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Using computational modeling to assess the impact of clinical decision support on cancer screening improvement strategies within the community health centers

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ABSTRACT

Our conceptual model demonstrates our goal to investigate the impact of clinical decision support (CDS) utilization on cancer screening improvement strategies in the community health care (CHC) setting. We employed a dual modeling technique using both statistical and computational modeling to evaluate impact. Our statistical model used the Spearman's Rho test to evaluate the strength of relationship between our proximal outcome measures (CDS utilization) against our distal outcome measure (provider self-reported cancer screening improvement). Our computational model relied on network evolution theory and made use of a tool called Construct-TM to model the use of CDS measured by the rate of organizational learning. We employed the use of previously collected survey data from community health centers Cancer Health Disparities Collaborative (HDCC). Our intent is to demonstrate the added valued gained by using a computational modeling tool in conjunction with a statistical analysis when evaluating the impact a health information technology, in the form of CDS, on health care quality process outcomes such as facility-level screening improvement. Significant simulated disparities in organizational learning over time were observed between community health centers beginning the simulation with high and low clinical decision support capability.

1. Introduction

According to the National Cancer Institute (NCI), an estimated 1,660,290 people in the United States were diagnosed with cancer in 2013, and, of these, 580,350 are expected to die of cancer [1]. Current estimates as to the number of these deaths that could have been avoided through screening vary from 3% to 35% depending upon assumptions regarding disease progression, prognosis, and environmental and lifestyle factors [2]. Three types of cancer screening—(1) the Pap test for cervical, (2) the mammography for breast, and (3) a battery of tests for colorectal cancer screening—have been found to detect cancer in its early stages and improve survival rates [3–11]. In spite of increased screening rates, Rutten et al. report that colorectal cancer screening rates found in their research lagged behind both Pap tests and mammography screenings [12]. Colorectal cancer screening performance rates are based on national guidelines and evidence-based best practices [3,5,13]. The American Cancer Society and the U.S. Preventive Services Task

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Force recommend that people over Age 50 be screened for colorectal cancer, that women over Age 40 receive annual mammograms, and that women be administered a Pap test at two-year intervals beginning either at the onset of sexual activity or at Age 21 [4,14]. Although guidelines for the Pap test have been available since 1997, barriers to screening remain [12].

Several strategies to improve systems-level cancer screening rates employ evidenced-based practices (EBP) [15]. Clinical decision support (CDS) has been particularly effective in achieving greater levels of health care EBP. In randomized controlled trials, 90% of clinician-directed CDS interventions display significantly improved patient care" [15,16]. However, few studies exist that show the impact of clinical decision support and information system (IS) applications—designed specifically to aid in meeting EBP guidelines and performance benchmarks—on community health center (CHC) colorectal, breast, and cervical cancer screening practices [17].

According to the February 2010 Patient Protection and the Affordable Care Act, CHC's play a critical role in providing quality care in underserved areas and to vulnerable populations [18]. About 1250 CHC's currently provide care to 20 million people at more than 7900 service-delivery sites, with an emphasis on preventive and primary care [18,19]. At least one CHC is located in every U.S. state, the District of Columbia, Puerto Rico, the U.S. Virgin Islands, and the Pacific Basin [19]. Slightly more than half, or 52%, of these centers serve rural America, with the remainder serving urban communities [19]. Over 45% of CHC patients participate in Medicaid, Medicare, CHIP (Child Health Insurance Protection), or some other form of public insurance, and nearly 40% are uninsured [19].

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 CHC's supported by the Health Resources and Services Administration (HRSA) and National Cancer Institute (NCI) to serve financially, functionally, and culturally vulnerable populations [20,21].

A sampling of 44 CHC's were chosen to examine organizational structure, level of implementation of Chronic Care Model components, and contextual factors (e.g., teamwork and leadership) [22,23]. The 2006 HDCC survey administered to community health centers captured organizational factors, patient characteristics, and provider characteristics that affected cancer screening quality outcomes. The survey respondent categories included (1) director (CEO) role, (2) chief financial officer (CFO) role, (3) provider (physicians, nurses) role, (4) general staff (e.g., lab, pharmacy, etc.) role, and (5) informatics officer (CIO) role. Topics such as clinic processes, management strategies, community outreach, information systems, leadership, and teams were explored. In an earlier study [24], we identified 99 unique questions and grouped them into 37 summary measures based on internal advisory team and subject matter expert recommendations. We calculated a consensus score for each of the 44 community health centers on each summary measure. The conceptual model—a modified Zapka framework henceforth referred to as the Zapka et al. framework [25–27]—outlines the complete list of summary measures, their respective categories (e.g., organizational, patient, or provider), and the overall study design (see Fig. 1).

We employed two types of modeling in this secondary analysis of the NCI/HRSA HDCC survey data. Through empirical statistical modeling, the impact of clinical decision support use on cancer screening quality outcomes was examined reflected in the relationship between our proximal and distal outcomes. Then, computational modeling was used to examine the same phenomenon over a ten-year simulated period and generate hypotheses about CHC cancer screening behaviors in presence of CDS.

2. Rationale for a dual modeling approach

Since the American health care system is layered, "build[ing] a research foundation that acknowledges this multilayer world" [28] is essential, and traditional modeling methods may fail to adequately capture its complexity. Further, practices inconsistent with evidence persist since evidence-based innovations are not readily accepted, and new technologies require 17 years on average to become widely adopted [28].

Recognizing these limitations, the National Cancer Institute and the Institute of Medicine are now encouraging a systems-thinking approach, which the NIH's Office of Behavioral and Social Sciences Research (OBSSR) defines as follows:

> Systems-thinking (systems-science) 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 [29].

One methodology available for investigating and analyzing complex systems is computational modeling, which employs computer-based simulations, probabilistic models of systems or processes that emulate and so predict real-world behavior under varying assumptions and conditions. Simulation analyses provide a basis for developing hypotheses which can then be tested in actual intervention studies and/or technology implementations [30]. Computational modeling is becoming an increasingly trusted tool for analyzing complex, dynamic, adaptive, and nonlinear processes. By permitting investigation of their functioning, it addresses questions that traditional statistical methods alone cannot.

Groups, teams, organizations, and organizational command and control architectures [30] comprise one type of system to which computational modeling is being applied in order to discover new concepts, theories, and knowledge about them. Group or team behavior emerges from interactions within and between the agents or entities which comprise it. Not only humans but also objects, locations, methods, knowledge, and motivations may be considered as agents or entities making up such a system. Identifying key factors that contribute in varying degrees toward both individual and group-level actions is an important objective of such exploration [30].

In this study, a single point-in-time HDCC survey of CHC cancer screening practices was considered insufficient evidence to demonstrate the extent to which (1) the utilization of CDS impacts facility-level cancer screening improvement and (2) the 37 summary measures (i.e., organizational and/or practice factors, patient characteristics, and provider characteristics), singly and/or in interaction, contribute to continued CDS utilization over time. Therefore, we selected computational modeling to incorporate systems-thinking into this study.

The computational model's main performance measures are the rates at which knowledge is acquired and at which learning subsequent to the acquisition of knowledge occurs. These learning rates are evidenced by (1) by the level of efficiency the model's agents (organizations, roles, or objects) demonstrate in performing cancer-screening-specific tasks following the introduction of CDS and (2) the extent to which these agents utilize a set of defined knowledge resources designated as critical to overall community health center (CHC) cancer screening performance. Within the