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Social Influence and Innovation Adoption in the Clinical Setting

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By

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Abstract

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Advanced use of electronic health record (EHR) tools that standardize care and increase patient access to their providers are purported to improve care quality and safety; however, clinician uptake of these advanced tools has been slow. As U.S. health care reform measures continue to encourage the use of teams in care delivery, team dynamics may play a role in innovation adoption decisions of clinicians. Little detail is known about whether clinicians' use of technological innovations is influenced by peer and team use patterns.

From the patient perspective, clinical trials are the primary mechanism by which new approaches to cancer treatment are evaluated; yet, only a small proportion of eligible cancer patients are offered the opportunity to participate in clinical trials, and fewer actually become enrolled. Trends toward more patient-centered care delivery have encouraged shared decision-making between patients and their care providers, which may influence patient awareness and consideration of medical innovations as treatment options, and ultimately decide to enroll in clinical trials.

This dissertation research assesses whether there are team effects associated with individual adoption of innovations, as well as whether there are normative pressures or internal motivations, as opposed to more passive interpersonal influences, that are related to clinician innovation adoption. It also assesses whether individual attitudes and awareness alone, or more active information sharing are more likely to result in patient innovation uptake.

Findings from self-reported clinician and patient surveys in an integrated delivery system suggest that interpersonal interactions contribute to individual clinician and patient awareness and eventual use of innovations in the clinical setting. Specifically, clinician adoption of advanced EHR tools was associated with their team members' use of the innovation. However, team cohesion was not directly associated with individual adoption and did not moderate the relationship between team use and eventual individual use of advanced tools. This suggests that more a passive transfer of knowledge may account for team influence on individual team member's adoption of advanced EHR tools. Conversely, medical oncologist behaviors and patient care experience, both play important roles in patients' ultimate decision to enroll in cancer clinical trials. This points to the need for clinicians to more actively engage with their patients, and greater patient understanding of trials to effectively encourage cancer clinical trial participation.

CONTENTS

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CHAPTER 1: INTRODUCTION AND THEORETICAL FRAMEWORK

Introduction

In the workplace, the concept of social influence on behavior change among colleagues has been well documented. The concept has been attributed to shared moods among people in a work group (Barsade, 2002), participation in retirement plans based on colleague plan choices (Duflo & Saez, 2003), and similar prescribing patterns among collaborative, as opposed to independent, primary care clinicians in the Italian National Health Service (Fattore, Frosini, Salvatore, & Tozzi, 2009). U.S. health care reform measures continue to encourage the use of teams in care delivery (e.g., in primary care medical homes) (Reid et al., 2010), and although not well documented, team dynamics may also play a role in innovation adoption decisions of clinicians.

Likewise, trends toward more patient-centered care delivery have replaced more traditional paternalistic model of care in which health professionals are purported to know what is best for their patients, and therefore, patients should unquestioningly defer to their clinicians' treatment recommendations, disregarding their values and wishes (M. J. Barry & Edgman-Levitan, 2012). The increased expectation that shared decision-making between patients and their care providers patients about their diagnosis, prognosis, treatment options (including medical innovations), requires a great deal of high-quality patient-clinician communication in the clinical setting. Still, most research to understand barriers to patient adoption of medical innovations isolates patient perceptions and attitudes from their care experience. This separation potentially misses important information about how patients gain knowledge and form opinions about medical innovations, overlooking the potentially important influence that social interactions between patients and clinicians plays in patients' ultimate medical innovation adoption decisions.

In three sections, this dissertation research, examines the factors that impact clinician and patient decisions to adopt innovations at the individual-, dyadic-, and team-levels within a Northern California integrated delivery system. Specifically:

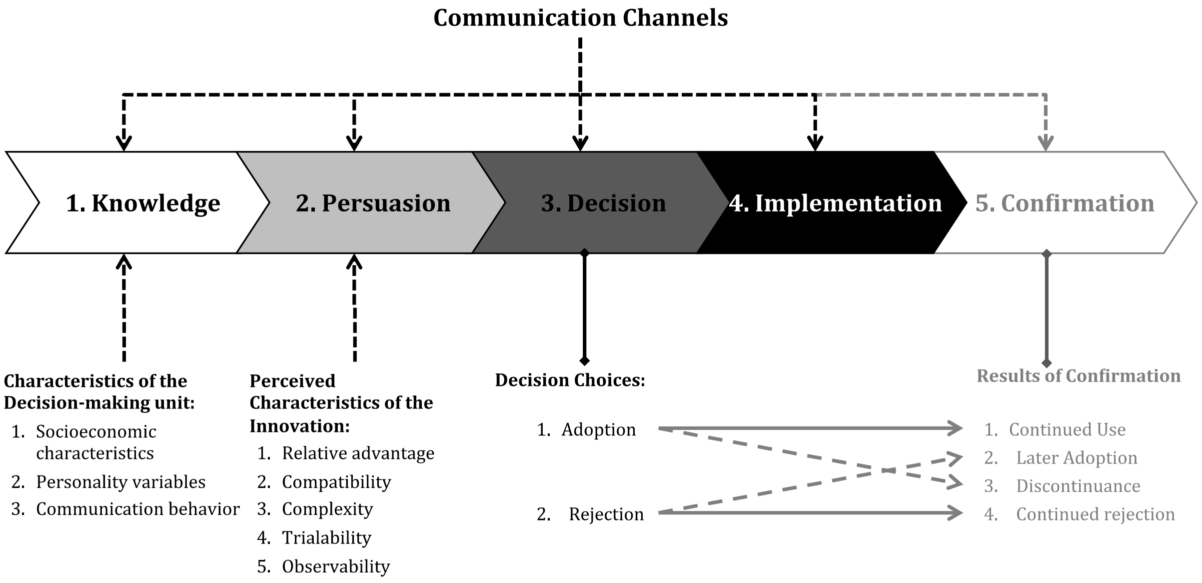
- **Chapter 2** assesses team-level effects on individual clinician's use of these advanced electronic health record (EHR) tools;
- **Chapter 3** examines the synergistic effects of team cohesion on individual clinician use of advanced EHR tools;
- **Chapter 4** identifies patient attitudinal and care experience factors associated with cancer clinical trial enrollment.

Theoretical Framework for Innovation Adoption

The central focus of this research is to clarify the factors that influence clinicians' innovation adoption decisions, and those that influence patients' decision to seek advance treatment innovations. Everett Rogers' Model of the Five Stages in the Innovation-Decision Process is widely used to understand the iterative phases through which individuals progress to determine whether or not to ultimately adopt, or make use of, an innovation (Berwick, 2003; Elwyn, Taubert, & Kowalczuk, 2007; Greer, 1977; Rogers, 2003a). Rogers' model consists of 5 stages, from an individual's knowledge of an innovation to the their ultimate sustained use of, or abstention from, an innovation (Rogers, 2003a).

As Rogers notes, the Innovation-Decision process is "essentially an information-seeking and information processing activity" in which an individual attempts to efficiently reduce the uncertainty associated with the use and the consequences of implementing an innovation (Rogers, 2003a). The model (depicted in Figure 1) can be applied quite broadly in understanding the process through which individuals, or decision-making units, assess and choose to use (or not use) any new idea, practice, or technology.

Figure 1. Rogers' Model of Five States in the Innovation-Decision Process



The innovation-decision process is the process through which an individual (or other decision-making unit) passes from first knowledge of an innovation to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision.

Adapted from Diffusion of Innovations (Rogers 2003, pg. 170)

In this model, an individual attempts to balance the costs and benefits of a new innovation based on the ways in which social structure supports or hinders the acquisition of information. Sequential in nature (though an individual may halt progression and restart the process multiple times), the 5-stages of the model include: 1) the Knowledge, 2) Persuasion; 3) Decision; 4) Implementation; and 5) the Confirmation Stages. At each stage, the model accounts for the individual and social factors that influence an individual's ultimate decision about an innovation.

The Knowledge Stage in the Innovation-Decision process begins once an individual is made aware of the innovation, either through happenstance or by actively seeking to fulfill an unmet need, and progresses as the individual learns more about the innovation. Rogers describes three types of knowledge that an individual seeks to acquire before moving to the next stage in the innovation-decision process. They attempt to answer the questions: 1) "What is the innovation" in order to obtain what Rogers calls awareness-knowledge; 2) "How does the innovation work" to have how-to knowledge; and 3) "Why does it work" to gain principles-knowledge (Rogers 2003, pg. 137). While typically, an individual uses this type of knowledge to inform their perceptions of the innovation and eventually decide whether or not to adopt it (the following two stages), principles-knowledge is also particularly useful in the later stages of the Innovation-Decision process as it can be used to evaluate the actual effectiveness of the innovation.

The Persuasion Stage occurs as an individual develops perceptions about and attitudes toward the innovation by assessing the information he or she learns about the innovation. This attitude development or change may result with or without the influence of others. Like the preceding stage, the opinions formed during the Persuasion Stage are the result of mental activity, the difference here, as Rogers specifies, being that the thoughts in the Persuasion Stage are based on emotion rather than the analytical thinking that took place in the Knowledge Stage. An individual forms opinions about the innovation as a means to minimize uncertainty about the innovation. Thus, the ability to overcome the uncertainties associated with adoption will inherently depend on the novelty of the innovation in question: the more novel the innovation, the greater the uncertainty associated with its use and the consequences thereof (Wejnert, 2002).

The Decision Stage represents the process by which an individual chooses to adopt or reject an innovation. Because Rogers' model is predicated upon the notion that individuals attempt to minimize the uncertainty associated with adopting an innovation, it is assumed that he or she will be more likely to decide to adopt an innovation if there is potential for continued evaluation of that innovation with minimal consequences, as would be the case if adopted on trial basis. Rogers also notes that, while the adoption of an innovation is inherently an active decision, an individual can actively or passively choose to reject the innovation. To actively reject the innovation, the individual must consider and then choose not to adopt it (this can even occur after an initial decision to adopt, resulting in what Rogers refers to as "Discontinuance," described in the Confirmation Stage). Conversely, an innovation can be passively rejected if an individual never really considers its use despite being aware of the innovation's existence. The activities that take place in the Decision Stage, as is the case with the two previous stages, are still only mental, as choosing to adopt does not alone guarantee the eventually uptake of an innovation.

The Implementation Stage occurs once an individual actually begins using the innovation. Until this point in the Innovation-Decision Process, all activities in which an individual engages are a series of active and passive analytical and emotional thought exercises. Conversely, entering the implementation stage explicitly indicates a change in behavior. This next step in the Innovation-Decision Process acknowledges that, after deciding to adopt an innovation, an individual likely faces barriers that need to be overcome before an innovation can be put into practice. As Rogers notes, " An individual particularly wants to know the answers to such questions as 'Where can I obtain the innovation?' 'How do I use it?' and ' What operational problems am I likely to encounter, and how can I solve them?' So active information seeking usually takes place at the implementation stage in order to answer these questions" (Rogers 2003, pg. 176). Thus, reaching this stage does not imply that an individual is certain of an innovation's outcome.

The Confirmation Stage is the final progression in the Innovation-Decision process. Although not a focus of this research, the Confirmation Stage is a key factor in an individual's long-term decision to ultimately adopt or reject an innovation. At this final stage in the

Innovation-Decision process, an individual seeks information to reaffirm or refute their previous decision to adopt or reject an innovation. Depending on the information collected, either based on experience engaging with the innovation or the outcomes from said engagement, an individual may choose continued use of the innovation, later adoption (changing one's decision from rejection to adoption), discontinuance (changing one's decision from adoption to rejection), or continued rejection. The confirmation stage may endure indefinitely as the certainty of the benefits of an innovation may never fully outweigh the disadvantages, ultimately leaving an individual's decision to adopt or reject an innovation in flux.

Communication Channels. While the ways in which and the type of information that reaches an individual is quite varied, the model suggests that some information must be transferred in order for an individual to first learn about an innovation and eventually adopt or reject it. Communication channels represent the mechanisms by which social interactions interact with an individual's knowledge of and attitude toward an innovation occurs, i.e., the circumstances by which an individual, who has yet to adopt the innovation, is exposed to the others who have adopted the innovation (Burt, 1987). In the health care context, Communication Channels include verbal and non-verbal socially-oriented cues that modify clinicians' cognitions, beliefs, attitudes, values, and behaviors as they progress through the stages of the Innovation-Decision Process (B. Barry & Watson, 1996; Dearing, 2008; Rogers, 2003b). Rogers suggests that the mechanisms by which communication channels assist in progressing through the stages of the Innovation-Decision process may vary. As an individual progresses to the Persuasion and later stages in the Innovation-Decision process, he or she must more actively seek information about the innovation and decide how to interprets the information.

Rogers' Communication Channels apply to active information seeking, as well as individual adoption of innovations that results from more passive exposure to individual's use of a given innovation. Burt (1987) also argues that structural equivalence, which generally describes competitive pressures for greater status and reputation, can motivate an individual's adoption of an innovation. In this case, the use of information may be more one-sided, with the potential adopter mimicking an earlier adopter to level competition or conform to evolving standards for credibility and status, regardless of whether the early adopter intentionally or willingly shares information about the adopted innovation.

Much of the established research in the U.S. clinical setting that assesses individual adoption of innovations is clustered in the Knowledge stage of Rogers' Innovation-Decision Process, with studies identifying the channels by which clinicians in independent practice become aware of new innovations (Bauer & Wortzel, 1966; Rogers & Kincaid, 1981; Valente, 1996). Similarly, many studies of patient participation in clinical trials focus on patient trial awareness (E. W. Ford, Menachemi, & Phillips, 2006; Lara Jr et al., 2005). However, the influence of interpersonal interactions on the ultimate use of innovations throughout the stages of the Innovation-Decision process, particularly in the clinical setting, is not well understood.

CHAPTER 2: THE ROLE OF THE CLINICAL TEAM IN ADVANCED ELECTRONIC HEALTH RECORDS USE IN AN INTEGRATED HEALTH CARE SYSTEM

Abstract

Background: While US electronic health record (EHR) adoption has increased, little detail is known about how often clinicians use more advanced EHR tools in clinical practice, and whether this is influenced by peer and team use patterns. Little research has examined the role of team-level effects on individual clinician's use of these advanced EHR tools. Using three waves of clinician survey data during EHR implementation across an integrated health care delivery system.

Purpose: This study examined the extent to which individual clinician and team characteristics influence individual team member's use of advanced EHR tools.

Methodology: Use of self-reported primary care clinician survey data collected in three waves between 2005-2008 to identify characteristics associated with use of advanced EHR tools and to whether team member use of advanced EHR tools was associated with individual use. Mixed and fixed effects Poisson regression models, controlling for team size, baseline team tenure, and survey year, were estimated to examine the respective association between advanced tool use and individual characteristics, and team use.

Results: After adjusting for increases in use of EHR tools over time, clinicians who were newer to the organization and those of non-White (compared to White) race were significantly more likely to be users of advanced tools. Individual clinicians were also significantly more likely to use advanced EHR if others in their team also used these tools.

Conclusion: Results indicate that that team-level factors were strongly associated with individual use, while individual demographic characteristics did not. These findings highlight the importance of teams for early adopters of EHRs.

Introduction

Researchers and policymakers alike have proposed Electronic Health Records (EHRs) as a means to simultaneously improve the quality, efficiency, and coordination of care delivered, as well as control health care costs. However, many researchers have concluded that the presence of health technology alone is not enough to achieve their purported benefits. Rather, studies have shown that achieving the care quality benefits associated with EHR adoption must be coupled with "Meaningful Use" of the technology, through the implementation and regular use of multiple EHR tools (Blumenthal & Tavenner, 2010; Classen & Bates, 2011).

To promote the use of new technologies, the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 authorizes up to $27 billion in federal payments to encourage "Meaningful Use" of EHRs. As opposed to simply requiring the purchase of new technologies, Meaningful Use incentives require clinicians and hospitals to use increasingly more advanced EHR tools over time with the objective of incrementally improving the quality, efficiency, and coordination of care delivered in the United States. There is substantial evidence that the incentives included in the HITECH Act have been successful. For example, in 2016, 93% of the over 100,000 providers participating in government-sponsored health IT Regional Extension Center (REC) program, which provided

EHR adoption assistance and best practices, were actively using EHR technology (Office of the National Coordinator for Health Information Technology, 2016). Yet, despite support from the REC program and financial incentives in place to increase use of more advanced EHR features—including Stage 1 Meaningful Use requirements for computerized physician order entry for medication and labs, as well as Stage 2 requirements for use of patient secure electronic messaging—REC-enrolled provider demonstration of Meaningful Use varies substantially (Office of the National Coordinator for Health Information Technology [ONCHIT], 2016a), with overall demonstration rates of actually adopting Stage 1 and 2 EHR tools hovering around 75 percent. Variation in Meaningful Use demonstration may stem from varying provider use of more advanced EHR tools (DesRoches, Worzala, Joshi, Kralovec, & Jha, 2012; Furukawa et al., 2014; Hsiao & Hing, 2014; Morton et al., 2015).

The use of teams in health care delivery (e.g., in primary care medical homes) represents a parallel transformation process within health care that is driven by changes from fee-for-service to value-based care incentives. Whether in-person or virtually, emerging evidence suggests that care team members can successfully work together to provide patients with comprehensive and coordinated care that improves care quality and accessibility (Baek & Seidman, 2015; Bodenheimer, Wagner, & Grumbach, 2002; Jaen et al., 2010). Although it is acknowledged that the use of health technology is key in successfully providing team-based health care (Agency for Healthcare Research and Quality [AHRQ], 2015; Classen & Bates, 2011), there is limited empirical evidence of how these two health care initiatives could interact.

Beyond financial incentives to meaningfully adopt health information technology, interpersonal influences may also influence physician adoption of new technologies. Sociological, social psychological and economic theories postulate that interpersonal relations act as an important pathway through which information and behaviors are spread within socially connected networks of individuals. Despite being designed for other purposes, the workplace serves as an environment ripe for informal social influences to shape the decisions of individuals. Evidence of the diffusion of behavior and attitudes through interpersonal influence processes among coworkers, or employer-created interpersonal networks, is diverse and widespread (Rogers, 2003). However, the effect of health care teams on individual clinicians' adoption of new technology is less clear.

In this paper, three waves of clinician survey data are used in which sampled clinicians indicate their use of advanced EHR tools that standardize care and increase patient access to their providers, such as order sets, using standard note templates (Rockswold & Finnell, 2010), and emailing with patients (Office of the National Coordinator for Health Information Technology [ONCHIT], 2016b). Of particular importance, all clinicians in the sample had similar access to training associated with EHR use. This uniformity in training and availability of practice resources may assist in isolating peer influences on adoption of the advanced tools.

The literature on individuals' adoption of innovations in health care is broad but suffers from several gaps. Indeed, previous studies have either focused solely on the contextual factors that influence organizational adoption of a technological innovation over time or solely focused on a single unit of analysis, usually the physician or, to a lesser extent, the health care team. While the literature is generally focused more on the ways in which an individual influences the behavior of another, little research has examined the ways members of groups in organizations use each other as instructors, sources of information, or models, despite the promise teams have shown for influencing individuals within organization studies. This multi-level study seeks to address these gaps in the literature by investigating how greater exposure to advanced peer users might influence individual clinician's use of advanced EHR tools.

Specifically, this study investigates how greater exposure to advanced peer users might influence individual clinician's own use of advanced EHR tools, specifically: 1) To what extent individual clinician characteristics are associated with use of advanced EHR tools; and 2) To what extent exposure to team members who use advanced EHR tools is associated with individual clinician's use of advanced EHR tools.

Prior Research and Hypotheses

This research considers the individual- and team-level characteristics that influence clinicians' use of, and attitudes toward, technological innovations. There is some evidence that individual clinicians' adoption of new technologies may be affected by individual characteristics, as well as the presence of and type of relationships with colleagues. However, it is unclear how these findings translate in the context of the current health care system, where team-based models of care have added more formal structure to relationships. In their reviews, Hackman and Edmondson outline the ways in which teams have been shown to efficiently share information, develop skills, and enhance learning among members (Hackman, 1992; Hackman & Edmondson, 2008), and teams within health care have been shown to enhance care coordination (Firth-Cozens, 1998) improve chronic disease care (Litaker et al., 2003; Shortell et al., 2004; Wasson, Godfrey, Nelson, Mohr, & Batalden, 2003), and improve patient health care experiences (Rodriguez, Rogers, Marshall, & Safran, 2007). Likewise, health care teams could aid in efficiently moving members through the stages of the Innovation-Decision Process (Rogers, 2003), accelerating individual clinicians' adoption of new technologies. At the extreme, individual clinicians could even choose to immediately adopt a new technology once becoming aware of teammates' use, as teammates' use could serve as proxies for individual's decision processing (Rogers, 2003). Thus, the research hypothesis is that *team member use of technological innovation (advanced EHR tools) will be positively associated with other clinical team members' adoption of the innovation*.

There is also some evidence from national surveys that younger physicians and those practicing in more urban settings, are more likely to adopt new technologies (Kimberly & Evanisko, 1981; Li, Talaei-Khoei, Seale, Ray, & MacIntyre, 2013a). Likewise, physicians practicing for longer are less likely to adopt new technologies (Menachemi, Langley, & Brooks, 2007). Within organizations, the influence of these individual characteristics becomes less clear (and sometimes irrelevant given commonalities, i.e., similar locations). Furthermore, the evidence is mixed (Bramble et al., 2010; Kaushal et al., 2009; Li et al., 2013; Menachemi, Powers, & Brooks, 2011; Shields et al., 2007), as group dynamics and norms have been shown to mute individual-level effects on work performance (Goncalo & Duguid, 2012; Trist & Bamforth, 1951) and even emotions (Barsade, 2002; Felps, Mitchell, & Byington, 2006; Glomb & Liao, 2003). Thus, this study also assessed whether individual characteristics were associated with use of advanced tools, even in the presence of team-level advanced tool use.

Methods

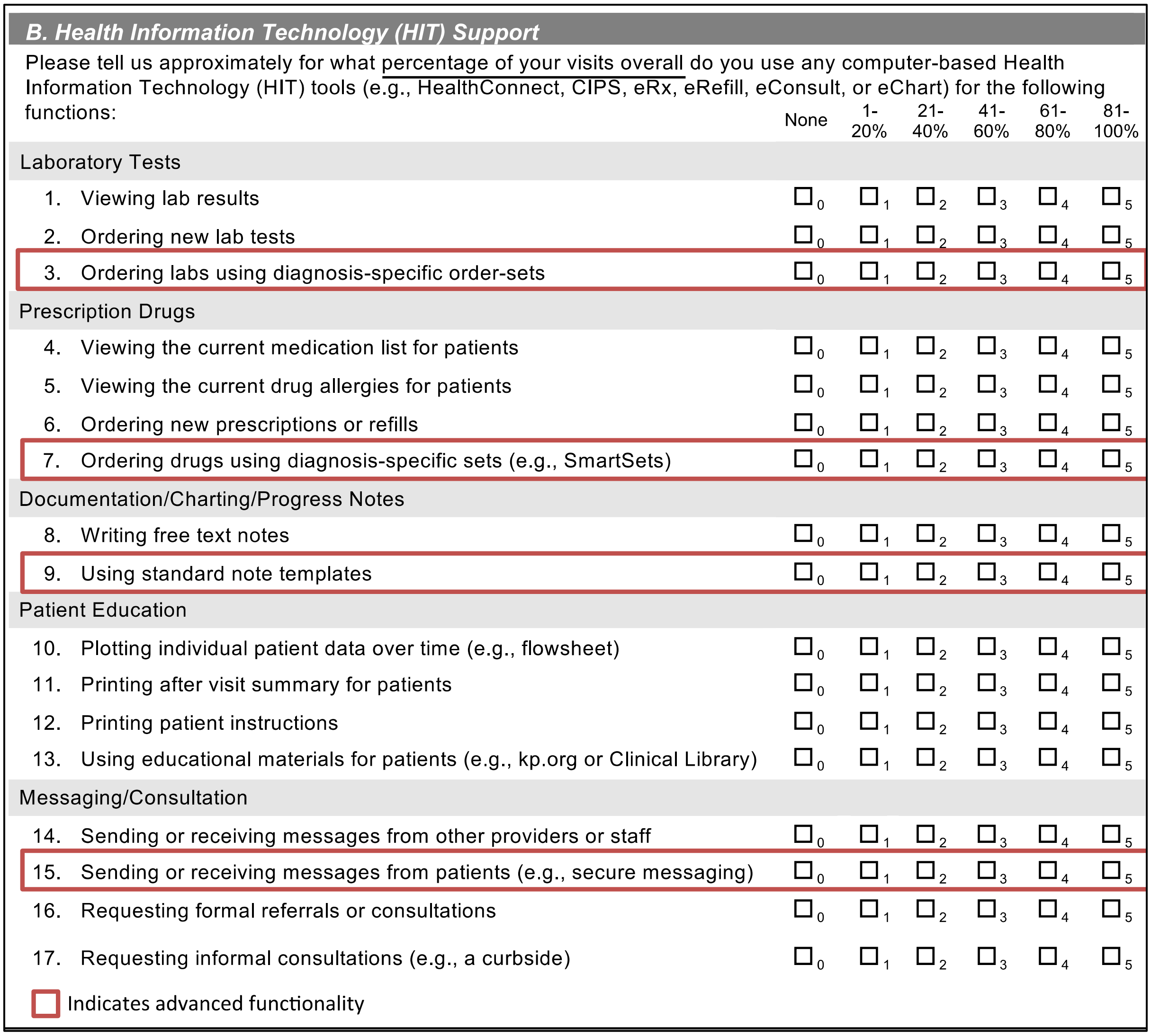
Study Setting and Data Sources. This study was conducted at Kaiser Permanente Northern California (KPNC), a large, Integrated Delivery System that provides comprehensive medical care using bundled prospective payments for over three million members. At the time of this study, primary care clinicians were grouped into one of 107 primary care teams, across 17 Medical Centers in the region. In 1998, KPNC created primary care teams in an effort to redesign care through multidisciplinary collaboration between Internal Medicine and Family Medicine physicians, Nurse Practitioners, Behavioral Medicine Specialists, Physical Therapists, Clinical Health Educators and Medical Assistants.

Between 2005 and 2008, KPNC implemented a commercially available outpatient certified EHR. The implementation was staggered across all 17 medical centers in the region, providing a natural quasi-experimental setting to examine the effects of team member use and EHR adoption. The outpatient EHR completely replaced the paper-based medical record and a limited patchwork of pre-existing non-integrated health information technology tools, obligating clinicians to use standard EHR tools such as ordering and reviewing labs and prescriptions, as well as inputting and reviewing patient medical history information. In addition to these standard EHR tools, clinicians also had the option of using more complex EHR tools that incorporated disease-specific order sets, standard note templates, and emailing with patients (ONCHIT, 2016b; Rockswold & Finnell, 2010a). All KPNC clinicians used the same EHR systems and continued to receive standardized training throughout the study period.

Data Collection. The Kaiser research team collected three waves of mailed self-administered questionnaires in 2005, 2006, and 2008. The team mailed study invitation letters and surveys with pre-addressed, postage paid return envelopes to all KPNC medical center primary care team members, including physicians, nurse practitioners, and physician assistants, in 2005 before the start of the EHR implementation, again in 2006, and finally in 2008 after system-wide implementation of the EHR was completed. Non-responders received up to three follow-up study reminder surveys unless they contacted the research team to decline participation.

Measures. Survey questions on EHR utilization were designed to describe how frequently respondents used each of the EHR system's tools. Specifically, respondents indicated the percentage of office visits in which they used the available (both optional and mandatory) EHR tools, with six categories: none, 1-20, 21-40, 41-60, 61-80, 81-100 percent of visits (see HIT Use survey questions in Figure 2). The research team also extracted administrative data on respondent demographic information including age, gender, race/ethnicity, tenure with the organization, and professional credentials and linked this data to survey responses.

Figure 2. EHR Tool Use Survey Questions



B. Health Information Technology (HIT) Support

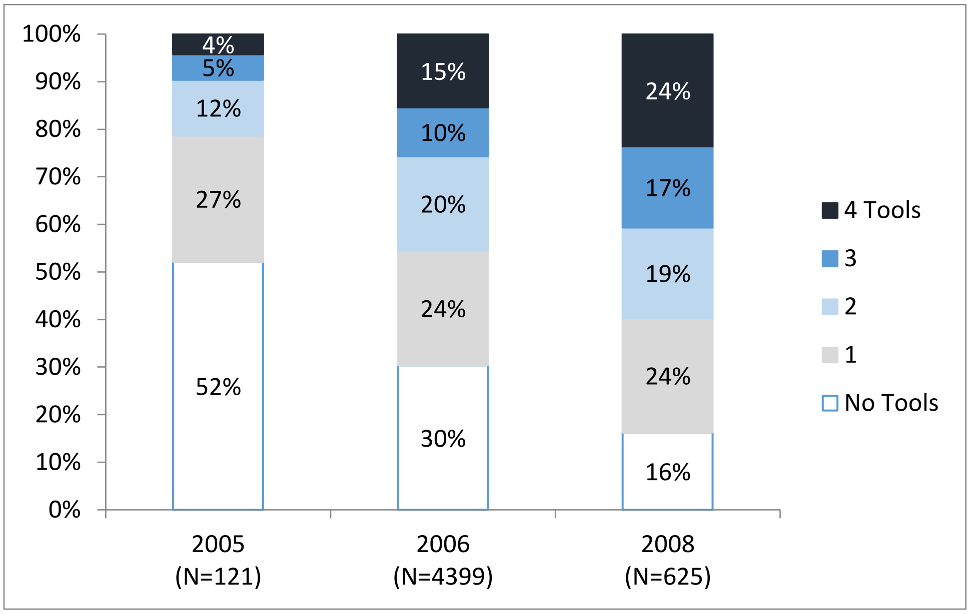
Please tell us approximately for what percentage of your visits overall do you use any computer-based Health Information Technology (HIT) tools (e.g., HealthConnect, CIPS, eRx, eRefill, eConsult, or eChart) for the following functions:

	None	1-20%	21-40%	41-60%	61-80%	81-100%
Laboratory Tests						
1. Viewing lab results	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
2. Ordering new lab tests	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
3. Ordering labs using diagnosis-specific order-sets	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
Prescription Drugs						
4. Viewing the current medication list for patients	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
5. Viewing the current drug allergies for patients	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
6. Ordering new prescriptions or refills	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
7. Ordering drugs using diagnosis-specific sets (e.g., SmartSets)	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
Documentation/Charting/Progress Notes						
8. Writing free text notes	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
9. Using standard note templates	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
Patient Education						
10. Plotting individual patient data over time (e.g., flowsheet)	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
11. Printing after visit summary for patients	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
12. Printing patient instructions	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
13. Using educational materials for patients (e.g., kp.org or Clinical Library)	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
Messaging/Consultation						
14. Sending or receiving messages from other providers or staff	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
15. Sending or receiving messages from patients (e.g., secure messaging)	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
16. Requesting formal referrals or consultations	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$
17. Requesting informal consultations (e.g., a curbside)	☐$_0$	☐$_1$	☐$_2$	☐$_3$	☐$_4$	☐$_5$

🟥 Indicates advanced functionality

Dependent Variable: Individual Use of Advanced EHR Tools. For the outcome variable, advanced tools were defined as more complex EHR tools (ONCHIT, 2016b; Rockswold & Finnell, 2010) whose use was not required during the study period, which corresponded with the early implementation of the new EHR system within the various medical centers. These tools include ordering drugs using diagnosis-specific sets (e.g., SmartSets), ordering labs using diagnosis-specific sets, using standard note templates, and sending to or receiving emails from patients. In the baseline year of the study, 2005, clinicians with access to the EHR in their medical center indicated that, on average, they used any the four advanced tools during less than 21% of office visits. By the 2008 wave of the survey, clinicians reported that average use of each advanced tools during office visits had increased to between 41-60% (Figure 3).

Figure 3. Number of advanced tools used by survey year



The outcome variable of interest represents individual clinician's use of advanced EHR tools in each survey from 2005 to 2008. Individual clinician use of each tool was dichotomized into advanced and non-advanced use. To be considered an advanced user of a particular advanced tool, the respondent must have reported using the tool during more than 60% of office visits. In the first year of the study, this cutoff represented the 90th percentile of EHR tool use for each of the four advanced tools. Dichotomized responses for each tool were summed, with the count outcome variable ranging from 0 to 4 (the number of advanced tools considered in this analysis).

Independent Variable: Team Use of Advanced EHR Tools. Since we hypothesized that advanced tool use for individual clinicians is associated with team-level EHR use, the main explanatory variable of interest is the percentage of advanced users on a given team. For each wave of the survey, we classified whether individual clinicians were users of all four advanced EHR tools during at least 61% of office visits. The proportion of advanced users per team, excluding an individual's own values, was assigned to each individual within a given team, then made into a categorical variable (0%, 1-24%, 25-49%, >50% of team members). Because team members' influence may not take effect immediately, a model with a lagged measure of the proportion of advanced users on a team was assessed to account for delayed diffusion of advanced user practices (not shown); however, due to a substantial drop in sample size (n=209) and team representation, the results could not be reliably interpreted. Using KPNC administrative data, team size, which ranges from 3 to 24 clinicians, was controlled for using a categorical variable that splits the sample into roughly into quarters as follows: 6 or less, 7-9, 10-12, and 13 or more team members.

Statistical Analyses

Team Influence Models. We sought to test the research hypothesis that the proportion of team members who are high users of advanced EHR tools was associated with individual team members' use of advanced EHR tools. We used a clinician-level fixed effects Poisson regression model due to distribution of the outcome variable (Wooldridge, 2010) (xtmepoisson in Stata 13) individuals' use of the EHR tools (count), with the proportion of high users within a care team at each time period, controlling for team size, as well as calendar and EHR adoption year. This model is presented with robust standard errors.

Advanced User Characteristics Model. To also identity individual characteristics associated with use of advanced EHR tools, we also used a mixed effects Poisson regression model (Wooldridge, 2010) (xtmepoisson in Stata 13), with categorical team proportion of high users of advanced tools and team size, and individual-level tenure (linear), age (linear), as well as categorical sex, race/ethnicity (White, Asian, or other), training (MD or NP/PA), and panel size (<1000 patients, 1000-1499, 1500-1999, and >=2000 patients) predictor variables (Li, Talaei-Khoei, Seale, Ray, & MacIntyre, 2013b; Weiss et al., 1990). The model also adjusts for calendar and EHR adoption year at the medical center-level. In order to account for the data's two levels—repeated observations and medical center clustering—this model also included random intercepts for clinician and medical center, and the covariance structure was set to unstructured.

Sensitivity Analysis. To test the robustness of the results based on team size, a first sensitivity analyses was conducted removing teams with varying counts of member representation, as suggested for instance in Glomb and Liao (2003). To test the robustness of the results based on access to EHR, a second sensitivity analysis was conducted by including clinicians without EHR access at any time during the study period.

All analyses were conducted in STATA version 13, and statistical significance was considered at the alpha level of $p < 0.05$.

Results

Non-Response and Excluded Observations. The target population for this research includes all primary care clinicians who had access to the implemented EHR system during the year that they completed the questionnaire. Among this population, response rates reached 50%, 64%, and 61% in 2005 (N=121), 2006 (N=439), and 2008 (N=625) respectively. Forty-one respondents were excluded because they switched teams between survey waves, and an additional 24 individuals, representing 14 teams, were excluded from this study because fewer than 3 team members responded to the survey in any given study wave, and their team scores could not be computed reliably. This resulted in representation from 100%, 99%, and 91% of teams in medical centers using the EHR system in the respective 2005, 2006, and 2008 survey waves.

Respondent characteristics. Table 1 reports the characteristics of respondents who completed EHR use questions for the various waves of the survey, as well as descriptive statistics of non-responders. Respondents in the first two waves of the study (2005 and 2006) were more likely to be female compared to non-respondents. In the 2006 and 2008 survey waves, survey respondents, compared to non-respondents, were more likely to be younger and newer to KPNC. Otherwise, respondents and non-respondents were statistically similar based on measured demographic characteristics. Overall the study population consistently includes more women and clinicians of White and Asian race/ethnicity than male clinicians and clinicians of other races and ethnicities, with non-White clinicians less likely to respond in the final survey wave. Approximately two-thirds of respondents (66.1% in 2005 and 64.9% in 2006, and 65.8% in 2008) were forty years old or older, and, on average, represented clinicians had worked at KPNC for about 10 years by the end of the study. In 2005, 87.0% of the sample consisted of physicians and this proportion increased with subsequent survey waves resulting from an organizational effort to reduce the number of non-physicians on primary care teams. Over the study period, the proportion of respondents indicating that they were advanced users, i.e., users of all 4 advanced tools during at least 61% of office visits, increased from 4.1% of respondents in 2005 to 22.9% of respondents in 2008.

Teams characteristics. A summary of team-level characteristics can be found in Table 2. Team size fluctuated substantially between the 2005 and 2006 survey waves, remaining substantially lower in the latter two survey years, and averaging 9.7 members per team across the entire study period. As with individual clinicians, over time, the proportion of advanced users on teams increased. In 2005, only 1 team was comprised of more than 50 percent advanced users. By the study's completion in 2008, almost 10% of represented care teams were comprised of at least 50% advanced users.

Advanced User Characteristics Model. Table 3 provides results from the mixed effects model predicting individual- and team-level characteristics of users of advanced EHR tools. The results indicate that there are significant team effects, as being on teams with high users of advanced EHR tools was associated with greater individual use of advanced EHR tools compared to individuals on teams with no high users of the advanced tools. Specifically, being on teams with between 1-25% high users of advanced EHR tools was associated with 1.52 times greater likelihood of advanced EHR tool use than individuals on teams with no high users of advanced EHR tools. There is also evidence of a gradient effect: the higher the proportion of high users on the team, the higher the predicted rate of individual advanced tool use, and the coefficients on the team proportion variables were statistically different from each other (χ^2= 12.21; p= 0.05). Team members who had shorter tenure at KPNC (p<0.001) and those of Asian (vs. White—p=0.005) race were also significantly more likely to use advanced EHR tools. Specifically, holding other variables in the model constant, clinicians of Asian race/ethnicity were expected to use advanced EHR tools at a rate 1.15 times greater than their White-race counterparts. Conversely, for each additional year of tenure at KPNC, a clinician's rate ratio for advanced EHR tool use would be expected to decrease by a factor of 0.99, while holding all other variables in the model constant. This suggests support for the second research hypothesis, showing that, aside from the passage of time, team members' use of advanced EHR tools is an important predictor of individual use, whereas individual-level factors exhibit more modest or no significant effects.

Team Influence Models. Table 4 displays results from the fixed effects team influence model. The coefficients on the year dummy variables are jointly significant, suggesting that time trends account for a variation in changes in clinician use of EHR tools. After adjusting for these increases over time, there are still significant team effects. For example, an individual on a team with between 1-25% high users of advanced EHR tools was expected to use advanced EHR tools at rates of 1.47 (p=0.006) times greater than colleagues with no exposure to team members who were high users of advanced tools. This supports the research hypothesis that individual adoption would be positively associated with greater team member use of the advanced tools. Further, as with the aforementioned mixed effect model, there is evidence, albeit less pronounced, of a gradient effect. As the proportion of users of advanced EHR tools on a team increased, so did the rate of individual team member use of advanced tools.

Sensitivity Analyses: Varying Exclusions based on Team Size. The results from the sensitivity analysis for the fixed effects model can be found in Table 5. Removing teams with fewer than 3-6 members represented did not change findings from any of the models.

Sensitivity Analyses: Varying Exclusion Based on Access to EHR. Results from models including clinicians in medical centers without EHR system access are included in Table 6. When including or excluding physicians in medical centers without EHRs implemented, the results did not change substantially.

Discussion

Using a uniquely available dataset that captures clinician adoption of technology with longitudinal measures within a healthcare system that provided consistent training and resources to encourage clinicians' EHR adoption, this study highlights the importance of teams for early adopter of EHRs that are applicable to the United States' current health care environment. Use of electronic health records has the potential to improve care quality (Blumenthal & Tavenner, 2010; Classen & Bates, 2011); however, to date, evidence of meaningful adoption of EHR systems has been mixed. Even after early implementation of EHR systems within the Kaiser Permanente Northern California health system, there was substantial variation in primary care clinicians’ use of advanced EHR tools that had the potential to standardize care and improve patient access to their clinicians. We examined the relationship between being a member of a primary care team and varying degrees of exposure to high users of these advanced EHR tools. The findings support our hypotheses that clinical team members' use of advanced EHR tools is positively associated with individual member use of the advanced tools, and that team-level factors are more strongly associated with individual use, compared to individual demographic characteristics.

Interestingly, at the study's end in 2008, 21 percent of care teams that did not have any advanced users at baseline still did not have any high user team members. This is particularly interesting given the stark rise in adoption and the sustained use of the studied advanced tools over time among individuals on other teams, suggesting that most clinicians found value in these EHR tools. For individuals on teams with no advanced users, this lack of exposure to an advanced user may support continued non-use of advanced EHR tools, despite increased use across the organization.

There are some limitations that may bias these findings. Secondly, although there is minimal evidence to suggest that responders and non-responders to EHR use survey questions differed based on captured demographic characteristics, it is unclear whether non-responders’ lack of “EHR use responses is systematically related to their EHR utilization. It is very possible that low EHR users chose not to answer questions about their use. Excluding their utilization data from this analysis could potentially bias the results. Secondly, as is the case with any survey-based study, there is concern of response bias. Clinicians may have systematically over- or under-reported use of advanced EHR tools for reasons unknown to the study's researchers. However, given the low reported use of advanced tools in the first wave of the study and the general trend of increasing use over the study period, there is some face validity suggesting accurate reporting across the survey waves.

Lastly, although teams were formed before EHR implementation and were not based on familiarity with technology, outside of the organization deliberately assigning teams based on technology-related information, it is possible that teams are more likely to be composed of more tech-savvy individuals by random chance. While team composition is unlikely to be directly the result of members' HIT ability, it is conceivable that HIT ability is systematically distributed differently among teams. For example, less tenured clinicians may be on the same team because a new team was created when they joined KPNC. However, using panel data allows for these potential time invariant unobserved group effects to be differenced out of the equations (Durlauf & Ioannides, 2010; Hoxby, 2000) and concerns of unobserved group effects are mitigated by the study design.

The data presented here show strong evidence of team influence on individual team members' use of technology. For complete adoption of EHR systems, diffusion of advanced EHR tool use among members of teams that lack high users may require unique training or opportunities to spend time on teams with high users of advanced tools.

Table 1. Primary care team member characteristics by year and response status

	Respondents						Non-Respondents					
	2005 (N=121)		2006 (N=439)		2008 (N=625)		2005 (N=121)		2006 (N=246)		2008 (N=404)	
Age: 25-39	33.9%	(41)	35.1%	(154)	33.9%	(212)	28.9%	(35)	27.6%	(68)	**24%**	**(97)**
40-54	53.7%	(65)	50.1%	(220)	50.1%	(315)	57%	(69)	**53.7%**	**(68)**	**53.7%**	**(229)**
55+	12.4%	(15)	14.8%	(65)	15.7%	(98)	14.1%	(17)	18.7%	(46)	19.3%	(78)
Sex: Female	54.8%	(63)	54.2%	(219)	52.1%	(308)	**43.3%**	**(55)**	**44.8%**	**(126)**	48%	(210)
Race/Ethnicity: White	50.4%	(58)	45.1%	(182)	42.8%	(246)	39.4%	(50)	47%	(132)	**34.8%**	**(151)**
Asian	40%	(46)	47%	(190)	50.4%	(290)	49.6%	(63)	44.1%	(124)	51.4%	(223)
Other	9.6%	(11)	7.9%	(32)	6.8%	(39)	11%	(14)	8.9%	(25)	13.8%	(60)
Credentials: MD/DO	87%	(100)	87.4%	(353)	94.4%	(558)	90.6%	(115)	93.2%	(262)	95.7%	(419)
NP/PA	13%	(15)	12.6%	(51)	5.6%	(33)	9.5%	(12)	**6.8%**	**(19)**	4.3%	(19)
Baseline Tenure at KP: <5 years	32%	(146)	37.5%	(230)	31.5%	(186)	28.4%	(25)	27.5%	(77)	22.8%	(100)
5-9 Years	31.1%	(142)	28.9%	(177)	33.7%	(199)	43.2%	(38)	29.6%	(83)	28.8%	(126)
10-14 Years	9.2%	(42)	7.7%	(47)	12.4%	(73)	8%	(7)	7.9%	(22)	18%	(79)
>=15 Years	27.8%	(127)	25.9%	(159)	22.5%	(133)	20.5%	(18)	**35%**	**(98)**	**30.4%**	**(133)**
Panel Size: <1000 Patients	21.7%	(25)	18.1%	(72)	14%	(65)	18.1%	(23)	13.6%	(38)	13.9%	(50)
1000-1499 patients	27%	(31)	24.7%	(98)	24.5%	(114)	25.2%	(32)	20.8%	(58)	20.3%	(73)
1500-1999 patients	27%	(31)	34.5%	(137)	31.3%	(146)	29.1%	(37)	44.1%	(123)	36.5%	(131)
>2000	24.4%	(28)	22.7%	(90)	30.3%	(141)	27.6%	(35)	21.5%	(60)	29.3%	(105)
Advanced User (61% of visits)	4.1%	(5)	14.1%	(62)	22.9%	(143)	--		--		--	
Age: mean (SD)	44.9 (SD=9.1)		44.9 (SD=9)		44.9 (SD=8.7)		45.6 (SD=9.1)		46.5 (SD=8.8)		46.1 (SD=8.9)	
Tenure at KPNC: mean (SD)	9.9 (SD=8.1)		10.1 (SD=8.8)		9.7 (SD=7.8)		10.7 (SD=8.4)		11.5 (SD=8.9)		11 (SD=8.8)	
Panel Size: mean (SD)	1500 (SD=610)		1520 (SD=618)		1652 (SD=564)		524 (SD=682)		1562 (SD=598)		1631 (SD=577)	

Table 2. Represented Team Characteristics by Year

	2005 (N=23)		2006 (N=69)		2008 (N=97)	
Team Proportion Advanced Users: 0%	78.3%	(18)	37.7%	(26)	23.7%	(23)
>0-25% team members	13%	(3)	30.4%	(21)	29.9%	(29)
>25-50% team members	4.3%	(1)	26.1%	(18)	37.1%	(36)
>50% team members	4.3%	(1)	5.8%	(4)	9.3%	(9)
Team Size: <7 team members	8.7%	(2)	8.7%	(6)	70.1%	(68)
7-9 team members	21.7%	(5)	44.9%	(31)	21.6%	(21)
10-12 team members	47.8%	(11)	29%	(20)	5.2%	(5)
>12 team members	21.7%	(5)	17.4%	(12)	3.1%	(3)

Table 3. Team Characteristics Associated with Individual Use of Advanced EHR Tools

Fixed Effects Model (n=477)	**IRR (Coef.)**	**Std. Err.**	**P-Value**
Team Proportion Advanced Users:			
1-25% team members (vs. 0%)	**1.47 (0.39)**	**0.21**	**0.006**
>25-50% team members	**1.6 (0.47)**	**0.21**	**0.000**
>50% team members	**1.58 (0.46)**	**0.36**	**0.048**
Team Size: 7-9 team members (vs. <7)	0.84 (-0.18)	0.16	0.351
10-12 team members	0.78 (-0.24)	0.19	0.320
>12 team members	0.71 (-0.34)	0.22	0.271
Year: 2006 (vs. 2005)	1.51 (0.41)	0.25	**0.013**
2008	1.51 (0.41)	0.26	**0.015**

Table 4. Individual and Team Characteristics Associated with Use of Advanced EHR Tools

Mixed Effects Model (n=851)	**IRR (Coef.)**	**Std. Err.**	**P-Value**
Team Proportion Advanced Users:			
1-25% team members (vs. 0%)	**1.52 (0.42)**	**0.12**	**<0.001**
>25-50% team members	**1.81 (0.59)**	**0.14**	**<0.001**
>50% team members	**2.27 (0.82)**	**0.27**	**<0.001**
Team Size: 7-9 team members (vs. <7)	1.03 (0.03)	0.10	0.797
10-12 team members	1.08 (0.07)	0.11	0.456
>12 team members	0.98 (-0.02)	0.12	0.864
Age	1.00 (0.00)	0.01	0.559
Sex: Female (vs. Male)	1.09 (0.09)	0.07	0.155
Race/Ethnicity: Asian (vs. White)	**1.15 (0.14)**	**0.08**	**0.035**
Other	**1.26 (0.23)**	**0.14**	**0.03**
Credentials: NP/PA (vs. MD/DO)	1.02 (0.02)	0.11	0.864
Baseline Tenure at Kaiser	**0.99 (-0.01)**	**0.01**	**0.01**
Panel Size: 1000-1499 patients (vs. <1000)	0.978 (-0.022)	0.09	0.805
1500-1999 patients	0.91 (-0.1)	0.08	0.271
>2000	0.99 (-0.01)	0.09	0.905
Year: 2006 (vs. 2005)	**1.43 (0.36)**	**0.19**	**0.007**
2008	**1.69 (0.52)**	**0.22**	**<0.001**

Table 5. Results from fixed effects model with varying represented team count

Dropped Teams with Less Than 4 (n=408)	**IRR**	**Std. Err.**
Team Proportion Advanced Users:		
1-25% team members (vs. 0%)	**1.44**	**0.22**
>25-50% team members	**1.57**	**0.24**
>50% team members	1.38	0.32
Team Size: 7-9 team members (vs. <7)	0.94	0.27
10-12 team members	0.90	0.30
>12 team members	0.84	0.33
Year: 2006 (vs. 2005)	**1.55**	**0.29**
2008	**1.55**	**0.30**
Dropped Teams with Less Than 5 (n=346)	**IRR**	**Std. Err.**
Team Proportion Advanced Users:		
1-25% team members (vs. 0%)	**1.40**	**0.23**
>25-50% team members	**1.55**	**0.24**
>50% team members	1.24	0.29
Team Size: 7-9 team members (vs. <7)	0.46	0.26
10-12 team members	0.44	0.26
>12 team members	0.35	0.22
Year: **2006 (vs. 2005)**	**1.66**	**0.33**
2008	**1.62**	**0.32**
Dropped Teams with Less Than 6 (n=218)	**IRR**	**Std. Err.**
Team Proportion Advanced Users:		
1-25% team members (vs. 0%)	**1.47**	**0.30**
>25-50% team members	**1.51**	**0.33**
>50% team members	0.34	0.43
Team Size: 7-9 team members (vs. <7)	0.91	0.64
10-12 team members	0.71	0.55
>12 team members	0.46	0.40
Year: **2006 (vs. 2005)**	**1.50**	**0.36**
2008	**1.39**	**0.41**

Table 6. Results from fixed effects models including clinicians without access to EHR system

Team Effects (n=980)	IRR (Coef.)	Std. Err.	P-Value
Team Proportion Advanced Users:			
1-25% team members (vs. 0%)	**1.45 (0.37)**	**0.16**	**0.001**
>25-50% team members	**1.53 (0.43)**	**0.16**	**<0.001**
>50% team members	**1.54 (0.44)**	**0.27**	**0.015**
Team Size: 7-9 team members (vs. <7)	0.96 (-0.004)	0.15	0.826
10-12 team members	0.94 (-0.06)	0.21	0.774
>12 team members	1.04 (0.03)	0.27	0.895
EHR Status: Available (vs. Not Available)	**1.67 (0.51)**	**0.19**	**<0.001**
Year: 2006 (vs. 2005)	**1.39 (0.33)**	**0.14**	**0.001**
2008	**1.54 (0.43)**	**0.19**	**<0.001**
Team Effects with Lag (n=386)	**IRR (Coef.)**	**Std. Err.**	**P-Value**
Lagged Team Proportion Advanced Users:			
_>0-25% team members (vs. 0%)	**0.65 (-0.29)**	**0.12**	**0.021**
_>25-50% team members	0.74 (-0.06)	0.15	0.141
_>50% team members	0.87 (0.16)	0.29	0.679
Team Size: 7-9 team members (vs. <7)	1.08 (0.04)	0.27	0.742
10-12 team members	0.93 (-0.06)	0.35	0.853
>12 team members	0.91 (-0.15)	0.43	0.839
EHR Status: Available (vs. Not Available)	**2.35 (0.77)**	**0.45**	**<0.001**
Year: 2006 (vs. 2005)	**0.74 (-0.12)**	**0.14**	**0.124**

CHAPTER 3: GREATER TEAM COHESION DOES NOT TRANSLATE TO INCREASED PRIMARY CARE CLINICIAN USE OF ADVANCED ELECTRONIC HEALTH RECORD TOOLS

Abstract

Background: Studies conducted in the health care setting have left unanswered the question of whether clinician adoption of innovations is motivated by normative pressures and collaborative information-sharing, or instead individuals' passive exposure to peers using the innovation. This distinction in the underlying impetus for innovation adoption could inform the use of individual- or team-level strategies for behavior change among clinicians.
Purpose: This study seeks to better understand how teams may facilitate learning and engagement with advanced technologies by examining the synergistic effects of team cohesion on individual clinician use of advanced electronic health record (EHR) tools.
Methodology: Longitudinal analysis of three waves of clinician surveys (n=1,723; response rate= 57%) assessed advanced EHR tools and team cohesion. Mixed effects Poisson regression models were estimated to examine the interaction between the proportion of high users of advanced EHR tools and team cohesion, controlling for team size, baseline team tenure, and survey year.
Results: A higher proportion of team members using advanced EHR tools was significantly associated with a 1.33 times greater likelihood of individual advanced EHR tool use compared to clinicians on teams with a low proportion of advanced uses (p=0.038), but there was no significant direct or moderating effect of team cohesion on clinician adoption of advanced EHR tools.
Conclusion: Despite evidence that teams influence individual clinician's uptake of advanced tools, normative pressures or an internal desire to work as a cohesive team did not motivate individual clinician use of advanced EHR tools. Although team cohesion may not increase adoption of advanced technologies among team member, there may be opportunities for team interventions to stimulate advanced EHR use among clinicians by focusing on greater task interdependence and shared care.

Introduction

Despite continued funding and support for the adoption of electronic health records (EHRs), "meaningful use" of EHRs has been somewhat limited, with physicians, particularly those in smaller community-based practices, limiting their use of EHRs or not implementing the technology at all (Meigs & Solomon, 2016; Weeks, Keeney, Evans, Moore, & Conrad, 2015). Researchers have identified that the amount of time needed to properly document and find information in electronic health records is a major barrier to physicians' meaningful use of EHRs, and ultimately a main contributor to physician burnout (Adler-Milstein & Huckman, 2013; Bodenheimer & Sinsky, 2014).

A previous study (Hamity, 2017) found that clinicians' decisions to adopt technology in an integrated health care system were largely driven by peer influences, and individual clinicians were more likely to use advanced EHR tools to standardize care practices and improve care quality when a higher proportion of other members of their care team used advanced EHR tools. Team dynamics, rather than financial incentives alone, may facilitate use of technologies in the health care setting. This may be particularly true for integrated delivery systems in which incentives may be better aligned than many other care delivery models to encourage cooperation in order to improve care quality and efficiency (Enthoven, 2009; Shortell, Gillies, & Anderson, 1994). Understanding underlying clinician motivations will be beneficial, as policymakers and administrators alike devise strategies and incentives targeting individuals and teams to increase uptake of technologies for quality improvement in health care. The current study builds on prior research by clarifying the extent to which social cohesion and normative pressures to conform underlie previous findings that team member use of advanced EHR tools is associated with individual clinician use of advanced EHR tools (Burt, 1987; Coleman, Katz, & Menzel, 1966; Fligstein, 1985; Palmer, Jennings, & Zhou, 1993). Moreover, we explore the potential for team-level advanced EHR use and team cohesion to have synergistic effects on individual clinician use of advanced EHR use.

Theory

Everett Rogers' Model of Five Stages in the Innovation-Decision Process is widely used to understand the iterative phases through which individuals progress to determine whether or not to ultimately adopt, or make use of, an innovation (Berwick, 2003; Elwyn, Taubert, & Kowalczuk, 2007; Greer, 1977; Rogers, 2003). As Rogers notes, the Innovation-Decision process is "essentially an information-seeking and information processing activity" in which an individual attempts to efficiently reduce the uncertainty associated with the use and the consequences of implementing an innovation (Rogers, 2003). Rogers' model consists of 5 stages, from an individual's knowledge of an innovation to the individual's ultimate sustained use of, or abstention from, an innovation (Rogers, 2003). At each stage, the model accounts for the individual and social factors that influence an individual's ultimate decision about an innovation.

In health care settings, early literature on innovation adoption focused on individual physician influences on adoption, and did not account for the role of organizational factors because few physicians were practicing in formal organizations. Much of this early research identified the channels by which individual clinicians become aware of new innovations (Bauer & Wortzel, 1966; Rogers & Kincaid, 1981; Valente, 1996). In their often cited Medical Innovation study using prescribing data, Coleman, Katz, and Menzel advanced the notion that physicians' physical proximity to peers and exposure to pharmaceutical marketing influenced their likelihood to adopt new medication innovations (Coleman et al., 1966). The authors proposed that physicians in four cities passively obtained information about a new antibiotic, tetracycline, through advertising in medical journals, unsolicited discussions with pharmaceutical salespeople, and ostensibly from their geographically close colleagues. However, as the physicians gained more awareness of the medication, they began to more actively seek information, typically from their peers, to better understand the tetracycline's potential efficacy and ultimately determine whether to begin prescribing it to patients.

Previous work has not disentangled the effects of individual physician characteristics and preferences from social influence (Burt, 1987; Friedkin, 2010; Strang & Tuma, 1993; Valente, 1996; Van den Bulte & Lilien, 2001). Burt defines the construction of cohesion as the frequent and empathic communication among peers, to explain positive relationships, suggesting that both parties participate in an information exchange, allowing the potential adopter to "learn vicariously" from the early-adopting peer, or potentially succumb to normative pressures to follow the example of their peers (Westphal, Gulati, & Shortell, 1997).

Burt notes that, for individual relationships, group-level relationships may be a key differentiator in adoption behavior; however, the same adoption behavior can also result from competitively motivated by individuals' internal comparisons to their peers (Burt, 1987). Few empirical studies have sought to distinguish between opposing theoretical underpinnings in explaining individual uptake of innovations within organizations (cite stuff deleted). It is unclear how physician response to peers translates in the context of the current health care system, where team-based models of care have added more formal structure to clinical relationships. This study is designed to test whether individual and collective group perception of group cohesion further enhances team influence on individual clinician's adoption of technology. Specifically, this paper examines whether individual employee's perceptions of their team's cohesiveness moderates team-level influence on individual member’s adoption of advanced EHR functionalities.

Research Hypothesis

Group cohesion, and more specifically workgroup cohesion, has been an outcome in and of itself, and has also been examined for its effects on work group performance (Evans & Jarvis, 1980; Gully, Devine, & Whitney, 1995; Mullen & Copper, 1994). Using the same sample as the current study, Graetz et al. found that group cohesion moderated the effects of EHR use on care coordination, with more cohesive clinical teams reporting care coordination benefits after EHR implementation compared to less cohesive teams that reported no significant care coordination benefits (Graetz et al., 2014a). Still, there is limited research on team cohesion and individuals' adoptions of innovations. Researchers have hypothesized that the mechanisms by which group cohesion impacts group performance may be related to the group's ability to communicate and efficiently make decisions. Indeed, stronger cohesion among group members has been shown to be associated with better group communication and higher group performance efficiency (Back, 1951; Beal, Cohen, Burke, & McLendon, 2003). It follows that these purported benefits of group cohesion may assist in individuals' efficient progression through the stages of the Innovation-Decision process due to the same benefits cohesion has on group performance. Thus, I hypothesize that

H1: *team cohesion is positively associated with individual uptake of advanced EHR tools that would increase care quality and efficiency, thereby increasing team performance*.

In a previous study using a similar population(Hamity, 2017), I have shown that team members' uptake of advanced functionalities of an EHR is associated with individual group member's use. It follows that this relationship would be stronger among more cohesive teams, compared to less cohesive teams, as the opportunities for team influence on individual members are greater among team members who communicate well, share goals, and cooperate with each other. Thus, I also hypothesize that

> H2: *team cohesion moderates the relationship between team member advanced use of EHRs and individual use whereby the strength of the team member influences on use of advanced EHR features will be stronger in more cohesive teams compared to less cohesive teams.*

Methods

Study Setting and Data Sources. This sample represents primary care team members from across Kaiser Permanente Northern California's 17 medical centers. The KPNC primary care teams were created in 1998 and typically comprised of Internal Medicine and Family Medicine physicians, Nurse Practitioners, Behavioral Medicine Specialists, Physical Therapists, Clinical Health Educators and Medical Assistants

The study period, 2005 to 2008, encompasses the timeframe within which KPNC implemented its commercially available outpatient certified EHR, which allowed care team members to store and share patient information electronically by completely replacing the paper-based patient chart. In addition to standard EHR tools that made patient health and medical histories available electronically and allowed clinicians to order lab test and prescriptions online, clinicians also had the option of using more complex EHR tools that incorporated disease-specific order sets, standard note templates, and emailing with patients (Office of the National Coordinator for Health Information Technology, 2016; Rockswold & Finnell, 2010a). Once implemented in a medical center, all clinicians across KPNC used the same EHR systems and continued to receive standardized training before and throughout the study period.

Data Collection. The survey-based data for this study were collected in three waves of mailings of mailed self-administered questionnaires in 2005, 2006, and 2008. The research team mailed study invitation letters and surveys with pre-addressed, postage paid return envelopes to all KPNC primary care team members in 2005, before the start of the EHR implementation, again in 2006, and finally in 2008, after system-wide implementation of the EHR was completed. Non-responders received up to three follow-up study reminders surveys unless they contacted the research team to decline participation.

Measured Variables. Survey questions on EHR utilization elicited information about respondents' use each of the EHR system’s tools. Specifically, respondents indicated the percentage of office visits in which they used the available (both optional and mandatory) EHR tools, with the option to select one of six choices: none, 1-20, 21-40, 41-60, 61-80, 81-100 percent of visits. The research team also extracted administrative data on demographic information including age, gender, race/ethnicity, tenure with the organization, professional credentials, and primary care team designation for all primary care team members and linked this data to survey responses when applicable.

Dependent Variable: Individual Use of Advanced EHR Tools. The outcome variable for this study represents individual clinician's stated use of advanced tools within the EHR system. Advanced EHR tools are classified as typically more complex EHR functionalities that assist with standardizing care and improving patient access to information from their provider (Office of the National Coordinator for Health Information Technology, 2016; Rockswold & Finnell, 2010b). These tools were not required to complete necessary clinical tasks during early implementation of the new EHR system, but were often developed and maintained by care teams interested in improving care quality and practice efficiency. These tools include prescribing drugs using diagnosis-specific order sets (e.g., SmartSets), ordering labs using diagnosis-specific sets, using standard note templates, and sending to or receiving emails from patients. In the baseline year of the study, 2005, clinicians with access to the EHR in their medical center indicated that, on average, they used any of the four advanced tools during less than 21% of office visits. By the 2008 wave of the survey, clinicians reported that average use of each advanced tools during office visits had increased to between 41-60%.

Individual clinician use of each tool was dichotomized into advanced and non-advanced use. To be considered an advanced user of a particular advanced tool, the respondent must have indicated using the tool during more than 60% of office visits[1]. In the first year of the study, this represented the 90th percentile of EHR tool use for all 4 advanced tools. Dichotomized responses for each tool were summed, with the count outcome variable ranging from 0 to 4, with zero representing no advanced use of any advanced tool and 4 representing advanced use of all advanced tools considered in this analysis.

Independent Variable: Team Use of Advanced EHR Tools. The main explanatory variable of interest is the percentage of advanced users on a given team. For each wave of the survey, an aggregated team use variable indicates the proportion of team members who were users of all 4 advanced EHR tools during at least 61% of office visits. The proportion of advanced users per team, excluding an individual’s own values, was assigned to each individual within a given team, then made into a binary variable (less than 50% and 50% or more of team members).

Interaction Variable: Team Cohesion. The research team developed survey questions on team cohesion using published, validated instruments (Graetz et al., 2014b; Ohman-Strickland et al., 2007a). Respondents indicated the extent to which they agreed or disagreed with statements about their perceptions of team climate and attitudes towards their primary care team using a five-point Likert scale. Team cohesion questions included: 1.) “When there is conflict on this team, the people involved usually talk it out and resolve the problem successfully”; 2.) “Our team members have constructive work relationships”; "There is often tension among people on this team"; 3) " There is often tension among people on this team.” (reverse coded); and 4)"the team members operate as a real team." The overall Cohesion measure demonstrated high internal consistency with a Cronbach alpha coefficient of reliability of 0.80. For each team in the sample, an average team score was calculated by aggregating responses to all four cohesion questions across all members from the same primary care team. Following the variable construction of team cohesion scores were categorized into quartiles, and then dichotomized into lowest team cohesion vs. higher team cohesion with the lowest category representing teams in the bottom quartile (Graetz et al., 2014a).

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[1] Sensitivity analyses were conducted in Paper 1, and showed that using 60% or 80% to represent advanced EHR tool use did not alter study findings.

Covariates. Data on race/ethnicity, gender, organizational tenure, team tenure, team size and clinical training were captured and treated as co-variates in the analysis. Since previous research indicated (Hamity, 2017) that individual characteristics were not associated with individual use of advanced EHR tool, they were subsequently deleted from this final analysis while team size, team tenure, and survey year were included.

Statistical Analyses. Mixed effects Poisson regression models were used (xtmepoisson in Stata 13) to test tested whether the proportion of team members who are high users of advanced EHR tools is associated with individual team members' use of advanced EHR tools. An interaction term for the proportion of team members who are high users of advanced EHR tools and team cohesion (one model using individual reports of team cohesion and the other model using an aggregation of team member reports of cohesion) was included to allow for potentially different team influence effects by team cohesion. The models control for team size, baseline individual tenure on the team, and survey year, using unstructured covariance. All analyses were conducted in STATA version 13, and statistical significance was considered at the alpha level of $p<0.05$.

Results

Non-Response and Excluded Observations. The target population for this research includes all primary care clinicians practicing in KPNC. Among this population, response rates reached 50%, 61%, and 61% in 2005 (N=565), 2006 (N=678), and 2008 (N=625) respectively. Responses from 101 surveys were excluded from this analysis because the respondent switched teams between survey waves, and an additional 47 individuals, representing 24 teams across the 3 survey waves, were excluded because fewer than 3 team members responded to the survey in any given study wave, and their team scores could not be computed reliably. This resulted in representation from 84%, 93%, and 90% of KPNC's primary care teams in the respective 2005, 2006, and 2008 survey waves.

Respondent characteristics. Individual characteristics of primary care team member survey respondents (N=1723) and non-respondents (N=1439) from each survey wave are shown in Table 1. Overall, individuals' perceived team cohesion did not change substantially across survey waves, ranging from an average of 14.7 (S.D.= 2.55), in 2006, to 14.88, in the 2008 survey wave, and averaging a score of 14.80 across all survey waves. Respondents' self-reported use of advanced EHR tool increased with time, with only 1.7% of the sample indicating that they were using all 4 advanced EHR tools for 61% or more of office visits in 2005, to almost a quarter of the sample being comprised of advanced users by the end of the study period in 2008. Generally, respondents and non-respondents did not differ significantly by characteristics measured in this study, though respondents in the 2005 wave more likely to be female and non-physicians compared to non-respondents that survey year. Likewise, respondents in the 2006 and 2008 survey years were more likely to be younger and of white race than their non-responding counterparts.

Teams characteristics. Table 2 reports team-level characteristics. Reports of average cohesion at the team level ranged from 6 to 19 (S.D.=1.25). Represented team size remained somewhat stable over the 3 survey waves, averaging about 11.4 (S.D.= 5.17) members per team during the study period. As an aggregated measure of individual high use of advanced tools, the proportion of advanced user team members increased with time.

Team influence models. Table 3 and Table 4 report team Influence Models with respectively, Individual Cohesion and with Aggregated Cohesion. Confirming findings from

Hamity 2017, greater team member use of advanced EHR tools was significantly associated with greater individual member use of the advanced tools. Being on teams with a high proportion of users of advanced EHR tools was associated with between 1.33 (p=0.039) and 1.54 (p<0.001) times greater likelihood of advanced EHR tool use than individuals on teams comprised of less than 50% of high users of advanced EHR tools. However, there was no evidence that the strength of the relationship between team members' and individual use was stronger in more cohesive, compared to less cohesive teams. There was no significant direct or moderating effect of team cohesion when measured at the individual level (Table 3) or aggregated to a team measure (Table 4); thus the hypotheses that *team cohesion is associate with individual advanced EHR use and moderates the relationship between team member advanced use of EHRs and individual use whereby the strength of the relationship between the team member and individual use will be stronger in more cohesive than less cohesive teams* were not supported.

Discussion

In this longitudinal analysis of care team experiences of EHR use and team cohesion, I found significant team effects: individuals on teams with a higher proportion of advanced users were more likely to be high users of advanced EHR tools overtime. However, the relationship between individual clinician and team member use of advanced EHR tools did not vary by reports of team cohesion. Despite strong evidence of a team effect on individual members' use of advanced tools, there was no evidence that the "cohesiveness" of the primary care teams significantly altered the relationship. Self-reports of team cohesion do not necessarily identify the level of the amount of socialization needed to complete various tasks or the level of socialization outside of task completion, and the type of stakes involved. These results suggest that individual clinicians' use of advanced EHR tools appears not to have been affected by how constructive the relationships were among team members or how they handled conflict and tension. It remains unclear, however, whether the observed team influence is instead due to individuals' desire to “fit in” or be seen as credible by equal or higher status team members, which remains an area for further examination.

The study results should be considered in light of important limitations. First, the clinicians included in this sample had substantially higher team cohesion scores than reported in other populations, for example, by the 2008 survey year, 81 percent of teams had high cohesion scores (Graetz et al., 2014a; Ohman-Strickland et al., 2007b). The limited variation in cohesion scores across teams may have limited the power of this study to assess the independent and moderating effects of team cohesion. Second, although clinical performance outcomes were not assessed, there is some evidence that the cohesion-performance relationship is strongest among teams that, because of the interconnectedness of shared tasks, have substantial, regular social interactions (Castaño, Watts, & Tekleab, 2013; Chiocchio & Essiembre, 2009). Unfortunately due to data limitations, it was not possible to assess the level of task interconnectedness or interpersonal communication requirements across teams or individuals; thus, these findings may represent an underestimation of the team cohesion effect, given the lack of information about team member interactions and task interconnectedness. Our results, however, indicate that technical requirements and workflow, rather than cohesion, may support greater technology adoption.

Clarifying the extent to which team cohesion or technical aspects of work influence have a relatively greater influence the adoption of new health information technologies may inform the development of team interventions and policies to promote use of tools to foster care coordination and patient engagement. New studies should consider measuring team cohesion and social interaction concurrently to assess the level of interaction (and exposure to the cohesiveness of a team) members have with each other, and in populations with more variation in cohesiveness. Additionally, studies examining the role of cohesion in adoption of innovations should consider also operationalizing and measuring structural equivalence within a team in order to identify the motivating mechanisms for differing effects of team influence on individual use of technology. The information and knowledge that care team members collectively produce and manage as they provide care for shared patients may facilitate learning as they engage with technology in their everyday work. Team interventions to stimulate EHR use among clinicians may be most impactful when they focus on improving task interdependence and shared care rather than team cohesion or other interpersonal aspects of teamwork.

Table 1. Primary care team member characteristics by year and response status

	Respondents						Non-Respondents					
	2005 (N=519)		2006 (N=613)		2008 (N=591)		2005 (N=610)		2006 (N=425)		2008 (N=404)	
Age: 25-39	33%	(171)	35.4%	(217)	34.5%	(204)	30.3%	(199)	24.7%	(121)	24%	(105)
40-54	50.9%	(264)	49.1%	(301)	49.1%	(296)	50%	(328)	54.3%	(121)	54.3%	(248)
55+	16.2%	(84)	15.5%	(95)	15.4%	(91)	19.7%	(129)	21%	(103)	19.4%	(85)
Sex: Male	45.1%	(234)	46.7%	(286)	47.9%	(283)	56.3%	(369)	50.8%	(249)	52.1%	(228)
Race/Ethnicity: White	50.6%	(262)	44.7%	(274)	42.8%	(246)	47.4%	(311)	46.1%	(226)	34.8%	(151)
Asian	42.1%	(218)	48%	(294)	50.4%	(290)	41%	(269)	44.3%	(217)	51.4%	(223)
Other	7.3%	(38)	7.3%	(45)	6.8%	(39)	11.6%	(76)	9.6%	(47)	13.8%	(60)
Credentials: MD/DO	84%	(436)	88.3%	(541)	94.4%	(558)	92.8%	(609)	92.9%	(455)	95.7%	(419)
NP/PA	16%	(83)	11.8%	(72)	5.6%	(33)	7.2%	(47)	7.1%	(35)	4.3%	(19)
Tenure at KP: <5 Years	30.9%	(154)	36%	(244)	30.4%	(190)	28.4%	(129)	25%	(106)	23.8%	(96)
5-9 Years	30.3%	(151)	28.9%	(196)	33.8%	(211)	30.8%	(140)	31.4%	(133)	28.2%	(114)
10-14 Years	10%	(50)	7.4%	(50)	12%	(75)	10.6%	(48)	9%	(38)	19.1%	(77)
>=15 Years	28.9%	(144)	27.7%	(188)	23.8%	(149)	30.2%	(137)	34.7%	(147)	29%	(117)
Panel Size: <1000 Patients	21%	(109)	19.9%	(120)	14%	(65)	19.4%	(127)	16.3%	(79)	13.9%	(50)
1000-1499 patients	27.6%	(143)	24.7%	(149)	24.5%	(114)	21.8%	(143)	22.7%	(110)	20.3%	(73)
1500-1999 patients	27.9%	(145)	32.7%	(197)	31.3%	(146)	32.5%	(213)	38.6%	(187)	36.5%	(131)
>2000	23.5%	(122)	22.7%	(137)	30.3%	(141)	26.4%	(173)	22.5%	(109)	29.3%	(105)
EHR Status: Available	22.2%	(115)	65.9%	(404)	100%	(591)	19.4%	(127)	57.4%	(281)	100%	(438)
Advanced User of all Tools	1.7%	(9)	11.6%	(71)	24.2%	(143)	--		--		--	
Cohesion Score: Mean (SD)	14.8 (2.65)		14.7 (2.62)		14.88 (2.39)		--		--		--	

Table 2. Team Characteristics, by Year

	2005 (N=105)		2006 (N=104)		2008 (N=97)	
Team Size: <7 team members	8.5%	(9)	10.5%	(11)	10.3%	(10)
7-9 team members	29.2%	(31)	36.2%	(38)	37.1%	(36)
10-12 team members	30.2%	(32)	25.7%	(27)	27.8%	(27)
>12 team members	32.1%	(34)	27.6%	(29)	24.7%	(24)
EHR Status: Available	21.7%	(23)	65.7%	(69)	100%	(97)
Team Proportion Advanced Users: 0%	91.4%	(96)	51.9%	(54)	23.7%	(23)
>0-25% team members	5.7%	(6)	26.9%	(28)	29.9%	(29)
>25-50% team members	2.9%	(3)	18.3%	(19)	38.1%	(37)
>50% team members	0%	(0)	2.9%	(3)	8.2%	(8)
High Team Cohesion Score	69%	(73)	69%	(73)	81%	(79)

Table 3. Results from Team Influence Models with Individual Cohesion

Mixed Effects Poisson Regression (n=1631)	**IRR (Std. Err.)**	**P-Value**
High Proportion of Advanced Users (vs. Less than 50%)	**1.33 (0.18)**	**0.039**
High Average Team Cohesion Score (vs. Low)	1.11 (0.09)	0.215
High Team Cohesion and High Proportion of Advanced Users	1.15 (0.17)	0.324
Tenure on Team (vs. <1 year): 1-5 Years	1.15 (0.15)	0.300
More than 5 Years	1.18 (0.14)	0.150
Team Size: 7-9 team members (vs. <7)	0.99 (0.07)	0.923
10-12 team members	1.01 (0.09)	0.951
>12 team members	1.06 (0.10)	0.529
EHR Status: Not Available	**1.67 (0.14)**	**<0.001**
Year: 2006 (vs. 2005)	**1.57 (0.13)**	**<0.001**
2008	**1.86 (0.20)**	**<0.001**

Table 4. Results from Team Influence Model with Aggregated Cohesion

Mixed Effects Poisson Regression (n=1631)	**IRR (Std. Err.)**	**P-Value**
High Proportion of Advanced Users (vs. Less than 50%)	**1.59 (0.16)**	**<0.001**
High Average Team Cohesion Score (vs. Low)	1.01 (0.07)	0.854
High Team Cohesion and High Proportion of Advanced Users	0.92 (0.11)	0.444
Tenure on Team (vs. <1 year): 1-5 Years	1.19 (0.16)	0.180
More than 5 Years	1.23 (0.14)	0.079
Team Size: 7-9 team members (vs. <7)	0.96 (0.07)	0.565
10-12 team members	1.03 (0.09)	0.738
>12 team members	1.03 (0.10)	0.723
EHR Status: Not Available	**1.68 (0.14)**	**<0.001**
Year: 2006 (vs. 2005)	**1.58 (0.12)**	**<0.001**
2008	**1.84 (0.19)**	**<0.001**

CHAPTER 4: PATIENT ENGAGEMENT BY MEDICAL ONCOLOGISTS MAY MITIGATE DISPARITIES IN CANCER CLINICAL TRIAL ENROLLMENT

Abstract

Purpose: To identify factors associated with patients that enroll in cancer clinical trials and inform future recruitment processes by understanding barriers to clinical trial enrollment among racial and ethnic minorities.

Methods: Data for this study were collected using a cross-sectional survey of 905 patients eligible for breast, colorectal, lung, and prostate cancer clinical trials following their first medical oncology appointment within an integrated delivery system in Northern California. Associations between actual clinical trial enrollment and patient-reports of clinical trial knowledge, perceived barriers to trial enrollment, and the medical oncology visit care experience were examined. Logistic regression models estimated the relative risk ratio of enrollment into clinical trials by age, education and race/ethnicity.

Results: In bivariate analyses, younger participants enrolled in clinical trials at higher frequencies than older participants (the odds of enrollment for a respondent 70 years or old was 0.20 that of a respondent 18-49 years old, p=0.001). Respondents with a graduate degree were 4.1 times as likely to enroll in cancer clinical than respondents with a high school degree or less education. But no differences were observed by race/ethnicity. In models controlling for demographic characteristics and exposure to a clinical trial education intervention, patient discussions with the oncologist about trial participation, a strong oncologist explanation of clinical trials, oncologist encouragement to participate, and receiving multiple treatment options were independently associated with clinical trial enrollment rather than patient age and education

Conclusions: After accounting for patients' experiences of learning about clinical trials, socioeconomic and age disparities in clinical trial enrollment were no longer observed. Oncologist behavior, as well as patient knowledge of trials, jointly play important roles in patients' ultimate decision to enroll in cancer clinical trials, and both may be important mechanisms by which to reduce disparities in trial participation nationally. Oncologists play a critical role in patient enrollment decisions by increasing patient understanding and encouraging patients to participate.

Introduction

Clinical trials are the primary mechanism by which new approaches to cancer treatment are evaluated; yet, only a small proportion of eligible cancer patients are offered the opportunity to participate in clinical trials, and fewer actually become enrolled. Overall, it is estimated that only 2-3% of cancer patients are enrolled into trials nationally, and studies have continually shown that participation in clinical trials is particularly low among racial and ethnic minorities and patients over 65 years of age (Hutchins, Unger, Crowley, Coltman Jr, & Albain, 1999; Institute of Medicine, 1999; Kemeny et al., 2003; Murthy, Krumholz, & Gross, 2004; Sateren et al., 2002; Tejeda et al., 1996). Low enrollment results in more costly studies (and therefore more costly treatment) and slower progress in developing and disseminating effective treatments. Underrepresentation of various patient groups can limit the generalizability of trial results and limits opportunities for tailored therapies.

There have been numerous efforts to understand barriers to cancer trial enrollment; however, findings have been mixed. Particularly relevant to this research are strategies to overcome barriers to successful recruitment of eligible elderly and racial/ethnic minority patients into clinical trials. There is an established association between lack of awareness and reduced clinical trial participation (E. W. Ford, Menachemi, & Phillips, 2006; Lara Jr et al., 2005). Compared to White women, minority women have been shown to be less likely to know of someone who had participated in a clinical trial and are less likely to report that their oncologist talked to them about participating in a trial (Brown, Fouad, Basen-Engquist, & Tortolero-Luna, 2000; E. W. Ford et al., 2006; Rivers, August, Sehovic, Green, & Quinn, 2013; Wendler et al., 2005). Conversely, Millon-Underwood et al. found that, African Americans in their study did, in fact, know about clinical trials but were still less willing to participate in cancer clinical trials (Millon-Underwood, 1993). Conversely, in a review of the literature of 20 studies that reported consent rates by race/ethnicity that included over 70,000 individuals, Wendler et al., found small differences in consent rates among minorities compared to non-Hispanic Whites that contradict the view that racial ethnic minorities are less willing to participate in health research.

To that end, there has been substantial investigation to identify barriers to enrollment acceptance among elderly and racial/ethnic minority patients, with evidence that negative attitudes towards clinical trials, low levels of knowledge about trials, religious beliefs, patient perceptions of their physician's attitudes towards the trial, and structural barriers (such as transportation, childcare, and access to health care) each play a key role in willingness to enroll in trials, particularly among African Americans (J. G. Ford et al., 2008; Millon-Underwood, 1993; Mills et al., 2006). A 2006 systematic review of qualitative and quantitative studies conducted in the USA, UK, Canada, and Denmark found that the most common patient-reported barriers to trial enrollment centered around patient perceptions and attitudes, including general aversion to "being experimented on," discomfort with randomization, concerns about treatment side effects, perceived loss of decision-making control, and the belief that treatments in trials provide no clinical benefit (Mills et al., 2006). There is also evidence that mistrust of oncologists and the health care system in general may play a role in the underrepresentation of racial/ethnic minorities in cancer clinical trials (Ellington, Wahab, Sahami Martin, Field, & Mooney, 2006; Murthy et al., 2004).

While research on barriers to clinical trial enrollment has been abundant, there is concern that about the validity of available studies about barriers to cancer trial participation. Particularly, a 2007 systematic review of 56 studies of barriers to enrollment in cancer randomized control trials conducted in Europe, Australia, Canada, and the US (Fayter, McDaid, & Eastwood, 2007) found that represented studies often used indirect evidence by asking healthcare professionals why patients do not participate in trials. Some studies of patients also had limited external validity because barriers to trial enrollment were identified through hypothetical questions about trial participation rather than study participants' being asked to participate in an actual trial (Fayter et al., 2007).

Oncologists' attitudes toward trials that found that oncologists' attitudes and beliefs about clinical trials played a key role in their accrual of patients into trials (Somkin et al., 2013). We sought to also understand the attitudes, perceptions, and care experience factors associated with clinical trial enrollment among patients cared for by the previously studied oncologists in the same health care system. To inform future educational interventions and identify opportunities to improve standard recruitment procedures for clinical trial enrollment, this study was specifically designed to understand attitudes, perceptions, and care experience factors associated with patients that enroll in cancer clinical trials. We also sought to understand if these factors differed by race/ethnicity, serving as barriers to enrollment and potentially contributing to established racial and ethnic disparities in cancer clinical trial enrollment.

Methods

Study Setting and Sample. The study was conducted at Kaiser Permanente Northern California (KPNC), a large nonprofit, integrated health care delivery system that provides comprehensive medical care using bundled prospective payments for over four million members. KPNC's membership represents approximately 40% of the insured market in Northern California and an adult population that is comparable to the general adult insured population in Northern California with slightly higher levels of income and education (Gordon, 2012). At the time of this study, members received 99% of their cancer care within the KPNC system, compromised of 17 medical centers, over 40 clinics, and approximately 88 oncologists.

Data from this study were derived from a cluster randomized controlled trial to evaluate the effectiveness of a patient outreach and education intervention (consisting of patient invitation letter and brochure followed by tailored telephone counseling) compared to standard clinical trials recruitment procedures to increase enrollment in cancer clinical trials. The intervention study randomly assigned all KPNC 17 medical centers that provide cancer care services to either the intervention or usual care study arm. Patients who received their care at a facility randomized to the usual care group received that facility's usual clinical trials' recruitment procedures, and patients receiving their care at a facility randomized to the intervention group received the intervention in addition to that facility's usual recruitment procedures, which was not standardized across the broader organization.

This study's population represents all adult (aged >17 years) breast, colorectal, and lung cancer patients who received care from a medical oncologist practicing at one of the medical centers included in the cluster randomized study, and who were eligible for at least one of 8 breast cancer trials, 3 colorectal cancer trials, and 6 lung cancer trials. Patients were identified for clinical trial eligibility from September 2009 through December 2011, and were excluded from the study if they dis-enrolled from KPNC during the study's clinical trial enrollment follow-up period, which ended in March 2012.

In addition to meeting all trial eligibility criteria, to be eligible for the study a patient could not have had a prior oncology appointment in which treatment options were discussed. Other ineligibility criteria included language other than English or Spanish (all study documents were translated into Spanish) or other characteristics mentioned in the medical record, which would preclude the patient from participating in a clinical trial. The identification of potentially eligible patients was based on batch searching of automated data that was uploaded daily to the project database. Eligibility for each of the specific clinical trials and the research study was verified by staff research nurses who reviewed each patient's electronic medical record, evaluating any information that was not obtainable through automated data, to ensure that all criteria for entry into the study were met.

Study Design

From October 2009 to February 2012, the Kaiser research team mailed self-administered surveys, along with study invitation letters and pre-addressed, postage paid return envelopes, to eligible participants 3 weeks following their first medical oncology appointment. Non-responders received up to 3 follow-up study reminders and surveys, unless they contacted the research team to decline participation. Study patients were followed until the end of the study in February 2012 to identify those that eventually enrolled in a clinical trial. Clinical trial enrollment status for all study participants was ascertained by matching patients to an administrative dataset, maintained by Kaiser Permanente's department for Oncology Clinical Trials, which contains all clinical trial enrollment data. Administrative data on demographic information including age, gender, race/ethnicity were integrated into the analytic file.

This study was approved by the Kaiser Permanente Northern California Institutional Review Board.

Measures

Survey questions were designed to describe respondents' care experience, attitudes, and trial knowledge and were based on a wide review of the literature (Ellis, Butow, Tattersall, Dunn, & Houssami, 2001). Questions were developed by an iterative consensus process with input from clinicians, researchers, and experts in questionnaire development. The research team also convened a Patient Advisory Panel of 8 cancer patients from diverse racial/ethnic backgrounds, which participated in 2 meetings to help refine the recruitment materials and survey instrument. In collaboration with the Patient Advisory Panel, we pilot tested the survey with both cognitive interviews and semi-structured interviews. Pretesting and review of study materials helped to ensure sensitivity of the recruitment letter and verify the clarity and understanding of the questions.

The patient surveys included multi-item composite measures representing the following constructs: (1) medical oncology and treatment decision-making experience (k =14); (2) cancer clinical trial knowledge (k =6); (3) perceived value of trials (k =9); (4) barriers to clinical trial enrollment (k=9); and (5) sociodemographic characteristics.

Questions about the Medical Oncology and Treatment Decision-Making Experience (α=0.87) were developed to assess respondents' perceptions of provider and other care team members' behaviors and whether the care team met respondents' information and decision-making needs and expectations. These questions assessed whether respondents felt rushed during the appointment, whether the patient was offered more than one treatment option, who was involved in making the final treatment decision, the respondent's satisfaction with their treatment plan, and whether the care team discussed the possibility of joining a clinical trial, using a Likert scale ranging from "Disagree A lot" to "Agree A Lot."

Cancer Clinical Trial Knowledge questions (α=0.84) asked respondents to indicate how well they understood the terms Randomization, Voluntary Participation, Right to Withdraw, and Informed Consent on a 4-point scale ranging from "I've never heard of it" to "I understand it very well." To assess perceived value of clinical trial enrollment, respondents indicated the extent to which they agreed or disagreed with statements about personal and societal benefits (and detriments) of clinical trials using a five-point Likert scale. Sample statements that assessed the perceived value of clinical trials questions include: "I believe patients in a clinical trial get the latest cancer treatments" and "Clinical trials benefit researchers more than they benefit patients." Perceived Barriers to and Enablers of Clinical Trial Enrollment (α=0.89) were assessed using 4 reasons why patients may want to participate in a clinical trial and an additional 4 reasons why patients may not want to participate in a clinical trial. Respondents rated the importance of each reason on a 3-point scale from " Not important at all" to " Very important," with the option to indicate that they had no opinion about each stated reason.

Statistical Analyses

Chi-square tests were used to examine differences in patient responses by participant characteristics including age, gender, race/ethnicity, income level, and education level. In order to test whether attitudes, perceptions, care experience, or trial knowledge independently associated with clinical trial enrollment, 3 logistic regression models were estimated with a binary clinical trial enrollment outcome variable, and categorical predictor variables corresponding to responses about attitudes, perceptions, care experience, or trial knowledge. Each model also controlled for binary indictor for self-reported intervention exposure (exposed/not exposed), as well as demographic characteristics using categorical age (<50 years, 50-59, 60-69, and 70+), sex (male/female) race/ethnicity (White Non-Hispanic, Asian/Island Pacific, Black Non-Hispanic, Hispanic, or Other/Multiple), completed education level (No College, Vocational/Technical, College, Graduate school), and annual income level (<$15,000, $15,000 to $19,999, $20,000 to $39,999, $40,000 to $59,999, $60,000-$99,999, and $100,000+). All analyses were carried out using STATA 13 (StataCorp, College Station, TX).

Results

Table 1 compares respondent and non-respondent patient characteristics. Of the 1119 patients eligible to complete the survey, 905 (81%) agreed to participate and completed most or all of the survey. Among study participants, the average age was 58.4 years (SD=10.2), 88.5% (n=800) were female, 66% (n=598) were of White race, 45% (n=404) indicated having at least a college degree, and 56.5% (n=467) noted having an annual income above $60,000. Slightly over a quarter (29%) of the study sample had a phone conversation with the nurse educator as part of the educational intervention to increase clinical trial participation. Compared to non-responders, survey respondents were more likely to be female, of White race (66% of respondents vs. 56% of non-respondents, p=0.02) and were more likely to eventually enroll in a clinical trial (10.9% of respondents vs. 5.3% non-respondents, p=0.0054, for an overall clinical trial enrollment rate of 6.75 for the study population), there were no statistically significant differences in age between respondents and non-respondents.

We also conducted bivariate associations between cancer clinical trial enrollment and respondent medical oncology visit experience, treatment decision-making experience, cancer clinical trial knowledge, perceived value of trials, barriers to clinical trial enrollment and sociodemographic characteristics. Bivariate associations between clinical trial enrollment and respondent demographic characteristics are presented in Table 2. Like other studies, we observed differences in clinical trial enrollment and age, with younger participants enrolling at higher frequencies than older participants (for example, the odds of enrollment for a respondent 70 years or older was 0.21 that of a respondent 18-49 years old, p=0.001). There were also significant associations in education level and enrollment. Respondents with a graduate school degree were 4.52 times as likely to enroll in a clinical trial compared with respondents with no college education (p<0.001). However, unlike findings from other studies in different organizational settings, no statistical differences in trial enrollment were found by race/ethnicity.

As shown in Table 3, the survey domains of clinical trial knowledge and barriers to clinical trials had the greatest number significant associations with clinical trial enrollment in bivariate logistical regression modeling. Knowledge about clinical trials was positively associated with trial enrollment. For example, compared with respondents that indicated they had never heard of the term randomization, respondents that indicated that they understood the term “very well” were 13.07 as likely to enroll in a clinical trial (p<0.001). Conversely, respondents that indicated that attitudinal barriers to clinical trial enrollment were important reasons why patients may not participate in a clinical trial were less likely to enroll in clinical trials. For example, the odds of trial enrollment for a respondent who indicated that "because they want their doctor to choose their treatment, or they want to choose their treatment themselves" was a “very important reason” to not participate in a clinical trial compared to respondents indicating it was “not at all an important reason” (OR=0.32; p=0.001). We also found that clinical trial awareness and physician encouragement were positively associated with trial enrollment. Respondents whose oncologist encouraged them to participate were 9.55 times as likely to enroll in a clinical trial compared with respondents who didn't receive oncologist encouragement (p<0.001).

Table 4 reports results from multivariate analyses of clinical trial enrollment, trial knowledge and barriers to enrollment, controlling for respondent demographic characteristics and self-reported exposure to the educational intervention. In the clinical trial knowledge model, patient age is independently associated with clinical trial enrollment. Respondents over the age of 69 years are 0.29 times as likely to enrolled in clinical trials compared with respondents under the age of 50 years (p=0.02). However, education level is not consistently associated with trial enrollment. Of the 5 clinical trial knowledge questions, none were consistently associated with trial enrollment, after controlling for demographic characteristics and reported intervention exposure. Only understanding the term randomization "Very Well" was associated with trial enrollment, with respondents indicating that they understood the term very well 3.74 times as likely to enroll in clinical trials compared to respondents that had never heard of the term (p=0.03). Similarly, none of the barriers identified as significantly associated with trial enrollment in bivariate analyses remained significant after controlling for demographic characteristics and intervention exposure.

The final model, presented in Table 5, assesses the association between clinical trial enrollment and the medical oncology care experience. Discussions with the oncologist about trial participation, a strong oncologist explanation of clinical trials, oncologist encouragement to participate, and receiving multiple treatment options were independently associated with actual clinical trial enrollment, after controlling for patient characteristics and reported exposure to the educational intervention. For example, respondents who received oncologist encouragement were 2.85 times as likely to enroll in a clinical trial compared with respondents that did not recall receiving encouragement (p=0.002). Respondents reporting that their oncologist explained the possibility of participating in a clinical trial Very Well were 17.3 times as likely to participate in a clinical trial compared to respondents reporting receiving a poor explanation (p=0.006). The association between participant age and clinical trial enrollment no longer remained after accounting for discussions of clinical trials during the Medical Oncology Care Experience.

Discussion

Unlike national patterns of clinical trial enrollment, we did not find racial/ethnic disparities in trial participation among our population of cancer clinical trial-eligible patients in an integrated delivery setting. This divergent finding may due to KPNC's unique population, which is skewed toward higher education-levels with higher employment rates than the general U.S. population (Gordon, 2012). Still, in this sample, older patients in the study and patients with lower levels of education were underrepresented in clinical trials based on bivariate analyses. After accounting for the patient experience of learning about clinical trials, those demographic characteristics commonly associated with disparities in clinical trial enrollment (Brown et al., 2000; J. G. Ford et al., 2008; Millon-Underwood, 1993) attenuated. Specifically, after modeling patient demographic characteristics, exposure to a clinical trials education intervention, and care experience, only patient-reports of oncologist encouragement to participate, receiving more than one treatment option, and strong oncologist explanation of clinical trials were associated with actual trial enrollment. In additional bivariate analyses (not shown), we also did not find differences in patient-reports of oncologist encouragement by race/ethnicity. This suggests that uniform oncologist behavior in increasing patient awareness about clinical trials and trial enrollment encouragement may contribute to the lack of racial/ethnic disparities in trial enrollment within the organization. This uniform treatment of patients, regardless of their race/ethnicity may also help to explain why there were not noted racial/ethnic differences in mistrust of oncologists among patients in this study, contrary to previous studies that examined disparities in trial enrollment (Ellington, Wahab, Sahami Martin, Field, & Mooney, 2006; Murthy et al., 2004).

There is evidence that disparities in cancer care outcomes (Bach, Cramer, Warren, & Begg, 1999; Bach, Pham, Schrag, Tate, & Hargraves, 2004; Shavers & Brown, 2002) are significantly reduced when African American and White patients receive the same quality of care (Bach et al., 2002). These findings similarly suggest that disparities in trial enrollment may be mitigated when all patients receive similar information about trials and encouragement to enroll in clinical trials from their oncologist. Many studies have assessed interventions that target either patients (Jenkins, Fallowfield, & Cox, 2005) or oncologists (Mills et al., 2006). Given our findings, interventions should consider engaging both patients and oncologists more actively in the information-sharing process, and increasing oncologist willingness to encourage trial enrollment in order to improve rates of cancer clinical trial enrollment.

Table 1. Demographic Characteristics, Enrollment and Intervention Status by Survey Response Status

	Responders (N=905)	Non-Responders (N=214)	P-Value
Age, Mean (SD)*	58.4 (10.16)	59.4 (9.38)	0.201
Age group, N (%):≤49 years	180 (19.89)	42 (19.63)	0.312
50-59	293 (32.38)	50 (23.36)	
60-69	297 (32.82)	90 (42.06)	
≥70	135 (14.92)	32 (14.95)	
Sex: Male	105 (11.6)	44 (20.56)	**0.0005**
Female	800 (88.4)	170 (79.44)	
Race/Ethnicity: White	598 (66.08)	120 (56.07)	**0.02**
Asian/Pacific Islander	136 (15.03	36 (16.82)	
Black	79 (8.73)	31 (14.49)	
Hispanic	82 (9.06)	26 (12.15)	
Other/Multiple	10 (1.10)	1 (0.47)	
Education: No College	189 (21.07)	N/A	
Some College	304 (33.89)		
College degree	245 (27.47)		
Graduate school degree	154 (17.26)		
Annual Family Income: <$15,000	34 (4.08)	N/A	
$15,000 to $19,999	40 (4.80)		
$20,000 to $39,999	131 (15.71)		
$40,000 to $59,999	162 (19.42)		
$60,000 to $99,999	246 (29.50)		
$100,000 to $199,999	221 (26.50)		
Intervention Exposure: None	641 (70.83)	N/A	
Exposed	264 (29.17)		

Table 2. Bivariate Demographics and Clinical Trial Enrollment

CT Enrollment	**OR**	**Confidence Interval**	**P-Value**
Age (vs. ≤49 years): 50-59	0.58	(0.35, 0.98)	**0.043**
60-69	0.43	(0.25, 0.74)	**0.003**
≥70	0.21	(0.08, 0.51)	**0.001**
Sex (vs. Male): Female	0.95	(0.5, 1.8)	0.864
Race/Ethnicity (vs. White): Asian/Pacific Islander	0.79	(0.41, 1.51)	0.475
Black/African American	0.67	(0.28, 1.62)	0.377
Hispanic	0.83	(0.41, 1.68)	0.603
Other/Multiple	0.68	(0.26, 1.75)	0.42
Education (vs. No College): Some College	4.52	(1.99, 10.24)	**<0.001**
College degree	2.95	(1.25, 6.99)	**0.014**
Graduate school degree	4.11	(1.7, 9.94)	**0.002**
Annual Family Income (vs. <$15k): $15,000 to $19,999	0.54	(0.09, 3.46)	0.519
$20,000 to $39,999	0.95	(0.25, 3.6)	0.937
$40,000 to $59,999	0.75	(0.2, 2.86)	0.676
$60,000 to $99,999	1.44	(0.41, 4.98)	0.57
$100,000 to $199,999	2.08	(0.6, 7.16)	0.246
Intervention Exposure (vs. None): Exposed	1.52	(0.99,2.35)	0.058

Table 3. Significant Bivariate Clinical Trial Knowledge and Trial Enrollment

CT Enrollment	**OR**	**CI**	**P-Value**
How well do you understand the term: Randomization			
I've heard of it but don't know what it means (vs. I've never heard of it)	3.82	(1.07, 13.62)	**0.039**
I think I understand it	4.20	(1.56, 11.32)	**0.005**
I understand it very well	13.07	(5.18, 32.99)	**<0.001**
How well do you understand the term: Voluntary participation			
I've heard of it but don't know what it means (vs. I understand it very well)	0.14	(0.02, 1.02)	0.053
I think I understand it	0.34	(0.18, 0.65)	**0.001**
How well do you understand the term: Right to withdraw			
I've heard of it but don't know what it means (vs. I've never heard of it)	3.22	(3.22, 4.6)	0.413
I think I understand it	5.99	(5.99, 6.32)	**0.09**
I understand it very well	19.07	(19.07, 19.29)	**0.004**
How well do you understand the term: Informed consent			
I've heard of it but don't know what it means (vs. I understand it very well)	0.17	(0.02, 1.26)	0.083
I think I understand it	0.34	(0.18, 0.63)	**0.001**
In a clinical trial, my doctor would decide what treatment I would get			
Disagree somewhat (vs. Disagree a lot)	0.49	(0.26, 0.95)	**0.035**
Neither/Don't Know	0.12	(0.06, 0.23)	**<0.001**
Agree somewhat	0.25	(0.11, 0.54)	**<0.001**
Agree a lot	0.44	(0.22, 0.86)	**0.017**
Significant Bivariate Barriers to Participation and Trial Enrollment			
CT Enrollment	**OR**	**CI**	**P-Value**
Barriers: Because they want their doctor to choose their treatment, or they want to choose their treatment themselves			
Somewhat important (vs. Not important at all)	0.79	(0.4, 1.56)	0.495
Very important	0.32	(0.16, 0.64)	**0.001**
No Opinion	0.36	(0.16, 0.8)	**0.012**
Because they think they might receive treatment that has not been tested well enough			
Somewhat important (vs. Not important at all)	0.68	(0.32, 1.44)	0.311
Very important	0.47	(0.23, 0.97)	**0.041**
No Opinion	0.17	(0.06, 0.52)	**0.002**
Because they are worried that they might get a placebo or sugar pill rather than actual treatment			
Somewhat important (vs. Not important at all)	0.66	(0.36, 1.21)	0.179
Very important	0.42	(0.25, 0.71)	**0.001**
No Opinion	0.19	(0.08, 0.45)	**<0.001**

Table 3 (Continued). Significant Bivariate Clinical Trial Knowledge and Trial Enrollment

Significant Bivariate Access to Information and Trial Enrollment			
CT Enrollment	**OR**	**CI**	**P-Value**
How well oncologist explain the possibility of participating in a clinical trial?			
Poorly (vs. Not Well At All)	13.5	(1.18, 153.81)	**0.036**
Fairly well	21.6	(2.83, 164.8)	**0.003**
Very well	54.78	(7.56, 397.1)	**<0.001**
Significant Bivariate Shared Decision Making and Trial Enrollment			
CT Enrollment	**OR**	**CI**	**P-Value**
Did your oncologist give you more than one treatment option?			
Yes (vs. No)	3.68	(2.04, 6.62)	**<0.001**
Significant Bivariate Clinical Trial Awareness and Trial Enrollment			
CT Enrollment	**OR**	**CI**	**P-Value**
Did your oncologist encourage you to take part in a clinical trial?			
Yes (vs. No)	9.55	(5.61, 16.26)	**<0.001**
When you and your oncologist talked about your cancer treatment, did you talk about the possibility of joining a clinical trial?			
Yes (vs. No)	24.5	(7.69, 78.11)	**<0.001**

Table 4. Clinical Trial Enrollment Models

Logistic Regression Model with Robust Standard Errors (n=896)	**OR**	**CI**	**P-Value**
Age (vs. ≤49 years): 50-59	0.48	(0.27, 0.84)	**0.011**
60-69	0.42	(0.23, 0.78)	**0.006**
≥70	0.29	(0.1, 0.83)	**0.02**
Education (vs. No College): Some College	2.64	(1.04, 6.7)	**0.041**
College degree	1.2	(0.45, 3.18)	0.712
Graduate school degree	1.19	(0.43, 3.3)	0.734
Intervention Exposure (vs. None): Exposed	1.00	(0.63, 1.59)	0.993
How well do you understand the term: Randomization			
I've heard of it but don't know what it means (vs. I've never heard of it)	2.45	(0.6, 10.03)	0.213
I think I understand it	1.64	(0.52, 5.19)	0.403
I understand it very well	3.74	(1.14, 12.34)	**0.03**
How well do you understand the term: Voluntary participation			
I've heard of it but don't know what it means (vs. I understand it very well)	0.99	(0.13, 7.88)	0.996
I think I understand it	1.25	(0.46, 3.41)	0.656
How well do you understand the term: Right to withdraw			
I've heard of it but don't know what it means (vs. I've never heard of it)	0.44	(0.03, 5.82)	0.535
I think I understand it	0.41	(0.05, 3.11)	0.391
I understand it very well	0.63	(0.09, 4.44)	0.645
How well do you understand the term: Informed consent			
I've heard of it but don't know what it means (vs. I understand it very well)	0.42	(0.03, 5.48)	0.509
I think I understand it	0.79	(0.34, 1.85)	0.585
In a clinical trial, my doctor would decide what treatment I would get			
Disagree somewhat (vs. Agree a lot)	0.54	(0.26, 1.11)	0.095
Neither/Don't Know	0.25	(0.13, 0.5)	**<0.001**
Agree somewhat	0.41	(0.18, 0.93)	**0.033**
Agree a lot	0.63	(0.29, 1.36)	0.238

Table 4 Continued. Clinical Trial Enrollment Models

Logistic Regression Model with Robust Standard Errors (n=896)	**OR**	**CI**	**P-Value**
Age (vs. <49 years): 50-59	0.51	(0.29, 0.9)	**0.019**
60-69	0.41	(0.22, 0.73)	**0.003**
>70	0.19	(0.07, 0.54)	**0.002**
Education (vs. No College): Some College	3.6	(1.59, 8.18)	**0.002**
College degree	2.04	(0.85, 4.88)	0.11
Graduate school degree	2.22	(0.9, 5.51)	0.084
Intervention Exposure (vs. None): Exposed	1.4	(0.86, 2.28)	0.182
Barriers: Because they want their doctor to choose their treatment, or they want to choose their treatment themselves			
Somewhat important (vs. Not important at all)	0.91	(0.44, 1.89)	0.796
Very important	0.5	(0.24, 1.05)	0.067
No Opinion	0.84	(0.34, 2.07)	0.705
Because they think they might receive treatment that has not been tested well enough			
Somewhat important (vs. Not important at all)	0.56	(0.23, 1.37)	0.205
Very important	0.64	(0.25, 1.65)	0.358
No Opinion	0.31	(0.07, 1.42)	0.132
Because they are worried that they might get a placebo or sugar pill rather than actual treatment			
Somewhat important (vs. Not important at all)	0.66	(0.34, 1.29)	0.226
Very important	0.57	(0.31, 1.06)	0.074
No Opinion	0.32	(0.11, 0.99)	**0.047**

Table 5. Clinical Trial Enrollment and Care Experience Model

Logistic Regression Model with Robust Standard Errors (n=905)	**OR**	**CI**	**P-Value**
Age (vs. <49 years): 50-59	0.51	(0.25, 1.03)	0.062
60-69	0.51	(0.22, 1.17)	0.111
>70	0.36	(0.12, 1.07)	0.067
Education (vs. No College): Some College	2.1	(0.36, 12.34)	0.410
College degree	1.28	(0.2, 8.18)	0.794
Graduate school degree	2.19	(0.4, 11.92)	0.363
Intervention Exposure (vs. None): Exposed	0.82	(0.46, 1.45)	0.495
How well oncologist explain the possibility of participating in a clinical trial?			
Poorly (vs. Not Well At All)	9.58	(0.73, 126.49)	0.086
Fairly well	5.71	(0.64, 51.25)	0.119
Very well	17.3	(2.24, 133.42)	**0.006**
Did your oncologist encourage you to take part in a clinical trial?			
Yes (vs. No)	2.85	(1.46, 5.54)	**0.002**
Did your oncologist give you more than one treatment option?			
Yes (vs. No)	2.34	(1.13, 4.83)	**0.021**
When you and your oncologist talked about your cancer treatment, did you talk about the possibility of joining a clinical trial?			
Yes (vs. No)	1.56	(0.39, 6.26)	0.527

CHAPTER 5: CONCLUSIONS

Many disciplines, including organizational behavior, sociology, social psychology, and economics, have empirically assessed the communication channels (by many different names) that act as important pathways through which information and behaviors are spread among socially connected individuals. This research considered the individual characteristics and interpersonal mechanisms that influence clinician and patient knowledge and use of, as well as attitudes toward, innovations in the clinical setting.

The findings from an integrated delivery system suggest that interpersonal interactions contribute to individual clinician and patient eventual adoption of innovations. Specifically, over time, primary care clinician adoption of technological innovations was associated with their team members' use of the innovation. However, team cohesion, measured at the individual and aggregate group level, was not directly associated with individual adoption and did not moderate the relationship between team use and eventual individual use of the innovation. This suggests that deliberate information sharing and intentional group decision-making may not be the mechanisms by which individual clinicians ultimately choose to adopt innovations in the clinical setting. Instead, more passive interpersonal connections and observations may drive the transfer of knowledge and attitudes between clinical team members.

Because these findings did not find a specific means by which social influence encourages clinician adoption of innovations, initiatives that encourage the spread of innovations in the clinical setting may be most successful if they simply increase the likelihood of exposure to users of the innovation. This could potentially be achieved by co-locating innovation user and non-user team members without minimal additional efforts to spread information or enhance normative pressures to confirm to new practices of using the innovation.

Conversely, findings from patient survey responses point to the need for clinicians to more actively engage with their patients to effectively encourage innovation uptake. Findings in Chapter 4 suggest that medical oncologist behaviors, as well as patient understanding of clinical trials, play important roles in patients' ultimate decision to enroll in cancer clinical trials. Both patient education and patient experience may be important in reducing or eliminating racial/ethnic disparities in trial participation. Interventions that seek to only increase patient understanding and engagement in discussions about clinical trial enrollment with their oncologist may miss a key opportunity by overlooking the oncologists' influential role in patient enrollment decisions. Additional analyses to more directly measure oncologist behavior, rather than measure it through patient recall, is an important next step in better understanding the complex relationships between patient and oncologist attitudes and behavior, and to identify physician and system-level strategies to increase trial participation.

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