systems is that of model validation (Carley, 1996). The "real world" and "simulated world" are described in detail by Sargent (2004), where these two domains were linked together by system theories. According to Sargent's "Real World and Simulation World Relationships with Verification and Validation Model," the real world is described by a set of system level experimental objectives about a system (problem/entity). Through experiments involving the entity or problem in question, system data/results are produced. The results can then lead to hypothesizing based upon system theory. A series of abstractions can also be drawn about the problem or entity based upon systems theory and, where needed, additional tests can be conducted (Sargent, 2004). Sargent goes on to explain that the simulated world begins with a set of simulation experimental objectives expressed in a conceptual model that has been shaped largely through system theories. The conceptual model undergoes specification and is eventually implemented as a simulation model. The simulation model is the tool that is used to conduct experiments leading to simulation model data/results. The results can lead to hypothesizing based upon system theory (Sargent, 2004). According to Sargent, the real world problem-solving process involves the use of theory validation, while the simulation world problem-solving involves conceptual model validation, specification verification, and implementation verification (Sargent, 2004). This study examined the problem of facility-level performance for both clinical decision support and cancer screening rates through the prism of both a "reduced" real world statistical model and a simulation. The relevant categories of validation of the simulated model are described below.

Recent literature has described the overall process of model validation in terms of both verification and validation. These terms are defined divergently by different accrediting institutions. For example, the AMS Committee for Verification and Validation in Computational Solid Mechanics defines verification as "the process of determining that a computational model accurately represents the underlying mathematical model and its solution" (ASME, 2006). The US Coast Guard Appropriations group, however, defines verification as "the process of determining that a model or simulation implementation accurately represents the developer's conceptual description and specifications" (USCG, 2006). Meanwhile, both parties define validation more narrowly. The ASME defines validation as "the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model" (ASME, 2006); whereas the US Coast Guard defines validation as "determining the degree to which the model or simulation is an accurate representation of the real world from the perspective of the intended uses." In both cases, the definition implies that a model is valid, or not, only within a certain context, which pertains to the intended use of that model. No model is universally valid. Only issues of validation will be discussed in reference to this study.

There are several categories of model validity, and the specific type and degree of validation needed will depend on the level of parsimony and generality claimed for the model in question (Carley, 1996). Each type of validity is then assessed in terms of whether or not there is an acceptable degree of validation as defined by the needs of the researcher (Carley, 1996). While the categories of validation may vary somewhat in the literature, the ones that will be discussed in this section are limited to (1) internal validity, (2) parameter validity, (3) process validity, (4) face validity, (5) pattern validity, (6) content validity, (7) external validity, and (8) theoretical validity.

Internal validity refers to whether the computer code is correct and error-free (Carley, 1996). This researcher employed strategies to ensure that all steps, including data collection, data entry, and all data transformations in the study, maintained a high degree of accuracy. These efforts are described in Chapter 3. One of the main steps taken to ensure internal validity was achieved through the use of a Code Generator in an Excel spreadsheet. This tool, designed by CASOS, allowed for all data entry to be performed in terms familiar to this researcher, rather than in complex XML statements. The code generator automatically compiled the XML statements to be used in the simulation from these basic instructions. This automated generation of XML statements minimized the degree of manual manipulation of code. Additional steps were taken to test and debug each series of statements in an iterative fashion to ensure that the output was consistent with expectations.

Parameter validity refers to whether or not the parameters used in the study are matched or are aromatically correct. The major challenge here consisted of ensuring that each of the 37 summary measures used in Aim 1 of this study were properly mapped to their corresponding computational category represented in the simulation (e.g., representation of a task, representation of a belief, representation of some measure of knowledge, representation of some agent in the simulation). This required an additional series of steps, where the logic and definitions for each element of the simulation were precisely defined. The definitions described in Chapter 3 and again in Appendix 11 were then used as the primary logic for the construction of the XML code generator Excel spreadsheet. Although Construct™ allows the specification of explicit interaction partners, the collected data did not support that specificity. Instead, this analysis used statistical means to reflect the average probability of an agent's knowledge bit (represented as k) according to the definitions listed in Appendix 11 and relied on Construct's homophily and expertise-seeking drives to suggest interaction. For each clinic, this study posited three representations of the “Cancer Screening Test” agent (e.g., colorectal cancer screening test, breast cancer screening test, and cervical cancer screening test), all of which represented the clinic’s competency at the key tests of interest. This study measured the saturation of knowledge in these three agents over time. Doing this allowed a straight-forward comparison across all test cases.

Process validity exists when the study is conducted in a dependable, competent manner, and effort is made to not simply praise existing practices (Wolcott, 1994). This can be also understood to be the extent to which actions and thought processes of test takers or survey responders demonstrate that they understand the construct in the same way it is defined by the researchers (Chen et al., 2009). This study relied on the use of secondary data and described the survey development efforts made by Haggstrom et al. in Chapter 3. However, the issues described in parameter validity are the same for process validity, in that steps had to be taken to ensure that this researcher’s interpretation of summary measure might be classified an agent, a task, a belief, or a measure of knowledge. These interpretations had to be validated through subject matter expert assessments of the treatment of these variables within the simulation. This also applied to the assignment of specific summary measures designated to describe the behavior of each of the five agents used in the simulation (as seen in Table 6), as well as in the assignment of each of the 44 community health centers to one of five performance levels used in the simulation (as seen in Tables 7, 15, and 16). The subject matter experts used in this study provided additional support to ensure that the logic of the survey questions and/or intent of the primary data collector were, in fact, maintained throughout the development of the simulation experiment. This can be extended to the issue of content validity, which was referenced in the Merrill et al. study, as the principle guide for formulating survey questions' specific relationships in a predefined network (Merrill et al., 2007; Wasserman et al., 1994). The HDCC survey used in this study can be considered a valid representation of the agents, knowledge, tasks, and beliefs of the community health center workers to the extent that the survey items are representative of those elements.

On the issues of pattern validity and face validity, the study results for the respective performance levels are relative to their initial states. This study is using the description of pattern validity, also called relational equivalence (Axtell, Axelrod, Epstein, & Cohen, 1996), as the degree to which patterns in the data reflect the observed. And, closely related is the notion of face validity, which is essential if this represents a reasonable representation of reality (Chang et al., 2004). In this study, two measures were used to construct a representation of overall community health center performance (1) CDS and IS scores facility-level scores ranging from 0 to 4 and (2) cancer screening improvement rate scores ranging from 0 to 3. Each of the 44 community health centers was assigned a score of high, medium, or low from these two categories. The combined score for each facility was then represented as a composite of these two score categories, where the first designation of high, medium, or low was for CDS and IS performance, and the second designation of high, medium, or low was for cancer screening performance. Based on these scores, each facility was assigned to one of five (initially six, but only five were used in the simulation) performance levels. This study started with the premise that better performing facilities will exhibit higher patterns of learning and knowledge absorption over time. Both the graphical representations of the data and the network visualizations of the data proved consistent with these expectations. The graphical results showed a clustering effect of the higher performers outperforming the clustering of lower performers. The study found that, within the individuals cluster groups, there was some degree of variation from the expected in that the group designated as high/high did not consistently outperform medium/high and high/low in all categories. The network visualizations provided greater insight into how factors, such as knowledge sharing, resource utilization, group cohesion, and network connections, might have influenced learning over time. In all instances, these results were considered reasonable representations of the reduced reality of community health center performance as reflected in the HDCC survey.

The Merrill et al. study accurately pointed out the issues with external validity or generalizability of the study results with respect to network analysis. “External validity refers to the adequacy and accuracy of the computational model in matching real world data” (Carley, 1996). Merrill et al. suggests that the validity of network data can be tested by correlation of the network findings with observed data (Merrill et al., 2007; Schrieber & Carley, 2003). This study did not perform formal correlation analyses on the simulation output; however, visual inspection of the clustering relative to performance levels for both CDS and IS, individually, and cancer screening, individually, appeared to be visually associated into the graphical results. This does not suggest that the model is indeed easily generalizable and ready for deployment in real-world implementation. It does suggest that this model—if evaluated within the context of stakeholders who are knowledgeable of both CDS and IS and cancer screening-related organizational structure and operations—could serve as a tool to enhance overall facility-level learning and knowledge absorption over time as related to these two outcomes.

Finally, the issue of theoretical validity represents the ability of the findings to reflect what is commonly found in the current theory. Essentially, do the assumptions presented in Table 6 fit the problem and were the model instances specified appropriately? The best way to express this was through graphical results and the shape of the curve. Published literature on the Diffusions of Innovations Theory suggests that learning over a period time—as a function of diffused innovation—should demonstrate a characteristic s-shaped curve (Rogers, 2003; Naim 1993). This theory suggests that the s-shaped curve represents an initial slow increase in learning, followed by a period of rapid improvement, which is then followed by a gradual leveling off towards the end of the cycle. The graphical results of the study did, in fact, achieve the same s-shaped curve as a representation of the overall knowledge absorption and learning over a 10-year period. Sargent (2004) used the term *Animation* to represent the simulated model's operational behavior being graphically displayed, as the model moves through time (Sargent, 2004). Both the relative pace of learning and the rate of knowledge absorption were represented by the slope of the curves and, as previously stated, these results were characteristic of the notion that higher performing firms had steeper slopes or higher rates of learning compared to lower performing firms.

Sargent (2004) described how model confidence is a function of the cost of conducting the test and value of the model to some predefined user (Sargent, 2004). According to Sargent, “the cost of model validation is usually quite significant, especially when extremely high model confidence is required (Sargent, 2004).” In this study, the specific tests chosen to be modeled in the simulation were based upon (1) the hypothesized relationships and statistical inferences drawn from the statistical model (the relatedness of the antecedents to both the proximal and distal outcomes), (2) the recognizable patterns found in the data set of community health center characteristics (e.g., the grouping of performance levels), and (3) expert guidance from subject matter experts (e.g., which antecedents should be used to inform which agents). While no formal cost curve was developed for this study, the measurement of cost versus value can be understood to add value obtained from a single point-in-time data source. This study used the community health center profile, which was captured in the 2006 HDCC survey items. In this reduced version of the real world or statistical model, the tests were aimed at describing current or previous behaviors. From these results, statistical inferences could be drawn about potential future behavior, assuming all of the factors remained relatively constant. However, in the simulated model, added value was gained by using the same data source to relate what could happen over a 10-year span; wherein the factors were not required to remain constant, which is the more expected response in real world interactions over time. The specific set of chosen tests, which examined (1) the rate of learning or knowledge absorption expressed in graphs and (2) the patterns of cohesion, interactions, and interconnections expressed as network diagrams, both added value to any long-term strategic planning effort aimed at addressing community health center performance objectives for cancer screening and clinical decision support. The cost of this simulated model can best be measured against the added inferential value projected over a 10-year period, which would otherwise have not been obtained from a single point-in-time survey of organizational practices.

Aim 2 Observations and Learning

There are two ways to described what was learned through this research. The first is to describe what was learned from the research, and the second is to describe what was learned from the process of doing this research. Describing the latter first, this researcher learned about the power and potential of computational modeling as a tool to aid a traditional research agenda. However, with that potential comes a tremendous amount of responsibility as to the management of data and a high level of learning in the programming of such an experiment. Even with the training and consultation this researcher received from Carnegie Mellon University CASOS, it is still very clear that there is much that is not known and even more that could have been done in terms of this virtual experiment. Based on what was learned from the research itself, this researcher demonstrated how a static point-in-time organizational survey can reveal a great deal of helpful and meaningful information to inform future research.

Although this portion of the research was largely described as a hypothesis generation exercise, there actually was a hypothesis tested. It was simply that there would be measured change in knowledge absorption Δk over time by performance level, where higher performers will present a greater slope than lower performers. This research successfully achieved that and, as such, accepted the hypothesis that higher performing firms outperformed lower performing firms for knowledge absorption over a 10-year period. Also noticed was a mixed degree of correlation within each cluster grouping for the cancer screening agent test. The test included all assigned tasks, showing that medium/high outperformed high/high in the higher cluster, and low/low outperformed low/high in the lower cluster. However, this researcher noted that there was a much stronger correlation in-between and within the cluster groups when only the cancer screening agent for the CDS and IS task was tested.

The network visualization of all agents and knowledge elements was used to assist in explaining any ambiguous results as a function of network density, network cohesion, group cooperation, and linkages to agents and knowledge resources. The current study's researcher feels that such an analytical approach, when combined with the theory-driven statistical modeling approach from Aim 1, can prove to be a valuable methodological tool in meeting the objective of the larger cancer prevention goals as expressed in the multilevel intervention research agenda. These results can serve as the foundation for future research that actually starts with data collected with computational modeling and network analysis in mind and makes better use of existing data sources not collected for such a network analysis by tying them together in novel ways that a model of this type can make use of to inform others.

Some of the critical questions the current study's author believe can lead to new research questions and/or hypotheses for future research, which were generated from this research, include:

- Are these performance rankings meaningful classifications of community health centers?
- What other task-related combinations of summary measures can be explored to gain insight into community health center cancer screening practices?
- Once the factors associated with high performance are identified, can they be operationalized into a meaningful plan for change and innovation related to cancer screening and CDS and IS adoption and use?
- What factors might be inhibiting the cohesion, knowledge sharing, and task performance that the current study's author revealed in the low/low and low/high performance levels?
- Why was the pattern of performance for CDS and IS only related to cancer screening tasks so evident and the one for all tasks more ambiguous?
- What factors contribute to unused or outmoded knowledge resources and/or unconnected agents within the health care organization?

Overall Conclusions for Aim 2

This research successfully produced a meaningful and substantial computational modeling virtual experiment that successfully mimicked some reported activity within the community health center sample in areas specifically associated with the cancer-screening test. The intent was to demonstrate that key agents who were assigned a given set of tasks, informed by a given set of knowledge elements, as gleaned from the HDCC survey instrument, can learn, over time, as expressed by the knowledge absorption coefficient Δk. This model did not allow for an absolute decline in knowledge expressed as a notion of forgetting and, as such, the rate of knowledge absorption was only measured in one direction from the start of the simulation of all agents having no knowledge. However, the model allowed for the agents used in the simulation to absorb knowledge at differing rates, as represented by the steepness in slope, compared to the others. While the expectation was for the simulated model to hold true to pre-assigned performance levels, there was equal enthusiasm for seeing that the model may actually be able to detect complex and adaptive agents changing over time. Such an analysis can dramatically aid in the analysis of health information technology use, adoption and/or implementation studies, and health outcomes research, where traditional statistical data may not totally account for such adaptive elements. This assertion will have to be explored further in future research.

Study Limitations

There are several limitations to the current study that can be understood from the perspective of each of the aims presented in this study. The limitations will be described first and the proposed recommendations for future research incorporated within each section.

Regarding the Aim 1 statistical model, any secondary data analysis has its limitations. This study was naturally bounded by the survey questions and their respective responses. In terms of the question that addresses understanding community health center behavior with respect to cancer screening and clinical decision support, the more obvious question may be, have there been other clinical decision support, information system, or electronic health record initiatives within the community health center population that might have had an impact on the outcomes of this current study? The fact remains that community health centers participate in several different types of collaboratives, not just the one focused on in this study, which is dedicated to health disparities and cancer screening. There are global technology collaboratives aimed at increasing the uptake of health information technology within community health centers (Lardiere, 2010). These types of collaboratives are not typically disease-focused; they are more focused on the overall uptake of any given form of health information technology. The current study did not examine the potential influence that such activities would have on outcomes, as the Haggstrom et al. survey predated the latest technology-focused collaborative effort. Further studies might examine the convergence of multiple collaboratives, where each has some relevance to the outcomes of interest, with the understanding that the community health center, like many health care organizations, is a multifaceted, dynamic, and complex environment with many crosscutting interests.

The current study could not explore the phased transitioning of technology into health care practice. Instead, it examined technology as the outcome itself. There is, however, evidence to suggest that the application of health information technology to health outcomes, such as cancer screening, must be examined further as a process, rather than an event. As a result, it might be advisable that future studies explore a primary data survey or secondary data source that might examine multiple points simultaneously. Such a time-sensitive data source could allow for assessments to be made regarding significance at multiple stages of technology diffusion from needs assessment, planning, design, implementing, to testing and maintenance.

In the treatment of this data, several limitations were recognized. The current study could have employed sophisticated methods in the management of missing data, the interpretation of survey responses, and the design of sophisticated algorithms to support database and data mining queries. All of these were considered well beyond the scope of this study and may indeed serve as suggestions for additional research related to this dataset or research question.

Finally, in regards to Aim 1, the issue of generalizability remains a factor. This community health center sample consisted of 44 centers. These actual identifying data on each center was not known to this researcher and, as such, no follow-up or secondary interviews related to current practices for this cohort were made possible. The results of this study, while meaningful, cannot be broadly generalized to the larger population of community health centers without additional evidence to support the claims of this study.

In terms of Aim 2, limitations revolve around volume, model applicability, and validation. First, any computer simulation is strengthened by rich, robust, and exhaustive data. Essentially, the axiom is that the more data one has to support assumptions, the stronger the simulation model. For the current study, the organizational survey did not have millions, thousands, or even hundreds of data points. Instead, Aim 2 of this study used the same 37 summary measures used in Aim 1. This study did add robustness to analysis by adding five agent classes, each having the ability to acquire some or all of the several hundred bits of knowledge (over 950), that had dynamic interactive capacity on a multiplicity of tasks, beliefs, and opportunities for learning. However, even this comes with limitations. Future research in this area may find it necessary to expand on the robustness of the data source used to support similar simulations aimed at examining network evolution of an organizational or social system. One strength in the current approach is that this model was easier to manipulate and required less computing time but the overall robustness of the data source can be challenged as a limitation of the study.

With respect to generalizability and applicability of the model, one has to accept as a limitation of this study the fact that not every combination of summary measures was assigned to each agent class within the simulation. Instead, attempts were made to purposefully limit the scope of the experiment and allow other considerations to be examined in the future. The current study focused largely on the cancer screening test agent, but it could have easily examined some of the other agent classifications with equal vigor. Additionally, the selection of which set of summary measures would be used to describe the behavior of each agent was a very rigorous one that dramatically limited the number of ways the agent learned, interacted, and evolved within the simulation. Future research might develop less rigid criteria for the inclusion of variables, employ a much more sophisticated algorithm that can test any or all combinations of variables, and also allow for agents in the simulation to forget, which the current study did not allow. Forgetting allows the agent to not only demonstrate learning over time, but loss of knowledge as well. This study chose to only examine knowledge in one direction and assume that, once an agent acquired knowledge, that knowledge was retained throughout the remainder of the simulation.

Finally, there is the issue of model validation. The current study did not include external validation of the simulation model. Future studies may be warranted, which are designed to solely validate this as a methodological framework that can be deployed on a larger scale.

On the Dual Modeling Approach: Traditional vs. Systems Thinking Findings Compared

This study was divided into two aims in an attempt to examine the extent to which clinical decision support presence and level of use could be explained by a set of organizational, patient, and provider level factors. Additionally, there was an assessment of the degree of association between clinical decision support use and cancer screening outcomes. A dual modeling approach was employed that would (1) examine these associations in Aim 1 in the hopes of identifying variables that would be targets for intervention studies to support the stated goals, and (2) examine how community health centers perform, learn, and perhaps even change over time. This study design was consistent with previous arguments that a dual approach encompassing both a statistical/empirical (sometimes referred to as traditional approach) and a computational model (sometimes referred to as a systems-thinking approach) serves to address the deficiencies found when using the empirical approach alone (Taplin et al., 2010). Taplin et al. argued that there are three primary limitations to using the empirical approach alone: (1) new technologies take an average of 17 years to be widely adopted, (2) innovations are not readily adopted, despite evidence to support their effectiveness, and (3) inconsistencies between practice and evidence-based best practices persist (Taplin et al., 2010). While it was essential to identify the key associations that could help explain clinical decision support uptake and intensity-of-use and its corresponding impact on cancer screening, the belief was that using the empirical model alone would be an insufficient study design to account for the limitations described by Taplin et al. To compensate for these limitations a second study aim or computational model was introduced which examined the predictability of high versus low performing firms over an extended period of time using the same HDCC organizational survey data. The virtual experimental design was consistent with several previous technology adoption and HIT impact studies that sought to use the predefined characteristic profile of a high performance health care setting and a low performance health care setting to test their hypotheses (Goins et al., 2003; Saleem et al., 2009; Shortell et al., 2005; Zapka et al., 2005). The expected outcome of this virtual experiment was focused on demonstrating how well the computational (simulation) model could successfully predict high performance over a 10-year period for cancer screening and its associated tasks. This information could hopefully then be used to support future interventions where other community health centers could actually try to repeat these outcomes in a real-world intervention.

With regard to this virtual experimental design, two arguments emerged. First is the argument of inevitability versus sustainability with regard to this virtual experiment. The argument of inevitability suggests that, if you start out the simulation with the community health centers already divided based on performance levels (e.g., high/high, medium/high, low/low, etc.), would you not expect them to finish the 10-year simulated period in a manner consistent with their original classifications for CDS and IS and cancer screening improvement?

In terms of the argument of inevitability, it should be reiterated that this Aim 2 study design used the same CDS and IS scores and the self-reported cancer screening improvement rate scores used in the Spearman's Rho test measuring the strength of relationship between these two factors. The statistical model was unable to detect a statistically significant relationship between these two variables in the community health centers. This suggests that rankings alone may not fully explain overall performance. Also, these two rankings for CDS and IS and cancer screening improvement were only two of 37 summary measures used in the building of the simulation. Hence, there were opportunities for greater degrees of differentiation between these ranked performance levels on more than just these two variables. While the rankings were used to group the firms, there were no consistently high scores in all 37 summary measures for the high/high ranking, nor were there any consistently low scores for the low/low ranking. Instead, the descriptive statistics for Aim 2 found in Table 19 show several summary measures, including electronic information retrieval and availability, quality improvement strategies, external support and connectedness, team characteristics, financial readiness (budget), financial readiness (cash reserves), and provider IT performance expectancy, where the mean scores for low/low actually exceed the mean scores for high/high. Additionally, low/low came close to equaling high/high in several other categories as well. As such, the argument of inevitability does not hold true when one understands that the original rankings were based solely on the composite scores for the two measures for CDS and IS and cancer screening improvement. These scores were merely used to group the community health centers into performance levels to distinguish one condition from another, but their overall firm behavior within the virtual experiment over the 10-year simulated period was based on more than just those two variables and, in some cases, the original scores for lower performers were actually higher than those of a higher performer at the start of the simulation. This suggests that there may be something hidden within the specific combinations of the 37 summary measure scores, which this simulation experiment has demonstrated requires more study.

In terms of the argument for sustainability, the current study's author again addressed the limitations raised by Taplin et al., where Taplin suggests that new technology takes years to adopt and there are many inconsistencies between actual practice and published evidence. It is argued that, while the empirical model is essential to defining critical associations to inform intervention strategy, it may not in fact address all issues associated with long-term impact and sustainability, such as socio-technical dynamics (Feifer et al., 2006; Goldstein et al., 2004; Kilsdonk et al., 2011; Niland et al., 2006), complex adaptive components (Ehrhart et al., 1999; Feifer et al., 2006; Nemeth et al., 2006; Sintchenko et al., 2007), the readiness for change (Weiner et al., 2008), and the capacity of the organization to learn over time based on some metrics, such as clinical know-how, knowledge management, knowledge absorption, intuition, information exchange, etc. (Anderson & Willson, 2009; Bruque et al., 2008; Salas et al., 2010; Sittig et al., 2010). This model addresses several of these additional factors by measuring overall performance relative to overall rate of knowledge absorption Δk using a network evolution model.

Combining both the statistical and computational model into this dual modeling approach can be essential to defining critical associations with respect to clinical decision support outcomes and cancer screening improvement. This approach can also be essential in allowing for those associations that can successfully predict high performance versus low performance over an extended period of time to be tested in a virtual environment. Riegelman et al. suggests that systems thinking is better understood by contrasting it with the traditional (statistical modeling) (Riegelman, 2009). Table 23 summarizes the potential multilevel intervention strategies based upon findings, advantages, and disadvantages from both the statistical modeling and computational modeling exercises.

Table 23: Comparison of Findings from the Traditional Approach Versus Systems Thinking and the Implications

	Aim 1 Statistical Model (Traditional Model)	Aim 2 Computational Model (Systems Thinking)
Key Findings	Key findings identified at the individual outcome level variables to intervene on: Goal: to increase the presence of CDS and IS–factors shown to be associated include: • HRSA Collaborative Experience • Work Importance of Cancer Screening Tasks • Provider IT Performance Expectancy Goal: to increase the level of use of CDS and IS–factors shown to be associated include: • HRSA Collaborative Experience • External Pressure, Support, Connectedness, and Collaborative Agreements • Cancer Screening Rate Reporting Behavior (Provider-Level)	Key findings identified at the agent level to intervene on: Goal: to measure 10-year Δk for cancer screening agent by examining all assigned tasks and all learning opportunities for this agent: • Identified two clusters of performance levels (higher performers and lower performers) for Δk • Some variation within the two clusters in terms of their visual correlation with our original performance rankings Goal: to measure 10-year Δk for cancer screening agent by examining only CDS task and all learning opportunities for this agent: • Identified two clusters of performance levels (higher performers and lower performers) for Δk • Strong visual correlation between the current study's original performance rankings and each of the two clusters Goal: to measure 10-year network diagram characteristics in an agent x knowledge network, including all five agent classes, including: (1) firm-administrative staff agent, (2) firm-patient care staff agent, (3) outside collaborator agent, (4) IT Systems agent, and (5) cancer screening task agent. • Identified several characteristic traits that differentiated higher performers from lower performers, including density, clustering, and unconnected agents and/or knowledge elements

Aim 1 Statistical Model (Traditional Model)	Aim 2 Computational Model (Systems Thinking)
Advantages	Advantages
• Identified a subset of variables that have shown some association with the presence of two aspects of CDS and IS presence: o CDS and IS Capacity o Provider Prompts at point-of-care • Identified a subset of three variables that have shown an association for CDS and IS intensity-of-use intervention	• Did not have to rely solely on the five total statistically significant variables found in Aim 1…Added robustness to the simulation by adding virtually all of the 37 summary measures to the model and their interactions with one another • Allows for extended over-time analysis from a single point-in-time survey • Allowed for complex adaptive elements not seen in the statistical analysis to be explored • Able to detect in a network diagram both unused and/or potentially outmoded knowledge resources, as well as unconnected agents or uninformed agents–not readily visible in the statistical analysis
Disadvantages	Disadvantages
• Found no variables to intervene on for two aspects of CDS and IS: o Computerized Clinical Reminders o Generated Correspondence with Patient Results • Did not find an association between community health center rankings for CDS and IS use and cancer screening improvement scores in order to support an intervention strategy • Identified organizational and provider level variables to intervene on for both the presence and use of CDS and IS but not the corresponding mediators and/or moderators to actually change these variables within the community health center environment. This suggests that the author of this study might know what to do but not how to do it in order to achieve the desired outcome.	• The subjective designation of the 37 summary measures to categories of representing a task, belief, knowledge element, or learning opportunity, may not be agreed upon by others choosing to duplicate this experiment • This "*between*" analysis represented a high level similarity analysis of community health center performance levels that provide only global firm level characteristics: o Not intended to be a "*within*" analysis that examines much greater granularity of interaction and process

	Aim 1 Statistical Model (Traditional Model)	Aim 2 Computational Model (Systems Thinking)

Proposed Intervention Strategy	To increase the presence of CDS and IS within community health centers
	• Either encourage participation in any future HRSA collaborative activity or find a way to identify lessons learned and best practices to be duplicated within each community health center
	• Increase clinical staff perceptions on the importance of cancer screening tasks
	• Increase provider expectations of IT performance
	
	To increase the level of use of CDS and IS within community health centers
	• Either encourage participation in any future HRSA collaborative activity or find a way to identify lessons learned and best practices to be duplicated within each community health center
	• Encourage increased collaboration and external partnerships with outside entities that support community health center objectives
	• Encourage cancer screening reporting behaviors that have been proven effective
		To design or maintain a high performance profile within community health centers for cancer screening and clinical decision support
		• To increase overall facility-level knowledge absorption Δk:
		  o Focus on the five agent classes and their associated task scores, belief scores, and knowledge learning opportunities for socio-technical intervention strategy
		  o Intervention is not based on a single variable but on groups of variables in association with their respective agent class
		
		• To increase collaboration, cooperation, information exchange, and cohesion. Examine the network diagram to identify:
		  o unused or outmoded knowledge resources
		  o unconnected or uninformed agents
		  o areas for lack of cohesion and collaboration
		  o reduce cliques or clusters that might decrease overall productivity

The Research Contribution

This research demonstrated how traditional statistical modeling can be combined with a computational model to examine health care organizational performance over time. Health care has not achieved the desired levels of efficiency, effectiveness, and performance. Large-scale initiatives sponsored by several sections of the Department of Health and Human Services focused on areas, such as Meaningful Use, Comparative Effectiveness, Translational Research, Multilevel Intervention Research, etc., all of which point to a national agenda aimed at improving health care through the introduction of technology and applied informatics. Each of these areas has at its core socio-technical issues (e.g., human, organizational, technical, etc.) that might help to determine the success or failure in meeting the stated goals and objectives. This research study is not designed to address the full breadth of research questions surrounding the design of a high performance health care organization that adequately addresses all of the socio-technical issues. Instead, it is designed to help (1) establish that the domain of organizational informatics has a role in shaping the national understanding of what an intelligent health care enterprise can and should be, (2) move the discussion of business intelligence beyond that of simply implementing electronic dashboards, data warehousing, and data mining and extend that conversation to actual metrics of organizational knowledge (*know-how*), organizational learning, and some comprehensive standard of organizational IQ, and (3) limit the reliance on health care organizational improvement strategies that fail to account for the complex adaptive environments that health care workers, researchers, administrators, providers, and policy makers, find themselves routinely practicing.

This research sought to propose a framework for individuals interested in organizational informatics research to employ wholly, or in part, in their quest to maximize information as a strategic resource within any organizational context.

APPENDICES

Appendix 1: Conceptual Definitions and Operational Definitions

Construct Name	Conceptual Definition - Construct	Operational Definition (Survey Mappings)	Scales	Relationship
Organizational Structure and Process Factors (Predictors/Independent Variables)				
Governance Strategy based upon HRSA Collaborative Experience	Overall Community Health Center Management Strategy, Policies, Procedures, etc.	Question Set {1, 2, 74} Question 1 Did you ever participate in any HRSA Health Disparities Collaborative prior to 2006? Question 2 Did you participate in the HRSA Health Disparities Cancer Collaborative anytime from 2002 through 2004? Question 74 Has your health center ever participated in any HRSA Collaborative?	1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 1 Total range for governance Y/N questions = 0 to 3	Governance will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications
Facility Age	Year community center was formed	Question Set {72, 73} Question 72 In what year did your organization open as a health center?	Numerical entry (data expressed as year) Facility Age(1) With date of survey as reference point (2006) • 2006–year =	Facility Age will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS

		Question 73 In what year did your health center begin receiving Bureau of Primary Health Care (BPHC) funding?	Facility Age(1) Range: 00 to 99 Facility Age(2) Numerical entry (data expressed as year) Facility Age(2) With date of survey as reference point (2006) • 2006 – year = Facility Age(2) Range: 00 to 99	applications
Clinic Processes	Community Health Center Clinical Operations	Question Set {5a, 5b, 5c, 6} Question 5a, 5b, 5c Does your health center have clinical guidelines available to health care providers (physicians, physician assistants, nurse practitioners) for cancer screening Question Set includes: • In writing in the room where they see patients? • On-line in the room where they see patients? • On-line at some other location than where they routinely see patients?	1=yes; 0=no Range: 0 to 3	Clinic Processes will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

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		Response Set yes=1 no=0 Question 6 Are individuals working at your health center instructed to document discussions about cancer screening?	1=yes; 0=no Range: 0 to 1 Total range for clinic processes = 0 to 4	
Information Dissemination Strategies (to patients)	Strategies employed to support patient decision making and informed choices and change behavior relative to cancer screening	Question Set {17,18,19,20,21,22,23,24} Question 17 How often does your health center connect patients with available community resources for cancer screening? Question 18 The available community resources for cancer screening are adequate for your health center's patient population Question 19 How often do you or the health center staff provide patients with educational materials about cancer screening, such as pamphlets or	4-Item Likert Scale (Items 3a-10a) 0=not at all; 1=Rarely; 2=Sometimes; 3=Often Range: 0 to 3 Range: 0 to 3 Range: 0 to 3	Information Dissemination (to patients) will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		brochures? Question 20 How often do you or the health center staff provide patients with written or online directories that provide guidance to cancer resources? Question 21 During acute care visits, how often are cancer screening guidelines discussed with eligible patients by you? Question 22 During acute care visits, how often are cancer screening guidelines discussed with eligible patients by others who work in the clinic? Question 23 During non-acute care visits, how often are cancer screening guidelines discussed with eligible patients by you? Question 24 During non-acute care visits, how often are cancer screening guidelines discussed with eligible patients by others who work in the clinic?	Range: 0 to 3 Range: 0 to 3 Range: 0 to 3 Range: 0 to 3 Range: 0 to 3 Note: Often and Routinely are considered	

			synonymous in this question response set. Total range for Information Dissemination 0 to 24	
Electronic Information Retrieval & Availability	Computer and internet access at the clinical for use in patient care	Question Set {47,48,49} Question 47 Is there a computer with Internet access available at your clinic to use for patient care? Question 48 Is there a computer with Internet access available at the point of care (e.g., exam room)? Question 49 Is there a computer with Internet access available at a work station, away from the point of care?	1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 1 Total range for Computer Access is 0 to 3	Electronic Information Retrieval & Availability will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications
Electronic Health Record Capabilities	Core functions performed by the Electronic Health Record (EHR)	Question 41a-f Indicate whether each piece of information listed is available in the clinic's computer system or electronic medical/health record (EHR) • Mammography results • Pap test results	1=yes; 0=no Range: 0 to 6	Electronic Health Record Capabilities will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS

		• Fecal occult blood test results • Results of procedures for breast cancer detection, including biopsy • Results of gynecologic procedures for cervical cancer detection, including colposcopy • Results of lower endoscopy procedures for colorectal cancer detection		applications
Work Importance of Cancer Screening Tasks	An individual's tendency or orientations to value of the work (specific cancer screening tasks) in general	Questions (3a-10a): DESCRIBE YOUR LEVEL OF AGREEMENT OR DISAGREEMENT WITH THE FOLLOWING STATEMENTS in terms of the response set below: • Providing formal assessment of patient self-management goal-setting (i.e., tracking whether patients meet their specified goals) for cancer screening and follow-up… • Initiating or maintaining programs to increase patient shared decision-making skills for cancer screening and follow-up… • Providing clinical guidelines to patients for cancer screening and follow-up… • Providing clinical guidelines to individual health care providers	3-Item Likert Scale (Items 7a-13a) 1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree Range: 8 to 32	Work Importance of Cancer Screening Tasks will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		(physicians, physician assistants, nurse practitioners) through reminders for cancer screening and follow-up… • Changing responsibilities of health care providers and staff in the clinic to enable them to function more like a team to deliver cancer screening and follow-up… • Designing the appointment system to facilitate the scheduling of cancer screening and follow-up at any related facility where screening occurs… • Providing written feedback reports or data to health care providers (physicians, physician assistants, nurse practitioners) regarding their performance of cancer screening and follow-up… • Providing written feedback reports or data to local clinic teams regarding their performance of cancer screening and follow-up… Response Set: • Is a useful activity		
Quality Improvement	Institute of Medicine's	Question Set {3,4a,4b,4c,4d,,25,26,		Quality Improvement

Strategies	(IOMs) definition of quality of care as "the degree to which health care services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge." A quality measure is a mechanism that enables the user to quantify the quality of a selected aspect of care by comparing it to a criterion. A subtype of a quality measure is a clinical performance measure. Specifically, a clinical performance measure is a mechanism for assessing the degree to which a provider competently and safely delivers clinical services that are appropriate for the patient in the optimal time period. Quality measures can be used for both quality improvement within an institution or system of	27a,27b,27c,27d,27e,27f,27g} Question 3 Have you ever participated, either formally or informally, in quality improvement activities at your health center? Question 4a-d How often do members of your health center engage in the following activities to improve cancer screening and follow-up? Response Set • Conference calls with experts outside your health center • E-mail (listserv) discussions with experts outside your health center • Visits from/to other health centers • Ongoing measurement of clinical performance at your center Question 25a-d In the last 12 months, did your health center use measures of either patient satisfaction or clinical performance to do any of the	1=yes; 0=no Range: 0 to 1 3-Item Likert Scale 1=not at all; 2=rarely; 3=sometimes; 4=often Range: 3 to 16 3-Item Likert Scale 0=used neither; 1=yes but only patient satisfaction or	Strategies will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

	care (internal quality improvement) or across institutions or systems of care (external quality improvement). Using measures for internal quality improvement involves three basic steps: identifying problems or opportunities for improvement, selecting appropriate measures and using them to obtain a baseline assessment of current practices, and using them to reassess or monitor the effect of improvement efforts on measure performance. Baseline quality measure results can be used to better understand a quality problem, provide motivation for change, and establish a basis for comparison across institutional units or over time. Baseline results also enable the user to prioritize areas for quality improvement. Results from repeated measurements of clinical	following? Response Set: • Pay health care provider bonuses • Adjust salary or base pay • Implement a quality improvement initiative • Have general discussions at practice meetings Question 26 In the past 12 months, did your health center compare its data on quality of care to data from other centers? Question 27a-g How much does your health center use each of the following strategies to ensure high quality care is delivered to primary care patients? Response Set • Health care providers' informal monitoring of each others' practice patterns • Chart reviews • Health care provider peer review of selected cases • Discussion of clinical guidelines at health center or team meetings	performance; 2=yes to both Range: 0 to 8 1=yes; 0=no Range: 0 to 1 3-Item Likert Scale 1=not at all; 2=a little; 3=some; 4=a lot Range: 7 to 28 Total range for Quality Improvement	

	performance can be used by internal quality improvement programs to assess whether performance has changed after improvement efforts have been implemented.	• Statistical reports of practice patterns • Morbidity or mortality conferences • External medical record audits (e.g., by representatives of the state or a health plan)	Strategies is 11 to 53	
External Pressure, Support, and Connectedness via Collaborative Agreements	*According to Iacovou et al. (1995), external pressure refers to influences from the organizational environment. Grandon and Pearson (2003) suggested five external pressure elements in ERP which are competition, social factors, dependency on other firms already using ERP, the industry, and government.*	Question Set {28,29,30,75,76} Questions 28 Does your organization make a list available of identified community cancer resources in an accessible format? Question 29 Does your organization have staff or resources allocated to ensure health care providers and patients make use of community cancer resources? Question 30a-g Have you set up informal or contractual agreements with the following organizations? Response Set: • Public health department • Radiology department • Gastroenterology practice • Community oncology practice	1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 7	External Pressure & Support via Collaborative Agreements will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		• Cancer center • Academic medical center • Cancer survivorship support group Question 75 Does the health center's Board of Directors receive updates on your center's Collaborative activities? Question 76 Does your health center have a formal or informal relationship with any hospitals (e.g., referrals for specialty care; training or residency programs; quality improvement data sharing)?	1=yes; 0=no Range: 0 to 1 1=yes; 0=no Range: 0 to 1 Total range for external pressure is 0 to 11	
Cancer Screening Rate Reporting Behavior (Facility Level)	The way that a situation is categorized or defined by formal reporting at the facility level. Assessment of over-arching goals (meeting clinical guidelines for colorectal, breast, and cervical cancer screening) will impact how the situation (cancer screening) is perceived.	Question Set {35a, 36a, 37a, 38a. 39a, 40a} In the past 12 months, did you receive any reports from your health center about rates of clinical services, screening for colorectal, breast, and cervical cancer screening, test results, or discussion with patients Response Set	1=yes; 0=no Range: 0 to 1 Total range for cancer screening reporting behavior is 0 to 6	Cancer Screening Rates Reports (Facility Level) will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		• At the health care facility (clinic) level Note: additional question frequency in months not currently included in this analysis		
Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions) *(The inclusion of this measure will depend on whether or not there is sufficient variability, as obtained in a frequency distribution, of the population)*	*Role Relevance*: The belief that the situation or action is relevant to the individual's role. For example, a person's belief about being clinically responsible is a significant contribution to how the individual carries out the relevant behavior.	Question Set {43,44,45,46} Question 43a-f Mark all members of the local clinic who participate in performing Breast Cancer Screening activity (e.g., mammography). Mark the consultant if that is a person who performs the activity. Mark "no one" if neither a consultant nor anyone in the local clinic performs the activity. Response Set: • Generates a list of patients due for screening • Actively contacts patients if due for screening • Discusses decision to screen with patients • Schedules screening mammogram • Actively contacts patients with abnormal screening results within 30 days • Arranges breast procedure if necessary (including biopsy)	0=no one assigned to task; 1=one person assigned to the task…5=five people assigned to the task (see types below) • physician • other provider (NP, PA) • nurse • other staff (office, lab) • GI consultant Range 0 to 30	Role Relevance for cancer-screening related activity will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		Question 44a-g Mark all members of the local clinic who participate in performing Cervical Cancer Screening activity (e.g., Pap test). Mark the consultant if that is a person who performs the activity. Mark “no one” if neither a consultant nor any one in the local clinic performs the activity. Response Set: • Generates a list of patients due for screening • Actively contacts patients if due for screening • Discusses decision to screen with patients • Schedules Pap test • Performs Pap test • Actively contacts patients with abnormal screening results within 30 days • Arranges gynecologic procedure, if necessary (including colposcopy)	0=no one assigned to task; 1=one personal assigned to the task…5=five people assigned to the task (see types below) • physician • other provider (NP, PA) • nurse • other staff (office, lab) • GI consultant Range 0 to 35	
		Question 45a-h Mark all members of the local clinic who participate in performing Colorectal Cancer Screening activity. Mark the consultant if that is a person who performs the activity. Mark “no one” if neither a	0=no one assigned to task; 1=one personal assigned to the task…5=five people assigned to the task (see types below)	

		consultant nor anyone in the local clinic performs the activity. Response Set: • Generates a list of patients due for screening • Actively contacts patients if due for screening • Discusses screening options with patients • Distributes fecal occult blood tests (stool cards) • Enters fecal occult blood test results (stool cards) into tracking database. • Schedules screening lower endoscopy • Actively contacts patients with abnormal screening results within 30 days • Schedules diagnostic lower endoscopy Question 46 For all screening tests - Arranges referral for treatment if cancer detected	• physician • other provider (NP, PA) • nurse • other staff (office, lab) • GI consultant Range 0 to 30 0=no one assigned to task; 1=one personal assigned to the task…5=five people assigned to the task (see types below) • physician • other provider (NP, PA)	

			• nurse • other staff (office, lab) • GI consultant Range 0 to 5 Total score for division of responsibilities or role relevance will range from 0 to 110	
Supportive Leadership Environment	*Supportive Leadership* Environment: The degree to which the environment is perceived as supportive, including organizational leaders, the physical structure, and even “help”.	Question 51 Please describe your level of agreement or disagreement with the following statements about senior leadership overall. Response Set: • Has demonstrated an ability to manage the changes (e.g., organizational, technological) needed to improve the quality of care and services. • Always listens to the concerns of other members of the organization • Provides needed feedback to members of the organization • Helps members of the organization work well together • Provides members of the	3-Item Likert Scale 1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree Range: 10 to 30 Higher score = better leadership	Supportive Leadership Environment will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		organization with a clear expectation of their roles • Makes sure people have the skills and knowledge to work in teams • Makes sure a local clinic team that does a good job gets special rewards or recognition • Strongly supports our work • Regularly reviews our progress in making change • Sees success in improving the quality of care as a high priority for the organization		
Supportive Local (Functional) Leadership	*Supportive Local (Functional) Leadership* Environment: The degree to which the environment is perceived as supportive, including organizational leaders, the physical structure and even "help" specifically related to clinical function.	Question 53 Please describe your level of agreement or disagreement with the following statements about functional (clinical) leadership overall. Response Set: • Possesses the functional expertise necessary for leading the local clinic team successfully • Always listens to the concerns of other local clinic team members • Provides needed feedback to other local clinic team members • Helps local clinic team members	3-Item Likert Scale 1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree Range: 5 to 20 Higher score = better leadership	Supportive Local (Functional) Leadership Environment will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		work well together • Provides local clinic team members with a clear expectation of their roles on this team		
Team Characteristics	Team: Group of individuals responsible for both delivering and improving the quality of care in the clinic, including both clinicians and non-clinicians. (2009 Haggstrom et al.)	Question 55 Please describe your level of agreement or disagreement with the following statements about team characteristics overall. Response Set: • The number of people on my local clinic team is about right for the work to be accomplished • The members of the local clinic team work together well as a team • Members of my local clinic team vary widely in their knowledge, skills, and abilities • Members of my local clinic team have skills and abilities that complement each other • I generally prefer to work as part of a team • Our local clinic team gets the information we need to plan our work • Our local clinic team has the authority to manage its work pretty much the way members	3-Item Likert Scale 1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree Range: 13 to 52	Team Characteristics will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		want to • There is a great deal of room for initiative and judgment in the work that we do • The participants on our local clinic team have substantial influence in managing care and influencing others to make improvements in care • When our local clinic team does not know something it needs to know to do its work, there are people available to teach or help • There are one or more well-respected members of our staff that support our work with their time, and verbal encouragement • Our local clinic team is able to identify measures that were tracked on a regular basis to assess our work • My skills, training, and experience are fully utilized		
Medical Specialist Availability	*A Board Certified Physician specifically trained to conduct colorectal cancer screening.*	Question 79 Which of the following categories best describes the availability of each of the specialists listed below to patients at your health center involved in cancer screening?	0=not available; 1=available Range: 0 to 10 Specialist score = greater the score the	Medical Specialist Availability will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening

		Response Set: • Gastroenterologist • Gynecologist • Oncologist • General Surgeon • Breast Cancer Surgeon • Gynecologic Surgeon • Colorectal Cancer Surgeon • Radiologist – general • Radiologist – interventional • Radiologist with training in breast imaging	more specialists available	CDS and IS applications
Organizational Structure/Size	Organizational Size: Likely surrogate for total and slack resources; ability to obtain and sustain technical expertise, organizational structure.	Question 80a-g How many of the following are employed by your health center? Response Sets: Number of People: • Physicians • Nurse Practitioners • Physician Assistants • Registered Nurses • Licensed Practical Nurses • Laboratory personnel • Scheduler/reception	Numerical entry Range: 0 to 9999 for each type	Organizational Size will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications
Financial Readiness *Note: Need to verify need for other financial information in the analysis*	Organizational readiness refers to the level of financial and technical resources of the firm (Kuan & Chau, 2001). There are two dimensions	Question Set {85,93} Question 85 What is your health center's annual operating budget (for the most recent fiscal year)? (in US dollars)	Financial Readiness(1) Numerical entry (dollar figure) Range: 0 to N for each type	Financial Readiness will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer

	to organizational readiness: financial and technical. Financial readiness refers to the financial resources available to pay for new technological innovation costs, implementation of any subsequent enhancements, and ongoing expenses during usage. Iacovou et al. (1995).	Note: Assume fiscal year 2006 unless otherwise stated Question 94 For your health center's most recent fiscal year, please circle the number of the phrase below that best reflects your center's financial situation. Response Set: • Operating expenses exceeded operating revenue by ≥ 25% = 1 • Operating expenses exceeded operating revenue by 11-23% = 2 • Operating expenses exceeded operating revenues by 1-10% = 3 • Broke even = 4 • Operating revenue exceeded operating expenses by 1-10% = 5 • Operating revenue exceeded operating expenses by 11-23% = 6 • Operating revenue exceeded operating expenses by ≥ 25% = 7	Financial Readiness(2) Range: 1 to 7 Where 1 is considered less "ideal" extreme and 7 is considered more "ideal" extreme	Screening CDS and IS applications
Patient Population Characteristics (Predictors/Independent Variables				

Payer mix	Payer mix represents the percentage of revenue coming from private insurance versus government insurance versus self-paying individuals.	Question Set {86,89a,89b,89c,89d} Question 86 Approximately what proportion of your health center patients are uninsured? Response Set % Uninsured 0–100% Question 89a-d What percentage of your patient revenue comes from each of the following sources? Response Set: • Medicare • Medicaid • Commercial • Self-Pay	Range: 0 to 100% Range: 0 to 100% for each member of the response set	Payer mix will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications
Patient Demographics	Percentage of patient population 50 years of age or older	Question Set {95,96,97,98,99} Patient Demographics(1) Question 95 What percentage of patients seen at your health center in the past 12 months speak a language other than English as their primary language? Response Set 0 to 100%	Range: 0 to 100%	Patient Demographics will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		Patient Demographics(2) Question 96 What percentage of patients seen at your health center in the past 12 months are Migrant or seasonal agricultural workers? Response Set 0 to 100% Question 97 What percentage of patients seen at your health center in the past 12 months are Homeless? Response Set 0 to 100% Patient Demographics(3) Question 99 Approximately what percentage of your patients seen in the past 12 months are 50 years of age of older? Response Set 1=Less than 25% 2=25-39% 3=50-73% 4=75-100% Note: Could be used as exclusion	Range: 0 to 100% Range: 0 to 100% Range: 1 to 4	

		criteria, for example, exclude centers where less than 25% are eligible for CRC screening.		
Provider Characteristics (Predictors/Independent Variables)				
Environmental Assessment of Cancer Screening and Follow-up Activities	The way that a situation is categorized or defined by the person (provider). Assessment of over-arching goals (meeting clinical guidelines for colorectal, breast, and cervical cancer screening) will impact how the situation (cancer screening) is perceived.	Questions (7b, c, & d-13b, c, & d): DESCRIBE YOUR LEVEL OF AGREEMENT OR DISAGREEMENT WITH THE FOLLOWING STATEMENTS in terms of the Question Set below: • Providing formal assessment of patient self-management goal-setting (i.e., tracking whether patients meet their specified goals) for cancer screening and follow-up… • Initiating or maintaining programs to increase patient shared decision-making skills for cancer screening and follow-up… • Providing clinical guidelines to patients for cancer screening and follow-up… • Providing clinical guidelines to individual health care providers (physicians, physician assistants, nurse practitioners) through reminders for cancer screening and follow-up… • Changing responsibilities of health care providers and staff in the clinic to enable them to	3-Item Likert Scale 1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree Total Range for Environmental Assessment: 22 to 88	Formative Evaluation of Cancer Screening Activities will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		function more like a team to deliver cancer screening and follow-up… • Designing the appointment system to facilitate the scheduling of cancer screening and follow-up at any related facility where screening occurs… • Providing written feedback reports or data to health care providers (physicians, physician assistants, nurse practitioners) regarding their performance of cancer screening and follow-up… • Providing written feedback reports or data to local clinic teams regarding their performance of cancer screening and follow-up… Response Set for items 7b,c,d-13b,c,d • is an activity about which our health center has educated health care providers and staff • has been supported by adequate resources from our health center. • has been implemented in our health center		

Cancer Screening Rate Reporting Behavior (Provider-Level)	The way that a situation is categorized or defined by formal reporting at the provider-level. Assessment of over-arching goals (meeting clinical guidelines for colorectal, breast, and cervical cancer screening) will impact how the situation (cancer screening) is perceived.	Question Set {35b,36b,37b,38b,39b,40b} Question 35b to 40b In the past 12 months, did you receive any reports from your health center about rates of screening for colorectal, breast, and cervical cancer screening Response Set • At the health care provider/individual level Note: additional question frequency in months not currently included in this analysis Response Set	1=yes; 0=no Range: 0 to 1 Total Range for Cancer Screening Reporting Behavior (provider level) = 0 to 6	Cancer Screening Rates Reports (Provider-Level) will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications
Provider IT Performance Expectancy	*Provider IT Performance Expectancy* is defined as the degree to which an individual provider believes that using IT will help him or her to attain gains in job performance	Question 42a-k Please describe your level of agreement or disagreement with the following statements about the information system in place at your health center: • The center's information system is adequate to accommodate the size of the population eligible for cancer screening. • The information system provides timely data on cancer screening and follow-up • The center continually tries to	3-Item Likert Scale 1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree Range: 11 to 44	Performance Expectancy will be associated with the presence and intensity of use of Colorectal, Breast, and Cervical Cancer Screening CDS and IS applications

		improve the timeliness of its data on cancer screening and follow-up • The center continually tries to improve the accuracy of its data on cancer screening and follow-up • The information system accurately documents cancer screening among the health center's patients • The information system accurately documents whether appropriate evaluation takes place after an abnormal screening result • The information system accurately documents whether appropriate treatment takes place after cancer detection • The data gathered in the information system is used by leadership to change the health center's activities related to cancer screening. • The data gathered in the information system is used by health care providers to change their behavior. • I use the data gathered in the information system to change my behavior. • The data gathered in the		

		information system is used by health care providers to change their behavior related to cancer screening		
IS & CDS Capacity for Measuring Cancer Screening	**<u>Clinical Decision Support (CDS)</u>– Promote clinical care that is consistent with scientific evidence and patient preferences** • Embed evidence-based guidelines into daily clinical practice • Share evidence-based guidelines and information with patients to encourage their participation • Use proven provider education methods • Integrate specialist expertise and primary care **<u>Clinical Information Systems (IS)</u>–Organize patient and population data to facilitate efficient and effective care**	Question 31 Does your health center's computer system have any capacity to measure cancer screening activities?	1=yes; 0=no Range: 0 to 1	A Composite score for each of the four combined CDS & IS variables will range from 0 to 4 and will be associated with Organizational and/or Practice Setting Factors, Patient Characteristics, and Provider Characteristics

	• Provide timely reminders for providers and patients • Identify relevant subpopulations for proactive care • Facilitate individual patient care planning • Share information with patients and providers to coordinate care • Monitor performance of practice team and care system			
Use of IS & CDS provider prompts at Point-of-Care	Same as above for CDS & IS	Question 32 Our health center is using an information system (not necessarily computerized) to send prompts to health care providers (physicians, physician assistants, nurse practitioners) at the time of the patient encounter about whether their patients are eligible for cancer screening.	1=yes; 0=no Range: 0 to 1	Same as above
Computerized Patient Reminders	Same as above for CDS & IS	Question 33 Our health center is using an information system to send correspondence or reminders to patients eligible for cancer	1=yes; 0=no Range: 0 to 1	Same as above

		screening.		
Generated Correspondence with Results to Patients	Same as above for CDS & IS	Question 34 Our health center is using an information system to send correspondence to patients about screening test results.	1=yes; 0=no Range: 0 to 1	Same as above
Cancer Screening Improvement Rates	Guideline concordant care for Colorectal, Breast, and Cervical Cancer	Question 16 In the past 12 months, our health center has been able to improve the rate of: Response Set: • Screening Mammography within the past 2 years • Pap test within the past 3 years • Appropriate screening for colorectal cancer	1=yes; 0=no Range: 0 to 3 Note: agreement in any sense constitutes a yes=1, disagreement in any sense constitutes a no=0. The greater the score the greater the increase in overall cancer screening (self-reported) rates. Hence, colorectal, breast, and cervical cancer screening (self-reported) rates are treated here as a composite score	The intensity of use of CDS and IS score will be associated with the community health center colorectal, breast, and cervical cancer screening improvement rate score

Appendix 2: Health Disparities Cancer Collaborative (HDCC) Organizational Survey Instrument (Referred to as Inventory)

Note: This study did not employ the use of any questions from the "Background Information Sections" that include questions 56-71 and 100-106…There were other exceptions. The author of this study maintained the original numerical configuration below in reporting which questions we used in the analysis

Introduction Section

Question 1
Did you ever participate in any HRSA Health Disparities Collaborative prior to 2006?

- Yes
- No
- Don't know

Question 2
Did you participate in the HRSA Health Disparities Cancer Collaborative anytime from 2002 through 2004?

- Yes
    - Would you say regarding implementation of the Cancer Collaborative that your health center is:
        - Mostly in the planning stage
        - Mostly in the early implementation stage
        - Now receiving usable data on implementation activities
- No
- Don't know

Question 3
Have you ever participated, either formally or informally, in quality improvement activities at your health center?

- Yes
- No
- Don't know

Question 4
How often do members of your health center engage in the following activities to improve cancer screening and follow-up?

- Conference calls with experts outside your health center
- E-mail (listserv) discussions with experts outside your health center
- Visits from/to other health centers
- Ongoing measurement of clinical performance at your center

Clinic Processes Section

Question 5
Does your health center have clinical guidelines available to health care providers (physicians, physician assistants, nurse practitioners) for cancer screening?

- In writing in the room where they see patients?
- On-line in the room where they see patients?
- On-line at some other location than where they routinely see patients?

Question 6
Are individuals working at your health center instructed to document discussions about cancer screening?

- Yes
- No
- Don't know

Questions 7-14
DESCRIBE YOUR LEVEL OF AGREEMENT OR DISAGREEMENT WITH THE FOLLOWING STATEMENTS in terms of *Response Set (Strongly Disagree; Disagree; Agree; Strongly Agree; Don't Know)*:

- Providing formal assessment of patient self-management goal-setting (i.e., tracking whether patients meet their specified goals) for cancer screening and follow-up…
- Initiating or maintaining programs to increase patient shared decision-making skills for cancer screening and follow-up…
- Providing clinical guidelines to patients for cancer screening and follow-up…
- Providing clinical guidelines to individual health care providers (physicians, physician assistants, nurse practitioners) through reminders for cancer screening and follow-up…
- Changing responsibilities of health care providers and staff in the clinic to enable them to function more like a team to deliver cancer screening and follow-up…
- Designing the appointment system to facilitate the scheduling of cancer screening and follow-up at any related facility where screening occurs…
- Providing written feedback reports or data to health care providers (physicians, physician assistants, nurse practitioners) regarding their performance of cancer screening and follow-up…
- Providing written feedback reports or data to local clinic teams regarding their performance of cancer screening and follow-up…

Question 15
Within the last 12 months, we have used a tool to assess the delivery system design, decision support, self-management support, information systems, and community linkages of our health center…*Response set (Never, 1-2 times; 3-4 times; or greater than 4 times)*:

Question 16
In the past 12 months, our health center has been able to improve the rate of:

- Screening Mammography within the past 2 years
- Pap test within the past 3 years
- Appropriate screening for colorectal cancer

Question 17
How often does your health center connect patients with available community resources for cancer screening? *Response Set (Never; Rarely; Sometimes; Routinely; or Don't Know)*

Question 18
The available community resources for cancer screening are adequate for your health center's patient population… *Response Set (Strongly Disagree; Disagree; Agree; Strongly Agree; Don't Know)*

Response Set for questions 19-24 (Never; Rarely; Sometimes; Routinely; or Don't Know)
Question 19
How often do you or the health center staff provide patients with educational materials about cancer screening, such as pamphlets or brochures?

Question 20
How often do you or the health center staff provide patients with written or online directories that provide guidance to cancer resources?

Question 21
During acute care visits, how often are cancer screening guidelines discussed with eligible patients by you?

Question 22
During acute care visits, how often are cancer screening guidelines discussed with eligible patients by others who work in the clinic?

Question 23
During non-acute care visits, how often are cancer screening guidelines discussed with eligible patients by you?

Question 24
During non-acute care visits, how often are cancer screening guidelines discussed with eligible patients by others who work in the clinic?

Management Strategies

Question 25
In the last 12 months, did your health center use measures of either patient satisfaction or clinical performance to do any of the following? *Response Set (Yes, used both patient satisfaction and clinical performance measures; Yes, but used only patient satisfaction measures; Yes, but used only performance measures; Used neither; Don't know)*:

- Pay health care provider bonuses
- Adjust salary or base pay
- Implement a quality improvement initiative
- Have general discussions at practice meetings

Question 26
In the past 12 months, did your health center compare its data on quality of care to data from other centers?

- Yes
- No
- Don't know

Question 27
How much does your health center use each of the following strategies to ensure high quality care is delivered to primary care patients? *Response Set (Not at all; A little; Some; A lot; Don't know)*:

- Health care providers' informal monitoring of each others' practice patterns
- Chart reviews
- Health care provider peer review of selected cases
- Discussion of clinical guidelines at health center or team meetings
- Statistical reports of practice patterns
- Morbidity or mortality conferences
- External medical record audits (e.g., by representatives of the state or a health plan)

Questions 28
Does your organization make a list available of identified community cancer resources in an accessible format?

- Yes
- No
- Don't know

Question 29
Does your organization have staff or resources allocated to ensure health care providers and patients make use of community cancer resources?

- Yes
- No
- Don't know

Question 30
Have you set up informal or contractual agreements with the following organizations?
Response set (Yes, No, Don't know):

- Public health department
- Radiology department
- Gastroenterology practice
- Community oncology practice
- Cancer center
- Academic medical center
- Cancer survivorship support group

Information Systems

Question 31
Does your health center's computer system have any capacity to measure cancer screening activities?

- Yes
- No
- Don't know

Question 32
Our health center is using an information system (not necessarily computerized) to send prompts to health care providers (physicians, physician assistants, nurse practitioners) at the time of the patient encounter about whether their patients are eligible for cancer screening.

- Yes
- No
- Don't know

Question 33
Our health center is using an information system to send correspondence or reminders to patients eligible for cancer screening.

- Yes
- No
- Don't know

Question 34
Our health center is using an information system to send correspondence to patients about screening test results.

- Yes
- No
- Don't know

Question 35-40

In the past 12 months, did you receive any reports from your health center about rates of clinical services; screening for colorectal cancer; screening for breast cancer; screening for cervical cancer screening; test results within 30 days of any cancer screening test; or discussions of cancer screening with patients?

- Clinic/local team level (Yes, No, Don't know)
- Health care provider/individual patient level (Yes, No, Don't know)

Question 41

Indicate whether each piece of information listed is available in the clinic's computer system or electronic medical/health record (EHR) *Response set (Yes, No)*:

- Mammography results
- Pap test results
- Fecal occult blood test results
- Results of procedures for breast cancer detection, including biopsy
- Results of gynecologic procedures for cervical cancer detection, including colposcopy
- Results of lower endoscopy procedures for colorectal cancer detection

Question 42

Please describe your level of agreement or disagreement with the following statements about the information system in place at your health center… *Response Set (Strongly Disagree; Disagree; Agree; Strongly Agree; Don't Know)*:

- The center's information system is adequate to accommodate the size of the population eligible for cancer screening.
- The information system provides timely data on cancer screening and follow-up
- The center continually tries to improve the timeliness of its data on cancer screening and follow-up
- The center continually tries to improve the accuracy of its data on cancer screening and follow-up
- The information system accurately documents cancer screening among the health center's patients
- The information system accurately documents whether appropriate evaluation takes place after an abnormal screening result
- The information system accurately documents whether appropriate treatment takes place after cancer detection
- The data gathered in the information system is used by leadership to change the health center's activities related to cancer screening.
- The data gathered in the information system is used by health care providers to change their behavior.
- I use the data gathered in the information system to change my behavior.
- The data gathered in the information system is used by health care providers to change their behavior related to cancer screening

Question 43
Mark all members of the local clinic who participate in performing Breast Cancer Screening activity (e.g., mammography). Mark the consultant if that is a person who performs the activity. Mark "no one" if neither a consultant nor anyone in the local clinic performs the activity. *Response set (Physician; Other provider (NP, PA); Nurse Other staff (office, lab); Radiology consultant; or No one)*:

- Generates a list of patients due for screening
- Actively contacts patients if due for screening
- Discusses decision to screen with patients
- Schedules screening mammogram
- Actively contacts patients with abnormal screening results within 30 days
- Arranges breast procedure if necessary (including biopsy)

Question 44
Mark all members of the local clinic who participate in performing Cervical Cancer Screening activity (e.g., Pap test). Mark the consultant if that is a person who performs the activity. Mark "no one" if neither a consultant nor anyone in the local clinic performs the activity. *Response set (Physician; Other provider (NP, PA); Nurse; Other staff (office, lab); Radiology consultant; or No one)*:

- Generates a list of patients due for screening
- Actively contacts patients if due for screening
- Discusses decision to screen with patients
- Schedules Pap test
- Performs Pap test
- Actively contacts patients with abnormal screening results within 30 days
- Arranges gynecologic procedure if necessary (including colposcopy)

Question 45
Mark all members of the local clinic who participate in performing Colorectal Cancer Screening activity. Mark the consultant if that is a person who performs the activity. Mark "no one" if neither a consultant nor anyone in the local clinic performs the activity. *Response set (Physician; Other provider (NP, PA); Nurse; Other staff (office, lab); Radiology consultant; or No one)*:

- Generates a list of patients due for screening
- Actively contacts patients if due for screening
- Discusses screening options with patients
- Distributes fecal occult blood tests (stool cards)
- Enters fecal occult blood test results (stool cards) into tracking database.
- Schedules screening lower endoscopy
- Actively contacts patients with abnormal screening results within 30 days
- Schedules diagnostic lower endoscopy

Question 46
For all screening tests - Arranges referral for treatment if cancer detected. *Response set (Physician; Other provider (NP, PA); Nurse; Other staff (office, lab); Radiology consultant; or No one)*:

Question 47
Is there a computer with Internet access available at your clinic to use for patient care?
- Yes
- No
- Don't know

Question 48
Is there a computer with Internet access available at the point of care (e.g., exam room)?
- Yes
- No
- Don't know

Question 49
Is there a computer with Internet access available at a work station, away from the point of care?
- Yes
- No
- Don't know

Question 50
The number of members of the health center's senior leadership who have left the organization over the past 12 months is?

Question 51
Please describe your level of agreement or disagreement with the following statements about senior leadership overall. *Response Set (Strongly Disagree; Disagree; Agree; Strongly Agree; Don't Know)*:
- Has demonstrated an ability to manage the changes (e.g., organizational, technological) needed to improve the quality of care and services.
- Always listens to the concerns of other members of the organization
- Provides needed feedback to members of the organization
- Helps members of the organization work well together
- Provides members of the organization with a clear expectation of their roles
- Makes sure people have the skills and knowledge to work in teams
- Makes sure a local clinic team that does a good job gets special rewards or recognition
- Strongly supports our work
- Regularly reviews our progress in making change

- Sees success in improving the quality of care as a high priority for the organization

Question 52
Do you consider yourself to be the local leader?
- Yes
- No
- Don't know

Question 53
Please describe your level of agreement or disagreement with the following statements about functional (clinical) leadership overall. *Response Set (Strongly Disagree; Disagree; Agree; Strongly Agree; Don't Know)*:
- Possesses the functional expertise necessary for leading the local clinic team successfully
- Always listens to the concerns of other local clinic team members
- Provides needed feedback to other local clinic team members
- Helps local clinic team members work well together
- Provides local clinic team members with a clear expectation of their roles on this team

Question 54
The number of members of the local clinic team who have left the organization over the past 12 months is?

Question 55
Please describe your level of agreement or disagreement with the following statements about team characteristics overall. *Response Set (Strongly Disagree; Disagree; Agree; Strongly Agree; Don't Know)*:
- The number of people on my local clinic team is about right for the work to be accomplished
- The members of the local clinic team work together well as a team
- Members of my local clinic team vary widely in their knowledge, skills, and abilities
- Members of my local clinic team have skills and abilities that complement each other
- I generally prefer to work as part of a team
- Our local clinic team gets the information we need to plan our work
- Our local clinic team has the authority to manage its work pretty much the way members want to
- There is a great deal of room for initiative and judgment in the work that we do
- The participants on our local clinic team have substantial influence in managing care and influencing others to make improvements in care
- When our local clinic team does not know something it needs to know to do its work, there are people available to teach or help

- There are one or more well-respected members of our staff that support our work with their time, and verbal encouragement
- Our local clinic team is able to identify measures that were tracked on a regular basis to assess our work
- My skills, training, and experience are fully utilized

Skip Questions 56-71 "Background Information" of survey respondents

Financial Officer Section

Question 72
In what year did your organization open as a health center? (date/year)

Question 73
In what year did your health center begin receiving Bureau of Primary Health Care (BPHC) funding? (date/year)

Question 74
Has your health center ever participated in any HRSA Collaborative?

- Yes
- No
- Don't know

Question 75
Does the health center's Board of Directors receive updates on your center's Collaborative activities?

- Yes
- No
- Don't know
- Never participated in Collaborative

Question 76
Does your health center have a formal or informal relationship with any hospitals (e.g., referrals for specialty care; training or residency programs; quality improvement data sharing)?

- Yes
- No
- Don't know

Question 77
[In response to question 76] How many?

Question 78
[In response to question 76] What is the nature of the relationship(s)? (Select all that apply)

- Health center refers insured patients (private and Medicare) to hospital(s) for specialty care
- Health center refers uninsured patients to hospital(s) for specialty care
- Health center refers Medicaid patients to hospital(s) for specialty care
- Health center serves as site for training or residency programs
- Health center and hospital share quality improvement data
- Health center is served by physicians who have clinical responsibilities at other hospitals
- Other (specify)

Question 79
Which of the following categories best describes the availability of each of the specialists listed below to patients at your health center involved in cancer screening?
Response set (Available on-site; Available in service area through referral; Available in service area, but does not accept referrals; or Not available):

- Gastroenterologist
- Gynecologist
- Oncologist
- General Surgeon
- Breast Cancer Surgeon
- Gynecologic Surgeon
- Colorectal Cancer Surgeon
- Radiologist – general
- Radiologist – interventional
- Radiologist with training in breast imaging

Question 80
How many of the following are employed by your health center?
Number of People:

- Physicians
- Nurse Practitioners
- Physician Assistants
- Registered Nurses
- Licensed Practical Nurses
- Laboratory personnel
- Scheduler/reception

Question 81
Have any health care administrators or clinicians left the health center in the past 12 months?

- Yes
- No

- Don’t know

Question 82
How many of each type of staff have left the center in then past 12 months?
Number of People/Number of people serving this role:
- CEO or Administrative leader
- Medical Director
- Physicians
- Nurse Practitioners
- Physician Assistants
- Registered Nurses
- Licensed Practical Nurses
- Laboratory personnel
- Scheduler/reception
- Other (specify)

Question 83
What percent of the following personnel are paid straight salary vs. salary plus pay for performance? *Response set (straight salary; salary + pay for performance; total)*:
- Physicians
- Nurse Practitioners
- Physician Assistants
- Registered Nurses
- Licensed Practical Nurses
- Clinical support staff (e.g., medical assistants)
- Scheduler/reception

Question 84
Does your organization use “360 degree performance appraisal”? A “360 degree performance review” is defined as a system of reviewing employee performance using input from one’s superiors, peers, and subordinates; and synthesizing this input to develop a constructive plan for employee growth and development.
- Yes
- No
- Don’t know

Question 85
What is your health center’s annual operating budget (for the most recent fiscal year)? (in US dollars)
Note: Assume fiscal year 2006 unless otherwise stated
Question 86
Approximately what proportion of your health center patients are uninsured?

Question 87
Approximately what proportion of your patients is enrolled in private managed care plans (i.e., HMOs and PPOs)?

Question 88
Approximately what proportion of your patients is enrolled in public managed care plans (i.e., HMOs and PPOs)?

Question 89
What percentage of your patient revenue comes from each of the following sources?
- Medicare
- Medicaid
- Commercial
- Self-Pay

Question 90
Approximately how many different insurance plans does your health center have contracts with?

Question 91
Is your health center an owner of an insurance plan, alone or in conjunction with other local or regional health centers?
- Yes
- No
- Don't know

Question 92
What percentage of the operating revenues of your organization are Medicare revenue under Diagnostic Related Groups (DRGs)?

Question 93
Capitation is defined as the pre-determined lump sum payment to care for patients regardless of how many or how few services they may need. Given this definition, what percentage of the operating revenues of your organization come from capitated payment (not including DRGs)?

Question 94
For your health center's most recent fiscal year, please circle the number of the phrase below that best reflects your center's financial situation.
- Operating expenses exceeded operating revenue by ≥ 25% = 1
- Operating expenses exceeded operating revenue by 11-23% = 2
- Operating expenses exceeded operating revenues by 1-10% = 3
- Broke even = 4
- Operating revenue exceeded operating expenses by 1-10% = 5
- Operating revenue exceeded operating expenses by 11-23% = 6
- Operating revenue exceeded operating expenses by ≥ 25% = 7

Patient Demographics

Question 95
What percentage of patients seen at your health center in the past 12 months speak a language other than English as their primary language?

Question 96
What percentage of patients seen at your health center in the past 12 months are Migrant or seasonal agricultural workers?

Question 97
What percentage of patients seen at your health center in the past 12 months are Homeless?

Question 98
How does your health center collect the patient race information documented in your center's registration database?
- Perception of intake clerk
- Patient self-report
- Race data not collected
- Other (specify)

Question 99
Approximately what percentage of your patients seen in the past 12 months are 50 years of age of older?
- Less than 25%
- 25-39%
- 50-73%
- 75-100%

Skipped Questions 100-106 "Background Information" of survey respondents

Appendix 3: Averaging Algorithm for Summary Measures

The survey responses were coded using two designations: "C" preceding facility number to represent participant in the NCI/HRSA Collaborative and "I" preceding the facility number to represent non-participant in the Collaborative. The survey responses were coded to each facility with these designations and would appear as digit 1 = collaborative participant designation, digit 2 and 3 = facility number (1 to 22), and digits 4, 5, and 6 representing the survey respondent type (e.g., CEO, CFO, etc.). A sample designation in the code set could appear as C15102, representing NCI/HRSA Collaborative Participant, facility 15, answered by the CFO. These designations allowed for the survey responses in the CSV data files to be properly mapped to each respondent type. These values were then compiled in a master Excel spreadsheet (actually a series of five worksheets) listing the responses to each of the 99 questions x 44 facilities x survey respondent type. This consolidated spreadsheet represented the first time the research team was able to examine any question to see which facilities responded to it, who within that facility answered the question, and whether or not that particular question had only one representative response or multiple responses that would have to be reconciled into a single value. Each question and its corresponding responses included a quality check, where the original coded response was compared against the coded survey and again in the original CSV file to ensure that the correct values were placed in the proper place within the master Excel spreadsheet before any consolidation took place.

Averaging Algorithm for Summary Measures

- Split cells with multiple responses using
    - Excel “text to columns format”
- Obtain numerical sum of responses across rows (insert into new column) (numerator)
    - Example: =SUM(A1:C1)
        - Send results to new column (e.g., D1)
- Obtain the number of cells in each row with values greater than zero (denominator)
    - Example: =COUNTIF(A1:C1,">0")
        - Send results to new column (e.g., E1)
- Divide SUM value/COUNTIF value
    - Example =D1/E1
        - Send results to new column (e.g., F1)
- Use Excel INT function to obtain round numbers to the nearest integer
    - Example =INT(F1)
        - Send Results to new column (e.g., G1)
- Input G1 into respective “Final Score” column in master SAS file
    - Note: may need to replace #DIV/0! with (.) for missing data

Appendix 4: Summary Measures Table

SAS Coded Variable	Summary Measures	Number of Items Drawn From HDCC Survey
X0	Participant in the HRSA Collaborative	1 item
X1	HRSA Collaborative Experience	3 items
X2	Facility Age1–Year began receiving BPHC funding	1 item
X3	Facility Age2–Number of Years in any HRSA Collaborative	1 item
X4	Clinic Processes	4 items
X5	Information Dissemination Strategies	8 items
X6	Electronic Information Retrieval & Availability	3 items
X7	Electronic Health Record (EHR) Functions Capabilities	1 item
X8	Work Importance of Cancer Screening Tasks	8 items
X9	Cancer Screening Rate Reporting Behavior (Facility Level)	6 items
X10	Quality Improvement Strategies	14 items
X11	External Pressure, Support, Connectedness, and Collaborative Agreements	5 items
X12	Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)	4 items
X13	Supportive Senior Leadership Environment	1 item–10 components
X14	Supportive Local (Functional) Leadership Environment	1 item–5 components
X15	Team Characteristics	1 item–13 components
X16	Medical Specialist Availability	1 item
X17	Organizational Structure & Size	1 item
X18	Financial Readiness1–Total Budget	1 item
X19	Financial Readiness2–Ratio of Revenues to Expenses	1 item
X20	Payer Mix1–% Uninsured	1 item
X21	Payer Mix2a–% Medicare	1 item
X22	Payer Mix2b–% Medicaid	1 item
X23	Payer Mix2c–% Commercial Insurance	1 item
X24	Payer Mix2d–% Self-Pay	1 item
X25	Patient Demographics (Language)	1 item
X26	Patient Demographics (Occupation Migrant Worker)	1 item
X27	Patient Demographics (Living Homeless)	1 item
X28	Patient Demographics (Age)	1 item
X29	Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback	22 items
X30	Cancer Screening Rate Reporting Behavior (Provider Level)	6 items
X31	Provider IT Performance Expectancy	1 item–32 components
Y1	CDS & IS Capacity for Measuring Cancer Screening (CDS1)	1 item
Y2	Use of CDS & IS Provider Prompts at Point-of-Care (CDS2)	1 item
Y3	Computerized Patient Reminders (CDS3)	1 item
Y4	Generated Correspondence with Results to Patients (CDS)	1 item

YCDS	CDS & IS Practices (Composite CDS Score)	4 items (Y1+Y2+Y3+Y4)
YCSI	12-Month (Self-Reported) Cancer Screening Improvement Rate Score	1 items–3 components

Appendix 5: Tests for Best Subset of Predictors by Category and Outcome Variable – Logistic Regression

Best Model or Best Subset of Predictors will be shaded and bolded in the text below

Organizational and/or Practice Setting Factors as a Measure of CDS and IS Capacity for Measuring Cancer Screening

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	3.7795	X0
2	8.2085	X0 X1
3	11.7275	X0 X1 X8
4	**14.2353**	**X0 X1 X8 X14**
5	16.1966	X0 X1 X8 X14 X19
6	17.7923	X0 X1 X8 X12 X14 X19

Patient Characteristics as a Measure of CDS and IS Capacity for Measuring Cancer Screening

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	0.7028	X20
2	**2.2884**	**X20 X28**
3	4.3503	X20 X25 X28
4	5.4402	X20 X22 X25 X28

Provider Characteristics as a Measure of CDS and IS Capacity for Measuring Cancer Screening

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	4.7621	X29
2	**13.0456**	**X29 X31**
3	13.3583	X29 X30 X31

Organizational and/or Practice Setting Factors as a Measure of Provider Prompts at Point-of-Care

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	2.6082	X0
2	**5.0062**	**X0 X6**
3	6.0784	X0 X6 X11
4	7.0710	X0 X5 X6 X19

Patient Characteristics as a Measure of Provider Prompts at Point-of-Care

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	2.8717	X20
2	**5.8183**	**X20 X22**
3	7.5750	X20 X23 X27
4	8.1501	X20 X23 X27 X28

Provider Characteristics as a Measure of Provider Prompts at Point-of-Care

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	5.4090	X29
2	**11.3189**	**X29 X31**
3	11.7669	X29 X30 X31

Organizational and/or Practice Setting Factors as a Measure of Computerized Patient Reminders

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	1.5548	X0
2	**4.6794**	**X0 X16**
3	5.7371	X0 X2 X16
4	7.1940	X0 X6 X7 X16

Patient Characteristics as a Measure of Computerized Patient Reminders

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	0.0844	X20
2	**3.2221**	**X20 X23**
3	4.4977	X20 X23 X26
4	5.2814	X20 X21 X23 X26

Provider Characteristics as a Measure of Computerized Patient Reminders

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	0.6903	X29
2	**2.6314**	**X29 X30**
3	2.7323	X29 X30 X31

Organizational and/or Practice Setting Factors as a Measure of Generated Correspondence with Results to Patients

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	2.6082	X0
2	**6.5910**	**X0 X7**
3	7.8636	X0 X7 X13
4	9.2681	X0 X7 X13 X14

Patient Characteristics as a Measure of Generated Correspondence with Results

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	0.7174	X20
2	**3.2235**	**X20 X22**
3	3.8351	X20 X22 X23
4	4.1255	X20 X22 X23 X27

Provider Characteristics as a Measure of Generated Correspondence with Results to Patients

Regression Models Selected by Score Criterion		
Number of Variables	Score Chi-Square	Variables Included in Model
1	0.0395	X29
2	**4.1444**	**X29 X31**
3	5.7853	X29 X30 X31

Appendix 6: Tests for Best Subset of Predictors by Category and Outcome Variable – Linear Regression

Best Model or Best Subset of Predictors will be shaded and bolded in the text below

Organizational and/or Practice Setting Factors as a Measure of CDS and IS Intensity-of-Use

Number in Model	Adjusted R-Square	R-Square	Variables in Model
1	0.1369	0.1631	X0
7	**0.3438**	**0.4830**	**X1 X2 X8 X11 X12 X14**
8	0.3359	0.4969	X1 X2 X7 X8 X11 X12 X14
9	0.3278	0.5111	X1 X2 X5 X8 X11 X12 X14 X15

Patient Characteristics as a Measure of CDS and IS Intensity-of-Use

Number in Model	Adjusted R-Square	R-Square	Variables in Model
1	0.0123	0.0535	X20
3	**0.0798**	**0.1949**	**X25 X28**
4	0.0685	0.2238	X25 X27 X28
2	0.0578	0.1363	X28

Provider Characteristics as a Measure of CDS and IS Intensity-of-Use

Number in Model	Adjusted R-Square	R-Square	Variables in Model
1	0.0084	0.0315	X29
3	**0.3126**	**0.3606**	**X30 X31**
2	0.2799	0.3134	X30
2	0.0916	0.1339	X31

Appendix 7: Model Fitting and Diagnostics Summary of Logistic Regression and Linear Regression Tests

Logistic Regression Diagnostics

	Name	Description of Test	Decision Criteria	Source
1	Best Subsets Analysis	See Model Reduction Section	Chi Square Score Statistic	(Hosmer & Lemeshow, 2000)
2	Analyzing ratio between variables and observations	See Model Reduction Section	N/A	(Good, 2011)
3	Hosmer and Lemeshow Good-of-Fit Test	Hosmer and Lemeshow (2000) proposed a statistic that they show, through simulation, is distributed as Chi-Square when there is no replication in any of the subpopulations. This test is available only for binary response models. The test assesses whether or not the observed event rates match expected event rates in subgroups of the model population. The Hosmer-Lemeshow test was developed to address the problem of having too few observations under some settings of the explanatory variables.	If p-value > .05 p-value fail to reject the null and conclude that the model fits the data.	(Hosmer & Lemeshow, 2000; SAS Institute, 2009)

	Name	Description of Test	Decision Criteria	Source
4	Leverage	measure of x outliers– • The diagonal elements of the hat matrix are useful in detecting extreme points in the design space where they tend to have larger values. (SAS) • In particular, the diagonal elements of the hat matrix are a useful indicator in a multivariable setting of whether or not a case is outlying with respect to its X values. (Kutner, 2004) • The values (also referred to as leverage) are always between 0 and 1, and the larger the value, the greater it is from the center of all X observations. (Kutner, 2004)	• A leverage value is usually considered to be large if it is more that twice as large as the mean leverage value, denoted by h_hat. Hence, leverage values greater than 2p/n (where p = the number of regression parameters, and n = the number of cases) are considered by rule to indicate outlying cases with regard to their X values. (Kutner, 2004) • Another guideline (Kutner, 2004) • >.5 indicate very high leverage • .2 to .5 indicate moderate leverage • Also examine gaps between most cases and one large value If outlying case(s) is detected, ascertain how influential the case is in the fitting of the regression model (Kutner, 2004)	(Kutner, 2004)

	Name	Description of Test	Decision Criteria	Source
5	CI Displacements C	Influence on the Parameter Estimates–C and CBAR are confidence interval displacement diagnostics that provide scalar measures of the influence of individual observations on b. These diagnostics are based on the same idea as the Cook distance in linear regression theory, and by using the one-step estimate. Typically, to use these statistics, you plot them against an index and look for outliers.	Visual inspection of graphs for extreme cases	(Peng et al., 2002; SAS Institute, 2009)
6	CI Displacements CBar	Same as above for (CI Displacements C)	Same as above	(Peng et al., 2002; SAS Institute, 2009)
7	Pearson Chi-Square Deletion Difference (DIFCHISQ)	DIFDEV and DIFCHISQ are diagnostics for detecting ill-fitted observations; in other words, observations that contribute heavily to the disagreement between the data and the predicted values of the fitted model. DIFDEV is the change in the deviance due to deleting an individual observation while DIFCHISQ is the change in the Pearson chi-square statistic for the same deletion.	Visual inspection of graphs for extreme cases	(SAS Institute, 2009)
8	Deviance Deletion Difference (DIFDEV)	Same as above	Same as above	(SAS Institute, 2009)
9	DFFITS	Measure of influence–measure of fit of regression line or a measure of the influence that a particular case has on the fitted regression line. The letters DF stand for the difference between the fitted value and *is defined as the change ("DFFIT"), in the predicted value for a point, obtained when that point is left out of the regression*	As a guideline for identifying influential cases: • >1 in small to med data sets • >2 in large data sets • Assume small to medium size for this research project	(Kutner et al., 2004)

	Name	Description of Test	Decision Criteria	Source
10	DfBetas (Influence on the Estimate of Individual Dependent Variable)	Measure of influence–influence of parameters or regression coefficients: represents the difference between the estimated coefficient based on all cases and the regression coefficient obtained when a particular case is omitted. When this estimate is divided by an estimate of the standard deviation the DFBETAS is obtained. (Kutner) The sign represents whether or not the inclusion of the case leads to an increase or decrease in the estimated regression coefficient, and its absolute magnitude shows the size of the difference relative to the estimated standard deviation of the regression coefficient.	As a guideline influential cases: • If >1 for small to med data sets • If >2/√n for large, where n is the number of observations • Assume small to medium size for this research project	(Kutner et al., 2004)

Linear Regression Diagnostics

	Name	Description of Test	Decision Criteria	Source
1	Best Subset Analysis	Adjusted R Squared Criterion • Use instead of R Squared Criterion, because it does not take into account the number of parameters in the model. This analysis is already sensitive to the number of parameters relative to the number of observations. See Model Reduction Section	Find adjusted r squared: this is maximum or so close to maximum that adding more variables is not worthwhile	(Kutner et al., 2004)
2	Analyzing ratio between variables and observations	See Model Reduction Section	N/A	(Good, 2011)
3	Test of First and Second Moment Specification	A test for heteroscedasticity, the White test. The White test tests the null hypothesis that the variance of the residuals is homogenous. Therefore, if the p-value is very small, the hypothesis would have to be rejected and the alternative hypothesis that the variance is not homogenous would have to be accepted.	If p-value > .05 fail to reject the null and conclude that the variance of the residual is homogeneous.	(Kutner et al., 2004)

	Name	Description of Test	Decision Criteria	Source
4	Cook's D	Measure of influence–Unlike DFFITS, which considers the influence of a particular case on the predicted value when said case is left out, Cook's distance considers the influence of said case on all cases used in determining the predicted value. (Kutner, 2004) Cook's D depends on two factors: (1) the size of the residual and (2) the leverage value. The larger either the residual or the leverage is, the larger the Cook's D is. Influential case can be the results of: • Large residual and moderate leverage • Large leverage and moderate residual • Large residual and large leverage (Kutner, 2004)	Several cutoff guidelines exist for Cook's D • Kutner suggests F(p, n-p) distribution and then ascertaining the corresponding percentile value • If <10 or 20% little influence • If near 50% or more major influence • Besley et al., as reported in the 9.22 SAS User Guide, suggests a simpler method of either 4/n, where n is the number of observations	(Belsley, Kuh, & Welsch, 1980; Kutner et al., 2004; SAS Institute, 2009)
5	Studentized Residuals (By Predicted Value)	Studentized Residuals, effective for detecting outlying Y observations, relies on the fact that residuals may have substantially different variances. This test measures the magnitude of each residual relative to its estimated standard deviation to give recognition to differences in the sampling errors of the residuals. While the residuals will have substantially different sampling variations if their standard deviations differ markedly, the studentized residuals have a constant variance (when the model is appropriate). (Kutner. 2004)	plot of stud res (use +/- 3 or 4) outliers - the internally studentized residuals are uniformly distributed (Cook)	(Cook & Weisberg, 1982; Kutner et al., 2004)

	Name	Description of Test	Decision Criteria	Source
6	Hat Diag H	measure of x outliers – • The diagonal elements of the hat matrix are useful in detecting extreme points in the design space where they tend to have larger values. (SAS) • In particular, the diagonal elements of the hat matrix are a useful indicator in a multivariable setting of whether or not a case is outlying with respect to its X values. (Kutner, 2004) • The values (also referred to as leverage) are always between 0 and 1, and the larger the value, the greater it is from the center of all X observations. (Kutner, 2004)	• A leverage value is usually considered to be large if it is more that twice as large as the mean leverage value, denoted by h_hat. Hence, leverage values greater than 2p/n, (where p = the number of regression parameters and n = the number of cases considered) by rule to indicate outlying cases with regard to their X values. Kutner) • Another guideline (Kutner, 2004) • >.5 indicate very high leverage • .2 to .5 indicate moderate leverage • Also examine gaps between most cases and one large value • If outlying case(s) is detected, ascertain how influential the case is in the fitting of the regression model (Kutner, 2004)	(Kutner et al., 2004)

	Name	Description of Test	Decision Criteria	Source
7	Cov Ratio	The Cov Ratio measures how much change there is in the determinant of the covariance matrix of the estimates when a particular case is deleted. The magnitude is a ratio of the estimated generalized variances of the regression coefficients with and without a particular case deleted from the data. It thus serves as a measure of the efficiency of the coefficient estimation. Belsley et al. suggest investigating observations with an absolute value of 1 +/- 3(p/n), (where p = the number of regression parameters and n = the number of cases considered). A value greater than one indicates that the absence of the associated observation impairs efficiency, while a value of less that one indicated the reverse. Values that lie outside the range defined by 1 +/- 3(p/n) can be considered extreme.	Belsley et al. suggest investigating observations with an absolute value of 1 +/- 3(p/n). A value greater than one indicates that the absence of the associated observation impairs efficiency, while a value of less that one indicates the reverse. Values that lie outside the range defined by 1 +/- 3(p/n) can be considered extreme.	(Belsley et al., 1980; SAS Institute, 2009)
8	DFFITS	Measure of influence–measure of fit of regression line or a measure of the influence that a particular case has on the fitted regression line. The letters DF stand for the difference between the fitted value and *is defined as the change ("DFFIT"), in the predicted value for a point, obtained when that point is left out of the regression.*	As a guideline for identifying influential cases: • >1 in small-to-med data sets • >2 in large data sets • Assume small-to medium-size for this research project	(Kutner et al., 2004)

	Name	Description of Test	Decision Criteria	Source
9	DfBetas (Intercept and each IV)	Measure of influence–influence of parameters or regression coefficients: represents the difference between the estimated coefficient based on all cases and the regression coefficient obtained when a particular case is omitted. When this estimate is divided by an estimate of the standard deviation, the DFBETAS is obtained. (Kutner) The sign represents whether or not the inclusion of the case leads to an increase or decrease in the estimated regression coefficient, and its absolute magnitude shows the size of the difference relative to the estimated standard deviation of the regression coefficient.	As a guideline influential cases: • If >1 for small-to-med data sets • If $>2/\sqrt{n}$ for large, where n is the number of observations • Assume small,-to-medium size for this research project	(Kutner et al., 2004)
10	Predicted R-Squared Test: 1 minus the ratio of Predicted Residuals SS (PRESS) and Sum of Squared Residuals (SSE)	PRESS given is for the best model–measure of generalizability (formula 1–(PRESS/SSE) x 100 A measure of the amount of variation in new data explained by the model. • Committee Advisory recommends a modified ratio that simply looks at the absolute value of PRESS/SSE	If the absolute value of PRESS/SSE is =/< 1.5, then conclude the model has acceptable generalizability given that other diagnostic measures fall into acceptable ranges	Committee Advisory Team (Kutner et al., 2004)

Appendix 8: Normalization Algorithm for Summary Measures

Excel function to carryout the normalization process:

- Data set min and max
  - Where A=min and B=max
- Normalized scale min and max
  - Where a=min (0) and b=max (1)
- Number in the data set (x)
- Normalized value (y)
- Formula
  - $[a + (x - A)(b - a)/(B - A)] = y$

Appendix 9: The Construct™ Variable Glossary Used in Aim 2 Simulations

Summary Measure	Construct™ Coded Variable
X1 = HRSA Collaborative Experience	CollaborativeExp
X2 = Facility Age1–Number of Years receiving BPHC funding	DateOpened
X3 = Facility Age2–Number of Years in any HRSA Collaborative	YrsHRSAFunded
X4 = Clinic Processes	ClinProcesses
X5 = Information Dissemination Strategies	InfoDissemination
X6 = Electronic Information Retrieval & Availability	ElecRetrieval
X7 = Electronic Health Record (EHR) Functions Capabilities	EHRFunctions
X8 = Work Importance of Cancer Screening Tasks	Screening_Task_Imp
X9 = Cancer Screening Rate Reporting Behavior (Facility Level)	FacilityScreeningBehavior
X10 = Quality Improvement Strategies	QIStrategy
X11 = External Pressure, Support, Connectedness, and Collaborative Agreements	ExtAgreements
X12 = Delivery System Design for Cancer Screening (e.g., Role Responsibility, Overlap, and Clinical Champions)	SystemDesign
X13 = Supportive Senior Leadership Environment	SrLeadership
X14 = Supportive Local (Functional) Leadership Environment	LocalLeadership
X15 = Team Characteristics	Team
X16 = Medical Specialist Availability	MedSpec
X17 = Organizational Structure & Size	OrgSize
X18 = Financial Readiness1–Total Budget	Budget_Size
X19 = Financial Readiness2–Ratio of Revenues to Expenses	CashResearves
X20 = Payer Mix1–% Uninsured	UninsuredPop
X21 = Payer Mix2a–% Medicare	MedicarePop
X22 = Payer Mix2b–% Medicaid	MedicaidPop
X23 = Payer Mix2c–% Commercial Insurance	CommercialPop
X24 = Payer Mix2d–% Self Pay	SelfPayPop
X25 = Patient Demographics (Language)	PatientLanguage
X26 = Patient Demographics (Occupation Migrant Worker)	MigrantPop
X27 = Patient Demographics (Living Homeless)	HomelessPop
X28 = Patient Demographics (Age)	PatientAge
X29 = Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback’	EnvAssessment
X30 = Cancer Screening Rate Reporting Behavior (Provider Level)’	ProviderScreeningBehavior
X31 = Provider IT Performance Expectancy	IT_Beliefs
Y1 = IS & CDS Capacity for Measuring Cancer Screening (CDS1)	IT_Capacity
Y2 = Use of IS & CDS Provider Prompts at Point-of-Care (CDS2)	Prompts
Y3 = Computerized Patient Reminders (CDS3)	Reminders
Y4 = Generated Correspondence with Results to Patients (CDS4)	PatientResults
YCDS = IS & CDS Practices (Composite CDS Score)	CDS_score
YCSI = Cancer Screening Improvement Rates	Screening_rate

Appendix 10: XML Variable Statements for Loading into Construct™

There are two ways to load the variable and its respective values into Construct™: (1) simply by coding the actual values into the XML syntax, as was seen in the demo input deck, or (2) by referencing the variable and its respective value from an external data source (e.g., a database, file, etc.). Because of the number and complexity of this analysis, the CASOS Consultant recommended the latter course of action. This required additional assistance in the design of CASOS scripting language to properly reference the variable and properly load it into Construct™.

The complete list of variables and their respective scripts are listed below. It should be pointed out that the variable marked "firm_row" refers to specific performance levels or conditions the researcher chose to test in the simulation. Each condition is tested separately and, at the start of every simulated virtual experiment, the researcher would declare which condition was chosen for testing. Each performance level or condition was based upon the matrix scoring table referenced in step five above.

```
<var name= “HRSA Collaborative Experience”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Facility Age(1) (as function of date opened)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Facility Age(2) (number of years being HRSA funded)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Clinic Processes”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Information Dissemination Strategies”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Electronic Information Retrieval & Availability”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Electronic Health Record (EHR) Functions Capabilities”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Work Importance of Cancer Screening Tasks”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
```

```
<var name= “Cancer Screening Rate Reporting Behavior (Facility Level)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Quality Improvement Strategies”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “External Pressure, Support, Connectedness, and Collaborative
Agreements”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Delivery System Design for Cancer Screening (e.g., Role
Responsibility, Overlap, and Clinical Champions”
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/>
<var name= “Supportive Senior Leadership Environment”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Supportive Local (Functional) Leadership Environment”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Team Characteristics”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Medical Specialist Availability”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Organizational Structure & Size”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Financial Readiness(1) (Total budget)”
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/>
<var name= “Financial Readiness(2) (Revenues to Expenses ratio)”
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/>
<var name= “Payer Mix(1) (% uninsured)”
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/>
<var name= “Payer Mix(2a) (% Medicare)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Payer Mix(2b) (% Medicaid)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
```

<var name= “Payer Mix(2c) (% Commercial)”
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/>
<var name= “Patient Demographics (Language)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Patient Demographics (Occupation Migrant Worker)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Patient Demographics (Living Homeless)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Patient Demographics (Age)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Environmental Assessment of Cancer Screening and Follow-up Activity via Provider Performance Feedback”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Cancer Screening Rate Reporting Behavior (Provider Level)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Provider IT Performance Expectancy”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “IS & CDS Capacity for Measuring Cancer Screening”
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/>
<var name= “Use of IS & CDS Provider Prompts at Point-of-Care”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Computerized Patient Reminders”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Generated Correspondence with Results to Patients”
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/>
<var name= “IS & CDS Practices (Summary)”
value="readFromCSVFile[Experiment_Variables.csv,construct::intvar::firm_row,2]"
/>
<var name= “Cancer Screening Rates (Summary)”
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/>

Appendix 11: Construct^{TM} Agent, Task, and Knowledge Definitions Used in Aim 2 Simulations

The agent definitions are as follows:

Firm_Start	0
Firm_End	(100 x Financial Readiness_Budget) - 1
Patient Staff_Start	0
Patient Staff_End	.6 x Firm_End
Adminstrative Staff_Start	Patient Staff_End + 1
Adminstrative Staff_End	Firm_End
IT System_Start	Firm_End + 1
IT System_End	IT System_Start
Outside Collaborators_Start	IT System_End + 1
Outside Collaborators_End	Outside Collaborators_Start
Cancer Screening Test_Start	Outside Collaborators_End + 1
Cancer Screening Test_End	Cancer Screening Test_Start + 2

The knowledge definitions are as follows:

Start_Index	End_Index	Saturation Variable	Descriptive Name
0	49	SrLeadership	Supportive Senior Leadership Environment
50	99	LocalLeadership	Supportive Local Leadership Environment
100	149	Team	Team Characteristics
150	199	ClinProcesses	Clinic Processes
200	249	Screening_Task_Imp	Work Importance of Cancer Screening Tasks
250	299	CDS_score	IS & CDS Practices
300	349	SystemDesign	Delivery System Design for Cancer Screening
350	399	ProviderScreeningBehavior	Cancer Screening Rate Reporting Behavior Provider Level
400	449	InsuranceType	Uninsured–PayerMix1, Public - PayerMix2a and 2b, Comm - PayerMix 2c
450	499	CashReserves	Financial Readiness_RevenueToExpense
500	549	Budget_Size	Combined Size and Budget
550	599	InfoDissemination	Information Dissemination Strategies
600	649	PatientAge	Patient Demographics (Age)
650	699	PatientLanguage	Patient Demogrphaics (language)
700	749	FacilityScreeningBehavior	Cancer Screening Rate Reporting Behavior Facility Level

The task definitions are as follows:

Descriptive	Task Index	Knowledge Start	K End
Clinic Processes	0	ClinProcesses_begin	ClinProcesses_end
Screening Tasks	1	Screening_Task_Imp_begin	Screening_Task_Imp_end
CDS Score	2	CDS_score_begin	CDS_score_end
System Design	3	SystemDesign_begin	SystemDesign_end
Provider Screening Behavior	4	ProviderScreeningBehavior_begin	ProviderScreeningBehavior_end
Insurance Type	5	InsuranceType_begin	InsuranceType_end
Cash Reserves	6	CashReserves_begin	CashReserves_end
Budget Size	7	Budget_Size_begin	Budget_Size_end
Dissemination Strategies	8	InfoDissemination_begin	InfoDissemination_end
Patient Age	9	PatientAge_begin	PatientAge_end
Patient Language	10	PatientLanguage_begin	PatientLanguage_end
Facility Screening Behavior	11	FacilityScreeningBehavior_begin	FacilityScreeningBehavior_end

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CURRICULUM VITAE

Timothy Jay Carney

Education

Indiana University Indianapolis, IN	PhD	2012	Health Informatics
DeVry University Keller Graduate School of Management, Atlanta, GA	MBA	2004	Information Technology
Tulane University School of Public Health New Orleans, LA	MPH	1998	Health Systems Management
Rutgers University Newark, NJ	BA	1993	Political Science
San Diego City College San Diego, CA	AA	1989	Business Administration

Professional Experience

2012 – 2013	Cancer Health Disparities Post-Doctoral Fellow, The University of North Carolina at Chapel Hill, Gillings School of Global Public Health/Lineberger Comprehensive Cancer Center, Chapel Hill, NC
2009 – 2012	Pre-Doctoral Fellow NCI-TRBOCC R25 Program, Indiana University, Indianapolis, IN
2008 – 2009	Research Assistant, Regenstrief Institute, Roudebush VA Medical Center, Indianapolis, IN
2004 – 2007	Centers for Disease Control and Prevention-Contractor, Informatics Specialist/Project Manager, Northrop Grumman IT, Atlanta, GA
2003 – 2004	Centers for Disease Control and Prevention-Contractor, Informatics Specialist, Scientific Technologies Corp, Atlanta, GA
2001 – 2003	Centers for Disease Control and Prevention-Associate Service Fellow/Informatics Specialist, Atlanta, GA

1998 – 2000	Centers for Disease Control and Prevention/ORISE Public Health Informatics Fellowship, Atlanta, GA
1982 – 1986	Hospital Corpsman, United States Navy, San Diego, CA

Honors

2009 – 2010	NCI Training in Behavioral Oncology and Cancer Control Program Pre-Doc Fellowship, R25 Program
2006 – 2008	Anthem/IHIE (Indiana Health Information Exchange) Fellowship Award
1993	Pi Sigma Alpha – Political Science Honor Society

Affiliations

Georgia Public Health Association: Information Systems and Health Assessment – Former member

American Public Health Associate (APHA) – Former member

American Medical Informatics Association (AMIA) – Former member

Publications

Journals

Haggstrom, D.A., Carney, T.J. (2009). Cancer Care Disparities: Research Regarding Timeliness and Potential Coordination. ***American Journal of Managed Care,*** 15(11): 778-80.

Thames, S.F., Gerlach, K., Martin, H.J., Carney, T., Penberthy, L.T., Lanzilotta, M., Peace, S. (2006). Introduction to the National Program of Cancer Registries-Modeling Electronic Reporting Project (NPCR-MERP). ***Journal of Registry Management,*** 33(3): 97-101.

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Technical Reports

Carney, T.J., et al. (2007). **White Paper on Building a Roadmap for Health Information Systems Interoperability for Public Health.** The Public Health Data Standards Consortium (PHDSC) and Integrating the Healthcare Enterprise (IHE).

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Carney, T.J., Gilliland, J, Zlot, A., (2003). **CDC/NCCDPHP Data Sharing and Data Release Report**. Centers for Disease Control and Prevention-National Center for Chronic Disease Prevention and Health Promotion (NCCDPHP).

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Conference Presentations

Carney, T.J, McDaniel, A.M., Weaver, M., Jones, J., Palakal, M.J., Haggstrom, D.A., (2011). An Organizational Informatics Approach to Studying Colorectal, Breast, and Cervical Cancer Screening Clinical Decision Support and Information Systems within Community Health Centers. Multilevel Interventions in Health Care: Building the Foundation for Future Research Conference, Las Vegas, NV

Carney, T.J, McDaniel, A.M., Weaver, M., Jones, J., Palakal, M.J., Haggstrom, D.A., (2011). An Organizational Informatics Approach to Studying Colorectal, Breast, and Cervical Cancer Screening Clinical Decision Support and Information Systems within Community Health Centers. IU Simon Cancer Center Cancer Research Day Conference, Indianapolis, IN

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Carney, T.J, McDaniel, A.M., Weaver, M., Jones, J., Palakal, M.J., Haggstrom, D.A., (2011). An Organizational Informatics Approach to Studying Colorectal, Breast, and Cervical Cancer Screening Clinical Decision Support and Information Systems within

Community Health Centers. Workshop on Interactive Systems in Healthcare (WISH), Washington, DC

Carney, T.J., Matthews, P., Thames, S., Rogers, J., Gerlach, K. (2007). CDC NPCR-MERP/HIMSS e-Surveillance Assessment for Electronic Reporting in Cancer Registry. Operations National Cancer Registrars Association Annual Meeting, Detroit, MI.

Carney, T.J. (2006). Analyzing Collection of Medical Data from EMR to Disease Registry: Based on Cancer Registry Examples United Kingdom Association of Cancer Registries (UKACR). The Netherlands Cancer Registry (NCR) Conference - The Role of Cancer Registries in Surveillance and Cancer Care, Amsterdam, Holland.

Carney, T.J., Thames, S., Lyalin, D., Burolla, M., Scharber, W. (2006). Conceptual Model of Electronic Reporting in Hospital and Central Cancer Registries: Initial Efforts. National Cancer Registrars Association Annual Meeting, Regina, Saskatchewan, Canada.

Carney, T.J., Thames, S., Lyalin, D., Burolla, M., Scharber, W., Agrawal, M. (2006). Analyzing Collection of Medical Data from EMR to Disease Registry: Based on Cancer Registration Examples. AMIA Spring Meeting, Phoenix, AZ.

Thames, S, Carney, T.J. (2006). NPCR-MERP: A National Model Phase II. Public Health Information Network (PHIN), Atlanta, GA.

Thames, S., Carney, T.J. (2006). NPCR-MERP: A National Model Phase II. National Cancer Registrars Association Annual Meeting, Regina, Saskatchewan, Canada.

Carney, T.J. (2005). NPCR-MERP National Program of Cancer Registries-Modeling Electronic Reporting Project Overview. Public Health Information Network (PHIN), Atlanta, GA.

Carney, T.J. (2005). NPCR-MERP National Program of Cancer Registries-Modeling Electronic Reporting Project Overview. National American Association of Central Cancer Registries Association, Boston, MA.

Carney, T.J. (2004). NPCR-MERP National Program of Cancer Registries-Modeling Electronic Reporting Project Overview. National Cancer Registrars Association Annual
Conference, New Orleans, LA.

Carney, T.J. (2002). Understanding HIPAA: Deciphering the Transaction Rule. 2002 National Breast Cervical Cancer Program Directors Meeting, Atlanta, GA.

Carney, T.J. (1999). Organizational Development Through Informatics: Building an Information Processing Entity. American Public Health Association Meeting, Chicago, IL.

Carney, T.J. (1998). Annual Surveillance Conference for E.I.S. Officers: An Evaluation of the Behavioral Risk Factor Surveillance System (BRFSS). CDC, Atlanta, GA.

Professional/Community Service

2005	Georgia Public Health Association Information Systems and Health Assessment Section –Chair
2005	Georgia Health Information Exchange/RHIO Executive Committee, Disease Management Workgroup – Volunteer Chair
1998	Health Ministry, Antioch North Baptist Church – Volunteer
1998	REACH Coalition – Volunteer member of the Atlanta based REACH Coalition. Fulton County, GA
1996	New Orleans Mayor's Office, Division of Economic Development – Volunteer
1982 – 1986	United States Navy Citations/Awards Sea Service Deployment Ribbon Navy Fleet Marine Force Ribbon Good Conduct Award

Certifications/Training

2009	Summer Institute for Network Analysis and Computational Modeling at Carnegie Mellon University, Computational Analysis of Social and Organizational Systems (CASOS).
	Georgia Institute of Technology Certificate Training: Introduction to Computing and Information Technology Relational Database Design Database Modeling

Information Security
Introduction to IT Project Management

Additional Computer Training/Experience:

SQL Server 2005 (In progress)
.Net Development Suite (In progress)
Xcelsius (Business Objects) Business Intelligence Tool
XML Development Tool
Ontology Development (Protégé)
SAS Version 9.2
Axure RP Pro 5.5
CDC/Emory University: Informatics Management Development Program
Public Health Informatics: A Course for Public Health Program Managers
G.I.S. Introduction to Arcview and Spatial Analysis Techniques
Data-Modeling Process Modeling concepts and applications