MODELING SECOND ORDER IMPACTS OF HEALTHCARE INNOVATION

A Dissertation

by

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ABSTRACT

Any single health service organization today is likely engaged in dozens of concurrent, often times unrelated change initiatives. Each of these change initiatives is likely supported by evidence that demonstrates the innovation's intended, first order impact. However, very little attention has been paid to the unintended, second order impacts of innovation. In this dissertation we introduce a model to provide a framework for inquiring about this very type of non-immediate impact. Next, using three innovations currently being implemented in the healthcare industry—training primary care residents to perform in-office colonoscopies, Studer Group's 'Evidence Based Leadership,' and implementation of electronic health records in a hospital-integrated pediatric network—we model the innovations' second order impacts within the context of our second order impact conceptual model. Cost effectiveness analysis, multiple analysis of variance (MANOVA), and two-level fixed effects modeling are used to across the three interventions. Results from the primary care residency intervention support further investment in colorectal cancer screening training for primary care residents. Results from the Studer Group's 'Evidence Based Leadership' intervention demonstrate mixed results across change interventions and across categories of tenure, suggesting receptivity towards change and organization tenure is highly dependent upon the nuances of a specific change intervention. Finally, results from the implementation of the electronic health record demonstrate improved charge capture.

We conclude that this further probing of popular innovations in the industry is warranted for multiple reasons. For one, it is entirely possible that social scientists and economists are prematurely ‘moving on’ to other innovations as soon they have published results from an initial round of inquiry. However, as we will demonstrate in our model, it is conceivable that after the “lights have dimmed” on an innovation’s initial glow, the artifacts of the innovation could very well continue to disrupt structures and processes long after its implementation. If these latent disruptions adversely affect the organization, one could argue that any initial positive impacts were likely overstated. Conversely, if these latent disruptions go on to produce additional benefit to the organization one could argue that any initial positive results were actually understated.

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CHAPTER I

INTRODUCTION: EXPLORING SECOND ORDER IMPACTS OF INNOVATION

Introduction

The issue of uncertainty is a significant barrier in the adoption of innovation. It is known that change recipients are more likely to adopt an innovative process when uncertainty is mitigated (Rogers, 2010). Knowledge of an innovation's impact is critical for ensuring its adoption, diffusion, and long-term sustainability. Empirically demonstrating the benefits of an innovation is the key driver behind the evidence-based management movement (Walshe & Rundall, 2001). While innovation research is a longstanding field—a 1943 study on hybrid corn farming serves as the field's *opus primus*—an overwhelming majority of the research has focused on the immediate and beneficial impacts of innovation. By one account, only 26 out of 26,300 innovation articles covered the *un*desirable consequences of innovation (Sveiby, Gripenberg, Segercrantz, Eriksson, & Aminoff, 2009). This "pro-innovation bias" has been traced back to the core belief that "innovation is good"—a belief that is self-servingly hawked by innovation financiers, change agents, government leaders, and even innovation researchers themselves. As such, experts in the field have called for more rigorous, objective evaluation of the impacts of innovation by investigating "the broader context in which an innovation diffuses" (Rogers, 2010, p. 98).

From the evidence-based management perspective, the strongest of innovations ought to be able to withstand not just the empirical prodding of their immediate, first order impacts (a requisite for meeting the definition of "evidence-based") but also their second order impacts, defined here as the indirect, unintended effects of an innovation. This dissertation aims to do just that. The goal of this study is to identify and explore the relationships between innovations in health care delivery and their *second* order impacts. Specifically, this study will investigate three current innovations in the healthcare industry. However, rather than focus only on their primary, first order impacts—something that is already well-documented in social science and economic literature—we will instead focus explicitly on the *second* order impacts of these innovations. Using a new bricolage conceptual model laid out here in Chapter 1, we will produce a taxonomy of second order impacts that will intertwine concepts from innovation diffusion theory and evidence-based management. Results from each of our three second order evaluations will either:

A) reveal beneficial, unintended, and anticipated consequences—envisaged windfall—for the innovation that were not previously measured or even considered in its demonstrations of first order impact;
B) reveal beneficial, unintended, and unanticipated consequences—naïve windfall—for the innovation that were not previously measured or even considered in its demonstrations of first order impact;
C) reveal non-beneficial, unintended, but anticipated consequences—sub-optimality—that should be carefully monitored and, when possible, mitigated by change agents, or;

D) reveal non-beneficial, unintended, and unanticipated consequences—counter-finality—that can now be considered in future implementations of the innovation.

Why are Second Order Impacts Important?

This is a timely study given the rapidly changing landscape of the US healthcare industry. Federal healthcare reform, an increasingly sick, aging population, and an evolving healthcare workforce has created an environment of continuous change for healthcare organizations. Both payers and patients are calling upon providers to improve the ways in which they deliver care while simultaneously reducing costs. As a result of these demands, any single health service organization today is likely engaged in dozens of concurrent, often times unrelated change initiatives (Bita A. Kash, Aaron Spaulding, Larry Gamm, & Christopher E. Johnson, 2013; A. Spaulding, Gamm, Kim, & Menser, 2014). Each of these change initiatives is likely supported by evidence that demonstrates the innovation's intended first order impact. Thus, electronic health records (the innovation) are being widely implemented to improve care coordination, error reduction, and clinical decision support (the first order impacts). Similarly, primary care physicians are now being trained to perform complex procedures, such as colonoscopy, in their own offices (the innovation) in order to improve patient access and adherence (the first order impact). Finally, cultural change initiatives such as Studer Group's 'Evidence Based Leadership' (the innovation) are being widely adopted by acute care hospitals in an effort to improve patient satisfaction scores and organizational accountability (the first order impact). However, like most innovation research, little if any attention has been paid to these three innovations' *second* order impacts (Sveiby et al., 2009). The model we introduce in the following section provides a framework for inquiring about this very type of non-immediate impact.

We contend that this further probing of popular innovations in the industry is warranted for multiple reasons. For one, it is entirely possible that social scientists and economists are prematurely 'moving on' to other innovations as soon they have published results from an initial round of inquiry. However, as we will demonstrate in our model, it is conceivable that after the "lights have dimmed" on an innovation's initial glow, the artifacts of the innovation could very well continue to disrupt structures and processes long after its implementation. If these latent disruptions adversely affect the organization, one could argue that any initial positive impacts were likely overstated. Conversely, if these latent disruptions go on to produce additional benefit to the organization one could argue that any initial positive results were actually understated. Examples of the latter have been documented by Zahra and George (2002) who demonstrate how organizations can exploit an innovation to produce subsequent, dynamic organizational capability.

Yet another justification for additional probing of popular innovations is to better understand why so many innovations fail to "catch on" among certain individuals, organizations, or the industry as a whole *despite* their positive first order impacts. A plausible hypothesis is that innovation designers and researchers get too caught up in the beneficial first order impacts and fail to account for the innovation's unintended fallout on individuals or economics. Such oversight can result in the failed detection and management of oppositional forces to the innovation. If these forces wield sufficient social, administrative, or financial capital, this otherwise positive innovation will likely end up discarded by the organization or the industry altogether as just another failed "flavor of the month".

Our final argument in favor of second order probing of popular innovations is to grow the knowledge base for each innovation. We began this chapter discussing how uncertainty is a significant barrier in the adoption of innovation. We argue that the more molecular our understanding for any single innovation, the more uncertainty we remove for change agents. Just as physicians are well-documented in their tenacity of asking, "Where's the evidence?" (Guyatt et al., 1992), so too should change agents be skeptical as they go about identifying and selecting innovations. As Sveiby and colleagues (2009) demonstrated, it is often easy to find straightforward, positive associations between an innovation and its first order impact. But astute managers and change agents must look beyond the here and now. In keeping with our physician metaphor, we do not consider it a triumph when: "The operation was wildly successful. Shame the patient died." We contend that inquiry of second order impacts extends the evaluation horizon for each innovation and, as a result, keeps us from solely focusing on the operation and to instead be mindful of both the operation and the patient.

Classification

Rogers (2010) introduced three dichotomies for the consequences of innovation: desirable versus undesirable, direct versus indirect, and anticipated versus unanticipated.

The first dichotomy is rather simplistic. The desirability of an innovation's outcome is determined at the outset by the change agent. It is important to specify perspective when discussing innovation. Only the change agent, whether that is an individual, group, or institution, serves as judge in determining whether or not an innovation's impact is beneficial. For example, an innovation might very well result in detrimental first order impacts to people, processes, or the environment, yet still be viewed as 'beneficial' from the perspective of the change agent. As mentioned earlier, over 99 percent of all innovation studies have focused on *desirable* outcomes related to innovation.

Rogers' second dichotomy, directness, is determined by whether or not an innovation's impact is causal and exclusive—a direct impact—or is instead the result of the "interplay between the action and the objective situation" and is not necessarily exclusive to the innovation—an indirect impact (Robert K. Merton, 1936, p. 895; Sveiby et al., 2009). Diffusion theory scholars amend this dichotomy with the concept of *intent.* They argue that knowing the intent of the change agent represents a more parsimonious measure for categorizing and understanding indirect consequences. For example, a manager might intend to improve workplace morale by offering a more comprehensive health insurance plan to employees. However, a number of intermediate cause-and-effect sequences must take place first before we would expect to see an impact on workplace morale (i.e., employees must first take advantage of the new health plan by seeking out preventive care, which would lead to fewer sick days, which would improve office efficiency, which might finally lead to a boost in office morale). Although the improvement in morale in this case fulfilled the original intent of the office manager, it was rather indirect. Thus, for the purposes of this study we combine the two measures by defining our variable of interest—second order impact—as the unintended, indirect impact of an innovation. So, in the example above, we would not consider improved office morale to be a second order impact of the enhanced health plan as it was a fulfillment of the manager's original intent.

Rogers' third dichotomy, anticipation, refers to the knowledge or awareness of a likely particular consequence by the change agent a priori. It is important to note here that an unintended consequence is distinctly different from an unanticipated consequence. The change agent establishes the intent of an innovation. That intent is either fulfilled or frustrated in the end. However, the means taken to realize that end can be either anticipated or unanticipated. For example, if the original intent of an innovation is fulfilled, that impact could have occurred via anticipated or unanticipated means. Baert (1991) provides the following illustration, albeit rather macabre: Person A intends to kill Person B by poison. On the way to Person B's house to conduct said poisoning, Person A accidentally runs over Person B in their driveway, killing them instantly. In this case, the intent of murder was fulfilled, but the method was unanticipated. This example demonstrates that unanticipated consequences occur when, at the time of intent, the change agent is either: A) unaware of the possibility, or B) aware of the possibility but incorrect in their prediction.

Using these three dichotomies, we now create a classification of second order impacts. Figure 1 illustrates the positioning of second order impacts in relation to the original innovation. The model begins by welcoming the evidence of first order impacts provided by the extant body of research on any single innovation. In this brave new world of evidence-based management, we would expect most popular organizational innovations in healthcare to have been vetted by practitioners, clinical scientists, and (we can hope) social scientists alike. The results from these studies would place them in one of the first four categories of first order impact. One would assume that any innovation whose impact falls into either of the bottom two categories of undesirability would not be widely diffused and its shelf-life to be short-lived. However, as the model indicates these undesirable innovations possess second order impacts nonetheless; we simply are not interested in pursuing further research on an ill-fated innovation.

Innovations whose primary impacts fall into the top two categories are, by definition, desirable. The only difference between the two is that initial research on an innovation can often demonstrate positive impacts, though the means by which the innovation attained its end were different from what was initially expected by the change agent. Edward Jenner's initial discovery of the smallpox vaccine occurred unexpectedly by infecting a small child with cowpox (Meynell, 1995). This initial 'evidence' would have fallen into the second category of first order impacts: the outcome was desirable, the intent was fulfilled, but Jenner had not anticipated the means. We should note however, that after Jenner's initial discovery and pronouncement, all subsequent research on cowpox as a smallpox prophylactic conducted by researchers who were aware of Jenner's findings would fall into the *first* category of first order impacts since the effects of cowpox on smallpox were now known *and* anticipated.

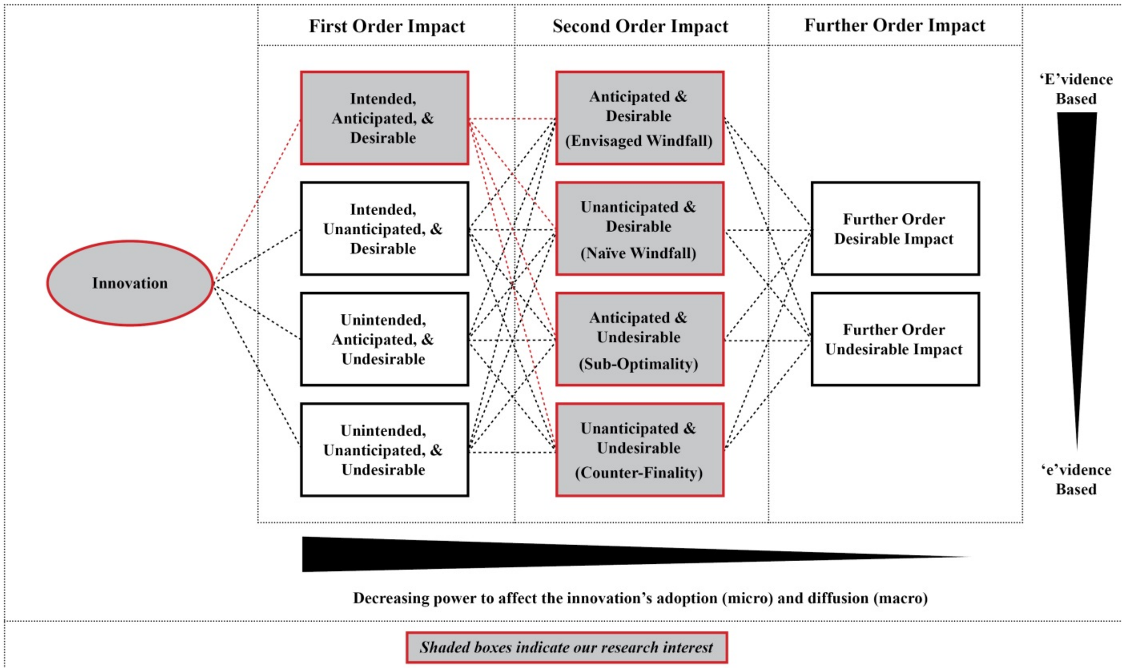

Figure 1: Second order impacts in relation to innovation. Adapted from Baert (1991), Rogers (2010), and Sveiby et al. (2009)

As indicated in the shaded boxes, this study is principally interested in the top category of first order impacts—that is, innovations with impacts that are intended, anticipated, and desirable. As highlighted earlier, over 99.9 percent of innovation research has been conducted within this category (Sveiby et al., 2009).

The second column in the model represents the focus of this study. This column answers the question, "What about the unintended, non-immediate impacts of these well-studied, intended, anticipated, and desirable innovations?" To answer this question we continue with two of Rogers' three dichotomies discussed earlier: desirability and anticipation. We now leave behind the dichotomy of *intent* as we are now only interested in impacts that were *un*intended at the time of innovation selection. Any outcomes that result from an innovation that *were* part of the original intent, by definition, are first order impacts.

Second order impacts are classified as being either desirable or undesirable. We further bifurcate this classification by contending that an outcome's desirability (or undesirability) can be either anticipated or unanticipated. We begin from the bottom of the four categories of second order impacts (see Figure 1). An innovation that initially produces intended, desirable, and anticipated impact can also result in unintended impacts that are undesirable and are unanticipated. In sociological literature this second order impact is referred to as counter-finality (Sartre, 2004). Examples of counter-finality abound in healthcare. The overuse of antibiotics provides a fine example. Social pressure from parents has been shown to induce primary care physicians into recklessly prescribing antibiotics for children with nonspecific upper respiratory tract infections (Barden, Dowell, Schwartz, & Lackey, 1998). We now know that this practice has led to the development of antibiotic-resistant pneumococci. However, at least for the prescribing physicians who were unaware of this possibility, the end result—patients with antibiotic-resistant pneumococci—was unintended, undesirable, and unanticipated. The original intent of having a healthy patient was countered by the physician's own actions.

Moving up to the next category of second order impacts, we find unintended impacts that are undesirable but were anticipated by the change agent. In sociological literature this second order impact is referred to as sub-optimality. Going back to our antibiotic example, not all of the physicians who recklessly prescribed were unaware of the implications for over-prescribing antibiotics. However, these physicians wrote prescriptions nonetheless. (Perhaps the physician was fearful of receiving a bad online review from an angry parent who just paid a $45 copay to be told their child only needs rest and hydration. After all, the rival physicians across the street would undoubtedly offer the prescription just to pacify the parent and capture a new patient.) The outcome for this case is sub-optimal: an action is carried out by the physician knowing that said action will likely have an unintended and undesirable consequence, but goes through with the prescription regardless.

Continuing upwards in the column, we find unintended impacts that are desirable but were not anticipated by the change agent. We term this category of second order impacts “naïve windfall” as the change agent was unaware of the possibility of this impact, but benefits from it nonetheless. The discovery of quinine—the anti-malarial drug that has now been used for centuries—is a health-related example of naïve windfall. A South American Indian infected with malaria was suffering from one of the disease’s common symptoms—unbearable thirst. Unable to walk to his typical source of drinking water, the Indian drank from a puddle of bitter water at the base of a cinchona tree (at that time the only known use of cinchona by the natives was as a poison). After the Indian’s fever abated, natives began harvesting cinchona and later introduced the medicine to Jesuit missionaries in 1630 (Achan et al., 2011). Though the original intent of the Indian was simply to quench his malaria-induced thirst, he unexpectedly also discovered the cure to his disease.

We have now arrived at the fourth and final category of second order impacts—those that are desirable and could have been anticipated by the change agent. We term this category of second order impacts “envisaged windfall” as the change agent was aware of the possibility of this desirable impact, but it was not a part of the original intent. If a hospital were to successfully treat a sick, but very wealthy patient and later acquire a large charitable donation from that same patient, no hospital foundation leader would ever claim fulfillment of original intent. The charitable donation in this case would be an envisaged windfall. The physicians and nurses healed the patient; fulfilling the hospital’s intent. However, a hospital foundation leader could anticipate that a wealthy patient who receives exceptional service during their stay might also donate funds for a new hospital wing.

We now transition away from the taxonomy component of the model and introduce the horizontally oriented diffusion/adoption axis and the vertically oriented “E”vidence-based management axis. (We use the terms “diffusion” and “adoption” synchronously here as the model can be applied at the individual level—beckoning the term “adoption”—or at the organizational level—beckoning the term “diffusion”. Thus, we concur with Rogers (2010) and other innovation scholars that the adoption of an innovation at the individual level is nested in that same innovation’s subsequent diffusion across groups, organizations, networks, and society (Kamakura & Balasubramanian, 1988; Robertson & Gatignon, 1986; Valente, 1993).) The basis for the diffusion/adoption axis is built upon Rogers’ (2010) diffusion moderator—observability—and the concept of innovation latency. Observability denotes the ease in which an innovation's impact is observed or felt by change agents and change recipients. An innovation with higher observability will diffuse more quickly through a network than an otherwise identical innovation with lower observability (Rogers, 2010). Meanwhile, latency denotes the amount of time required for an innovation to yield an observable impact. An innovation with lower latency will diffuse more quickly through a network than an otherwise identical innovation with higher latency (Hivner, Hopkins, & Hopkins, 2003).

Innovations in maternal health promotion provide a robust example of these two moderating factors at work. Maternal health innovations typically involve low observability as a result of the opacity of the relationship between maternal nutrition and fetal development. Aside from ultrasound, which is infrequent in developed countries and rarely accessible (if at all) in developing countries, mothers are not able to directly observe fetal development. As a result, health promoters must aggressively promote maternal health innovations through abstract educational processes about the importance of nutrition and other environmental factors on fetal development. This process requires significant financial and human capital that, in turn, impedes the adoption and diffusion of the innovation.

Similarly, maternal health innovations suffer from an extended latency relative to other health innovations. For example, a mother might wait up to ninth months to observe any birthing-related impacts stemming from a maternal health innovation, such as with docosahexaenoic acid supplementation during pregnancy and increased birth size (Ramakrishnan et al., 2010)). This latency is even higher when we consider maternal health innovations that target cognitive and physical health improvements in term infants and children, such as with docosahexaenoic acid supplementation during pregnancy and augmented IQ in children at four years of age (Helland, Smith, Saarem, Saugstad, & Drevon, 2003). With these two moderators combined it would be expected for innovations in maternal development, particularly in developing countries, to diffuse slower than other health-related innovations. For example, a sanitation or water purification project would exhibit higher observability (i.e., change recipients can physically see improved sanitary conditions in their schools, houses, or water supply) and lower latency (i.e., change recipients experience lower incidence rates of gastrointestinal disease within days of the intervention).

With these definitions in place, we contend that second order impacts of innovation typically exhibit lower observability, higher latency, or a combination of both when compared to their first order brethren. Lower observability here can emerge as a result of the innovation affecting an audience or object separate from the intended group of change recipients and thus, be less visible to the change agent(s). This can be the result from "tunnel vision" (where the change agents are only focused on the innovation's intended, immediate impacts), outright naiveté (where the change agent is simply unaware of second order impacts) or neglect (where the change agents are aware of second order impacts, but does consider them to be of significant concern). Second order impacts can also suffer from relatively lower observability due to basic attenuation in the innovation's impact as it is diffused across an organization or society. For example, innovations in the technology industry are typically met with fanfare from the media and public alike as early adopters and early majority adopters accept the innovation into their lives. However, less attention is paid to that same innovation later as the late majority and the laggards eventually adopt the technology. Although second order impacts do not always exhibit low observability, we would expect them to often exhibit low*er* observability than first order impacts given that a change agent had not intended them and, conceivably, was not looking for them.

Meanwhile, higher latency is typically associated with second order impacts as a result of the innovation's first order impacts needing to be absorbed first by an organization before subsequent behaviors and institutional changes begin to emerge in response to the initial innovation. Referring to our earlier discussion of the discovery of quinine, the unintended, unanticipated impact of the cinchona tree only occurred after the intended impact—the quenching of thirst—had been realized. Although second order impacts do not always exhibit high latency, we would expect them to often exhibit high*er* latency than first order impacts given the probable sequencing of an innovation's cause-and-effect relationship.

Using these two characteristics of second order impacts—observability and latency—we contend that second order impacts of an innovation contribute to the adoption or rejection of the innovation, albeit with relatively less influence than first order impacts. This component of the model allows us to connect back to the four categories of second order impact. When a second order impact of an innovation is detected and falls into the category of envisaged windfall, this outcome serves as positive feedback to the innovation's diffusion and supplements the positive feedback already being generated from its beneficial first order impact. Similarly, when a second order impact is detected and classified as naïve windfall, this also serves as positive, supplemental feedback to the innovation's continued adoption diffusion. Recall that the power of the feedback being provided by second order impacts here is of a lesser magnitude than the power of feedback from first order impacts. The degree of loss here is a function of the second order impact's observability and latency. Second order impacts with high observability and low latency would wield stronger supplemental feedback than second order impacts with low observability and high latency. Regardless, as long as a second order impact falls into one of these first two categories of desirability, support for the innovation's diffusion will be augmented.

Conversely, when a second order impact is detected and falls into one of the undesirable categories—sub-optimality or counter-finality—the impact serves as negative feedback to the innovation's diffusion and counteracts the positive feedback being generated from its desirable first order impact. The power of the second order impact here is very important. As discussed above, second order impacts with high observability and low latency possess more power to affect the innovation's diffusion. One can imagine instances where a second order impact with high observability and low latency could potentially disrupt and even terminate the diffusion of an innovation, in spite of the innovation's acclaimed first order impacts. A public health example of this counteraction is common with oral contraception use in developing countries, where the first order impact—effective family planning and reduced adolescent pregnancy—is counteracted by a second order impact—an increased fear by male partners and parents that this contraceptive method would promote promiscuity (Konje & Ladipo, 1999; Schoen, 2005). Alternately, if the second order impact is undesirable but exhibits low power (from low observability, high latency, or a combination of both), we would expect for it to produce negative feedback for the innovation's diffusion, but not enough to necessarily supersede the positive feedback from its desirable first order impact. In these cases, the second order impact will not reverse the innovation's diffusion, but may serve to diminish its rate of diffusion. An example of this undesirable-but-low-power second order impact can be illustrated again through our earlier example of poor antibiotic stewardship. Here the physician is aware of the undesirable second order impact, but that impact is not strong enough to counteract the physician's behavior. Specifically, the positive feedback produced from retaining the patient (a desirable first order impact) is greater than the negative feedback produced by contributing to the population's development antibiotic-resistant diseases (an undesirable second order impact). Perhaps not surprisingly, this undesirable second order impact exhibits both characteristics for an undesirable-but-low-power second order impact: low observability (not many patients will necessarily contract antibiotic-resistant pneumococci compared to other infectious diseases) and high latency (it might be years or decades (if ever) before the reckless physician's patient contracts antibiotic-resistant pneumococci).

The overuse of antibiotics example also provides us with a good illustration of the fluidity of the affect power of second order impacts. For example, if one were to improve the observability and reduce the latency of a second order impact, the subsequent increase in affect power could eventually reach a tipping point where the second order impact would counteract positive feedback from a first order impact. Public health experts and policymakers have begun efforts to increase the observability of antibiotic-resistant diseases through public awareness campaigns (Isaacs & Andresen, 2013), educational interventions (Paphitou, 2013), stricter laws for the dispensing of antibiotics (Fox, 2011), and improved clinical decision support systems (Rattinger et al., 2012). In the same vein, recent increases in the pervasiveness of antibiotic resistance (English & Gaur, 2010) is decreasing the latency for this undesirable second order impact. Although bad for society, this lower latency should increase the affect power of this undesirable second order impact. Given this combination of improved observability and lower latency, as our model would predict, we should perhaps not be surprised that we are beginning to see improvements in physicians' prescribing behaviors (Davey et al., 2013).

Finally, we transition to the last component of our model—the vertically oriented evidence-based management axis. Here we adopt Rousseau's (2006) sliding scale for evaluating, scrutinizing, and ranking evidence-based management practices. Rousseau's conceptual model argues that all business practices in an organization fall somewhere on a spectrum of social scientific scrutiny. At the low end of the spectrum, business practices are based on "little e evidence"—that is, subjective, unsystematic, anecdotal data. "We're doing it this way because we have always done it this way" is a classic, commonplace example and defense of "little e evidence." Still another example that could be overheard in almost any US hospital is "We're doing it this way because this is how they do it at (insert revered hospital name here)." To be clear, there is nothing inherently wrong with this category of business practices. Acting on anecdotal data is often times more prudent than acting on no data at all. In the right context, many of these "little e" business practices can be quite successful (Halm, 2009). Institutional theory predicts that mimicry alone helps in establishing and demonstrating the legitimacy of an organization (DiMaggio & Powell, 1983). Therefore managers *might* conclude that replicating an increasingly mainstream business practice is a safe bet, even if it has not been vetted by peer-reviewed research. However, these business practices often end up not being sustained by an organization and are commonly (and aptly) referred to as managerial "flavors of the month" (Beer, 2003; Gilbert & Ivancevich, 2000). Such business practices are frequently the byproducts of localized sensemaking versus careful reflection of established cause-and-effect relationships (Rousseau, 2006). Subsequently, when any of these business practices begin to erode or fall short of expectations, change agents are unable to identify or address the sources of the issue. Thus, with bewilderment the change agent responds, "It worked before," or "It works elsewhere." This uncertainty then leads to either a premature abandonment of the business practice—a managerial Type II error of sorts—or a 'doubling down' on an inherently flawed approach—a managerial Type I error.

"Big E evidence," on the other hand, would be a business practice that was built on social science knowledge where cause-and-effect linkages were known by the change agent *a priori* and were being exploited to fulfill original intent. The emphasis on social science knowledge here is not just a shameless plug for the field. Instead it is to highlight one of the field's strong suits—our ability to isolate variations that measurably affect desired outcomes (Rousseau, 2006). Without this ability, it is nearly impossible to know if a specific business practice works because of its content or merely because of the situational context in which it was implemented. This ability to separate chaff from seed is how social scientists have identified "Big E Evidence"-based practices such as goal setting (Locke & Latham, 1990), simplification heuristics (Kahneman & Tversky, 1979), reciprocal altruism (Trivers, 1971), feedback and redesign autonomy (Goodman, 2000) and stakeholder participation (Freeman, 2010), just to name a few. Use of these "Big E Evidence"-based business practices have been linked with more satisfied stockholders, employees, and customers (Goodman & Rousseau, 2004; Rucci, Kirn, & Quinn, 1998) and ensure more consistent attainment of organizational goals (Rousseau, 2006).

In order to incorporate Rousseau's evidence-based management component into our innovation-centric model, we will exchange Rousseau's use of the term "business practice" for "innovation." We contend that this change does not disrupt any of the key arguments behind her conceptual model since our definition of "innovation" only pertains to management practices that are novel to an organization or industry (Pierce & Delbecq, 1977) whereas Rousseau's focus on "business practice" includes both new *and* existing practices.

The logic behind our scale is that change agents' decisions to implement an innovation are often made using local, anecdotal data, if any data at all. Similar to what we have already discussed, these decisions can be the result of habit (e.g., to improve efficiency one must downsize), blindly following the latest "flavor of the month" business strategy, or relying on historical logic unique to the organization (i.e., flexible scheduling did not work for the organization in the past, so it certainly would not work now either). We contend that second order impact research can fill this void of evidence-less based management practices and provide meaningful, actionable solutions to change agents. Again, we are not attempting to debase the majority of first order impact research. To be clear, second order impact research is highly dependent on such research. Rather, research on second order impacts offers to broaden the spectrum of knowledge for any particular innovation. Thus, an innovation that has withstood the rigorous inquiry of both first *and* second order impacts would meet an even higher criteria of Rousseau's (2006) "Big E Evidence".

Finally, we contend that the horizontal diffusion/adoption axis and the vertical "E"vidence based management axis are interrelated; that one can inform the other, and vice-versa. This occurs through second order impact research by reducing managerial myopia, whether it is for good or bad. When we identify *desirable* second order impacts, we accelerate diffusion by reducing uncertainty and enabling change agents to visualize additional returns on their investment (envisaged windfall). This finding elevates a business practice on the "E"vidence based management axis while increasing the power driving its further adoption and innovation. In a sense, discovering cases of envisaged or naïve windfall moves the innovation upwards and to left.

Conversely, when we identify *un*desirable second order impacts, we prompt change agents to calculate a more accurate benefit-to-cost ratio and enable them to create strategies to address the now-expected sub-optimality or counter finality. This finding could degrade a business practice on the "E"vidence based management axis and slow its adoption and diffusion. However as discussed earlier, not all undesirable second order impacts spell doom for an innovation. In many cases first order benefits clearly trump any second order penalty. However, knowledge of undesirable second order impacts can still serve as valuable input for change agents. An investigation into the undesirability can provide logical meaning for why the innovation had not diffused as quickly as change agents might have expected. Should they choose to proceed anyway (sub-optimality) they are at least aware of adverse second order impacts and can attempt to mitigate them.

Application of the Second Order Impact Model

Using this conceptual model, we now transition to three specific change interventions that are currently being implemented in the healthcare industry. By choosing three interventions whose first order impacts are already well documented in the literature, we will provide three examples of how our conceptual model extends the evidence base for each respective intervention, by evaluating and categorizing their second order impacts. Should the findings yield envisaged windfall or naïve windfall, we will provide further support for their dissemination and improve their establishment as an evidence-based management practice. Conversely, should the findings yield sub-optimality or counter-finality, researchers and managers alike should: A) be more cautious of these interventions; B) better understand why the innovation is perhaps not diffusing as quickly as they might have initially suspected; and C) seek to mitigate these negative second order impacts.

Paper 1: Colorectal Cancer Screening in Family Medicine Residency

Purpose: To evaluate the clinical and economic implications of training primary care physicians via family medicine residency programs to offer colorectal cancer screening services as an in-office procedure.

Methods: Using previously established clinical and economic assumptions from existing literature and budget data from a local grant, we calculated incremental cost-effectiveness ratios (ICERs) that incorporate the costs of a national training program and subsequent improvements in patient compliance. Sensitivity analyses were also conducted.

Results: Despite high costs associated with the national training program, ICERs remain well below standard willingness-to-pay thresholds under base case assumptions. Interestingly, the status quo hierarchy of preferred screening strategies is disrupted by the policy intervention.

Conclusion: A national overhaul of family medicine residency programs offering training for colorectal cancer screening yields satisfactory ICERs. However, the model places high expectations on PCPs to improve current compliance levels in the US. With regards to our conceptual model, these results fall into the category of naïve windfall. Although these second order impacts are desirable, we contend they exhibit low to intermediate affect power.

Paper 2: Organization Tenure and Nurses' Perceptions of Change

Purpose: To evaluate the relationship between a nurse's organization tenure and their perceptions towards three different change interventions, each with varying levels of disruption to existing work processes.

Methods: An electronic survey was administered to approximately 1,600 medical-surgery nurses from a large, multi-hospital health system. Nurses were categorized into three categories of organization tenure: less than one year in the organization; between one and five years of experience in the organization; and more than five years in the organization. Confirmatory factor analysis was performed to confirm the presence of three factors: impact on patient care; impact on unit work change, and impact on individual job change. Nurses were asked the same questions for three different interventions: AIDET, hourly rounding, and discharge phone calls. A MANOVA was first performed for each of the three interventions to protect against inflating the Type 1 error rate in the follow-up ANOVAs (Cramer & Bock, 1966). Having satisfied significance thresholds with MANOVA, individual differences among tenure categories were subsequently examined using analysis of variance (ANOVA) and post hoc tests (Scheffe's method).

Results: Statistically significant MANOVAs were only found for two of the three interventions (AIDET and hourly rounding). ANOVAs revealed similar perceptions trends across all three subscales and all three categories of tenure.

Discussion: In at least some cases, significant differences in perceptions do exist depending on how long you have been in an organization. Looking across the three interventions it does not appear that the senior-most nurses categorically think less of the interventions than their junior counterparts. Instead, the mechanics and perceived disruptiveness of each individual intervention moderates nurse perceptions. With regards to our conceptual model, these results fall into two different categories. For nurses who are new to an organization (or for administrators looking to push out nurses who have been with the organization for more than 5 years) these results fall into the category of envisaged windfall. For nurse who are not new to an organization (or for administrators looking to retain nurses who have been with the organization for more than five years) these results fall into the category of sub-optimality. We argue these results exhibit potentially high affect power when viewed from the perspective of veteran nurses and the long-term sustainability of these three interventions.

Paper 3: Electronic Health Records' Impact on Charges and Collections

Purpose: To measure the impact of implementing an electronic health record on providers' charges and collections.

Methods: We analyzed financial data from a large, metropolitan integrated primary care pediatric (PCP) network comprised of 372 providers across 42 practices. This PCP network implemented EPIC electronic health record system in the fall of 2010. Specifically, the 42 practices were divided into four groups, each of which had 'go-live' dates spread across August, September, and November of 2010. Monthly encounter, charge, and collection data were collected from October of 2008 through September of 2013 for each provider. This range provided us with approximately two years of pre-implementation data and three years of post-implementation data, depending on a practice's go-live date. We used a multi-level fixed-effect least squares dummy variable (LSDV) regression model, which controls for both payer mix level- and year-specific effects, to estimate the impact of an EHR implementation on a provider's mean per patient charge, collection, and charge-to-collection ratio. Model selection between random effect and fixed effects was based on the Hausman test. The dependent variables were monthly provider-level charges per patient, collections per patient, and the charge-to-collection ratio per patient.

Results: EHRs increase per-patient charges by $17 ($p < .01$) and per-patient collections by $11 ($p < .01$). A minor decrease (-0.00941) in the charge-to-collection ratio was found, but was not significant ($p = .558$).

Discussion: Although the verdict is still out on EHRs' impact on care coordination (i.e., reduction in medical errors, newfound communication among and within health service organizations, improvement in disease management, etc.), our results demonstrate that EHRs are successful in increasing an organization's charges and collections. The big question generated from this study is: Are EHRs enabling providers to deliver higher quality care that is resulting in the $17 increase in charges? Or, is the EHR merely improving providers' charting processes that subsequently allow their organizations to increase charges by $17? With regards to our conceptual model, these results possibly fall into two different categories. From the organization's perspective, these results fall into the category of envisaged windfall. From the perspective of society (that is, patients and payers) these results fall into the category of sub-optimality. We argue these results exhibit potentially high affect power when viewed from the perspective of society.

Conclusion

We now proceed with the three independent investigations of second order impacts. In Chapter 5 we will revisit the second-order impacts conceptual model in light of insights gained from the studies introduced here. In addition to exploring their relative classifications within the second order impact conceptual framework, we will also address how each of the studies contribute to the original innovation's standing as an evidence based business practice. We will also describe how the results ought to impact the innovation's subsequent adoption and diffusion. Finally, we will briefly address some of the broader implications of these innovation studies and how our model can be applied to advance healthcare transformation.

CHAPTER II

EXPANDING NATIONAL CAPACITY FOR COLORECTAL CANCER SCREENING VIA FAMILY MEDICINE RESIDENCY PROGRAMS: EXPLORING CLINICAL AND ECONOMIC IMPLICATIONS

Introduction

Over 45 percent of US adults aged 50 to 75 are not up-to-date with colorectal cancer screening (Klabunde et al., 2011). This percentage is even higher among Hispanics and people lower on the socioeconomic scale (Klabunde et al., 2011). This is puzzling and frustrating to experts in colorectal cancer (CRC) prevention as the disease continues to be the second leading cause of cancer-related deaths in the US (Klabunde et al., 2011) despite its high survivability when detected early: 93.2 percent survival when discovered at Dukes stage A and 77 percent survival at Dukes stage B (National Cancer Intelligence Unit (NCIN), 2009). While policy-makers push to increase the demand for colonoscopies through awareness campaigns (Lupkin, 2013), increased Medicare reimbursement rates (Gross et al., 2006), and CRC research funding (Centers for Disease Control and Prevention, 2013), less attention has been given to the supply side of CRC screening; that is, the availability of well-trained, certified endoscopists.

Demand for a wide array of CRC screening strategies continues to outpace supply (S Vijan, Inadomi, Hayward, Hofer, & Fendrick, 2004). Even the less-intrusive flexible sigmoidoscopy (FS), which does not require sedation and is more likely than colonoscopy to be performed by a non-subspecialist, is not meeting demand (Wallace et al., 1999). Vijan et al estimated that between 1,360 to 32,700 additional gastroenterologists would be needed to meet demand for a wide array of CRC screening strategies (S Vijan et al., 2004). To reduce this deficit, a number of solutions have been proposed including: allowing advanced practice nurses to conduct FS, creating screening centers where one expert gastroenterologist supervises a number of endoscopists, and directing more research funding towards improving the accuracy of CT Colonography.

Yet another strategy, and the focus of this analysis, is to dramatically increase the number of primary care physicians (PCP) who are trained and supportive of performing office-based colonoscopies or FS. A handful of arguments can be made for this strategy. First, office-based colonoscopies have been associated to higher patient compliance than when performed by a subspecialist (Rogge et al., 1994). Other research has determined that trust and frequent reminders, something more likely to be established between patients and their PCP, are two of the most important factors in promoting CRC screening compliance (O'Malley, Beaton, Yabroff, Abramson, & Mandelblatt, 2004; Erin G Stone et al., 2002). Additionally, access issues related to CRC screening, specifically the dearth of gastroenterologists in rural areas, could be reduced more efficiently through the use of existing PCP networks and infrastructure. Finally, colonoscopies performed by PCPs have been demonstrated to be as safe and effective as those performed by specialists (Wilkins et al., 2009).

With such a strong case then for increasing the number of PCPs who are trained and supportive of performing office-based colonoscopies or FS, one might look to family medicine residency (FMR) programs as an ideal training ground. However, in a recent study, Wilkins and colleagues (2004a) discovered that that fewer than 50 percent of US FMR programs offer any colonoscopy training. Even more alarming, the survey revealed that fewer than 20 percent of FMR programs had trained at least one resident to do colonoscopies in the previous year. This dearth of training opportunities for family medicine residents is likely to be directly related to the current deficit of certified endoscopists.

In order to address this shortage of FMR training programs though, significant funding would need to be directed towards increasing the number of FMR programs that offer colonoscopy and FS training. However, creating and improving these training programs would be costly. FMR programs that do not already offer this training face high initial fixed costs (i.e., scopes, scope washers, endoscopy simulator, etc.). Wilkins and colleagues (2004b) found that nearly three-quarters of FMR programs rely on gastroenterologists (versus family physicians) to train residents, which results in higher variable costs as well. Given these high costs, if policy-makers *were* to pursue this strategy of developing FMR-based endoscopy training, these high training costs could disrupt the current cost-effectiveness data for various colorectal cancer screening strategies. For example, Vijan et al (2001) demonstrated in their multivariate sensitivity analysis how altering the cost of colonoscopy could result in colonoscopy losing its preferred strategy status. We argue that incorporating the costs of such an expansive training overhaul into the existing incremental cost effectiveness ratios for multiple colorectal cancer screening strategies is therefore warranted.

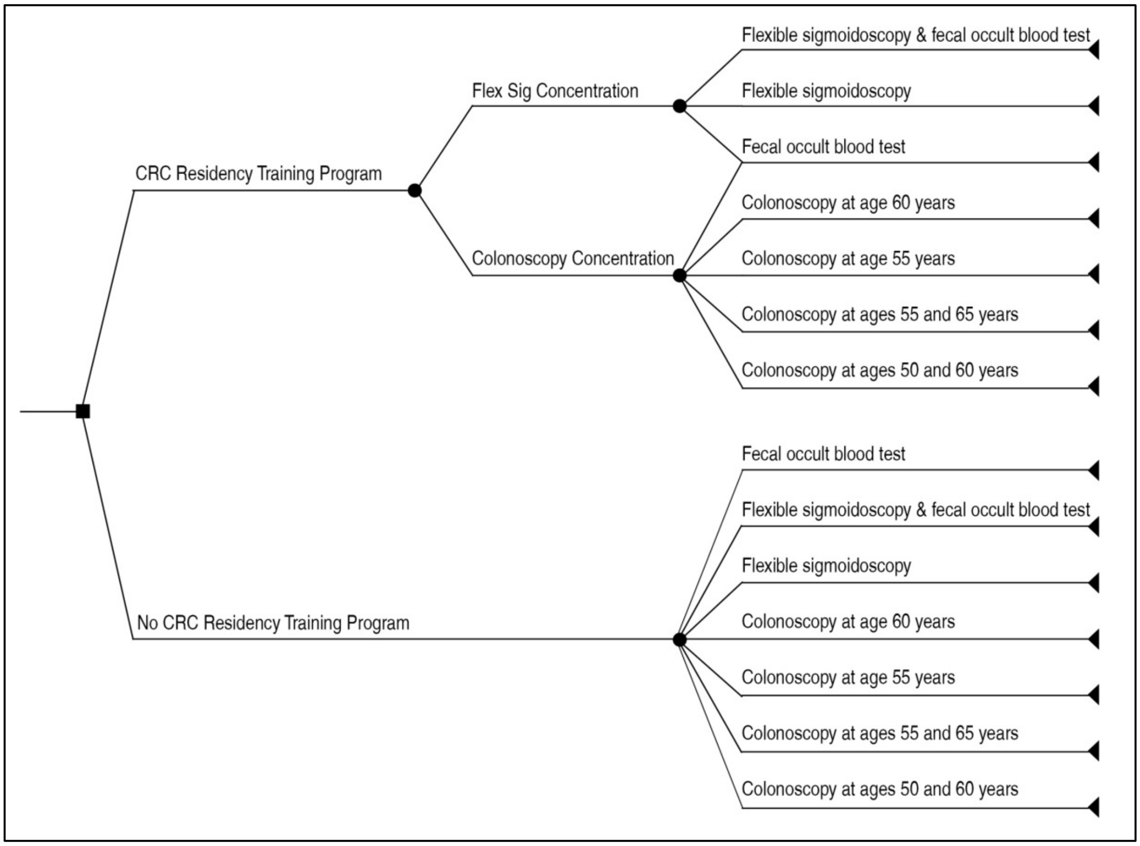

Figure 2: Markov decision model

Methods

Our model (see Figure 2) builds upon previously established assumptions from the Vijan et al (2001) model, which incorporates seven total CRC screening strategies, age-specific incidence of polyps, dwell time, CRC mortality rates, and direct medical costs. Using these assumptions as a foundation, we incorporated various fixed and variable training costs from both clinical literature and data from a CRC screening grant at the authors' home institution. Furthermore, we used Vijan et al's (2001) sensitivity analysis of patient compliance as a proxy assumption for our central argument that patient compliance improves when CRC screening is administered as a PCP-conducted, in-office procedure. See Table 1 for a complete list of model assumptions.

We estimated the costs of the training program by using the costs incurred by a single-site FMR program who recently introduced a drastic overhaul of its endoscopy training program. This particular FMR had offered endoscopy training prior to the grant, but would have fallen into Wilkins et al's (2004a) category of programs that officially offer colonoscopy training, but rarely train one or more residents (30 percent of FMR programs nationally). Purchases related to this training overhaul included an exam gurney, endoscopy simulator, endoscopy processor, argon plasma coagulator and jet wash pump. We contend that because this FMR program's training costs were to improve endoscopy training, versus introduce one, that these costs are conservative. The Wilkins et al's (2004a) study identified that 52 percent of all FMR programs offer no colonoscopy training at all. We also included variable costs of clinical faculty time using both grant data and training requirements as set by the American Society for Gastrointestinal Endoscopy (ASGE): 75 and 30 supervised training hours for colonoscopy and flexible sigmoidoscopy, respectively (American Society for Gastrointestinal Endoscopy, 1998).

Table 1: Model assumptions

	Base Case	Range Used in Sensitivity Analysis	References
Natural history			
Proportion of cancers arising from polyps	75%	~	Vijan et al., 2001
Prevalence of adenomatous polyps			
Age 50 years	20%	~	
Age 60 years	40%	~	
Age 70 years	50%	~	
Age 80 years	55%	~	
In patients with polyps			
Proportion of polyps >1 cm	15%	~	
Proportion with multiple polyps	35%	~	
Annual incidence of colorectal cancer			
Age 50 years	0.05%	~	
Age 55 years	0.09%	~	
Age 60 years	0.14%	~	
Age 65 years	0.20%	~	
Age 70 years	0.27%	~	
Age 75 years	0.35%	~	
Age 80 years	0.43%	~	
Age 85 years	0.45%	~	
5-Year colorectal cancer mortality			
Localized	10.50%	~	
Regional	35.10%	~	
Disseminated	91.70%	~	
Test characteristics			
Sensitivity of fecal occult blood testing for polyps	5%	~	
Specificity of fecal occult blood testing	97.50%	~	
Sensitivity of fecal occult blood testing for cancer			
Localized	30%	~	
Regional	50%	~	
Polyps or cancer reachable by flexible sigmoidoscopy	55%	~	
Sensitivity of colonoscopy or flexible sigmoidoscopy for polyps	85%	~	
Sensitivity of colonoscopy or flexible sigmoidoscopy for cancer	95%	~	
Perforation rate<comma> colonoscopy	0.10%	~	
Mortality rate<comma> perforation	7.50%	~	
Costs			
Fecal occult blood testing	$17	~	
Flexible sigmoidoscopy	$225	~	
Flexible sigmoidoscopy with biopsy	$240	~	
Colonoscopy	$550	~	
Polypectomy (including pathology)	$215	~	
Cancer care			
Localized	60000	~	
Regional	82800	~	
Disseminated	73000	~	
Treating colon perforation	20000	~	
New Program Material Costs			
Exam Guerney	$3,500	~	Grant Data
Endoscopy Simulator	$85,000	~	Grant Data
Endoscopy Processor	$64,000	~	Grant Data
Argon Plasma Coagulator	$20,000	~	Grant Data
Jet Wash Pump	$7,000	~	Grant Data
Insurance, maintenance, service	$0	~	Grant Data
Total	$179,500	$134,625 - $224,375	
New Program Training Costs			
Clinical Faculty Cost / hr	$120	$90 - $150	Grant Data
Facutly hours spent with COLO residents (x .5)	75	~	ASGE, 1998
Facutly hours spent with FS residents (x .5)	30	~	ASGE, 1999
New Program Output			
Residents trained (10 years)	63	47 - 79	Grant Data
Total number of expanded programs	38	29 - 48	Wilkins et al., 2004
% new physicians who actually conduct colonoscopy/fs in practice	50%	37.5% - 62.5%	Grant Data
Patient Compliance			
Status quo	50%	~	Vijan et al., 2001

Baseline estimates of the number of residents who participate in a single training program annually (nine), as well as the percentage of residents who go on to practice colonoscopies or FS post-residency (50 percent), were based on anecdotal feedback from clinical faculty and residents at the grant-sponsored FMR program. We estimate that among the 50 percent of trained residents who go on to perform colonoscopy or FS in their practice, that each would complete 60 colonoscopy or 100 FS procedures annually based on evidence from other studies of recently trained PCPs (T. Walker, Deutchman, Ingram, Walker, & Westfall, 2012; Wilkins, Gillies, Jester, & Kenrick, 2005). Finally, we set a baseline estimate of 38 new training programs to be implemented across the US. This figure would double the number of programs that currently train residents in colonoscopy at ASGE-recommended levels (Wilkins et al., 2004a).

We simulated the improved compliance rates by interpolating estimates created by Vijan et al (2001) in their sensitivity analysis (see Figure 3). Whereas Vijan et al (2001) assumed a 100 percent compliance rate, it is known that compliance in the US is much closer to 50 percent (Klabunde et al., 2011). We contend that an influx of PCPs who are trained and supportive of in-office colonoscopy or FS would result in a higher compliance rate. This assumption is supported by a number of studies which have demonstrated that PCP-conducted, in-office screening is a safe, effective, and often more convenient delivery method (O'Malley et al., 2004; Rogge et al., 1994; Erin G Stone et al., 2002; Wilkins et al., 2009). Thus, the baseline estimate in our model is set at 50 percent compliance for the status quo and 75 percent compliance with the intervention. We argue that this is a modest baseline estimate as a 75 percent compliance rate was obtained in at least one randomized trial of a CRC screening method (Mandel et al., 1993). Through interpolation of Vijan et al's compliance rates we adjust these rates in the sensitivity analysis (see Figure 3).

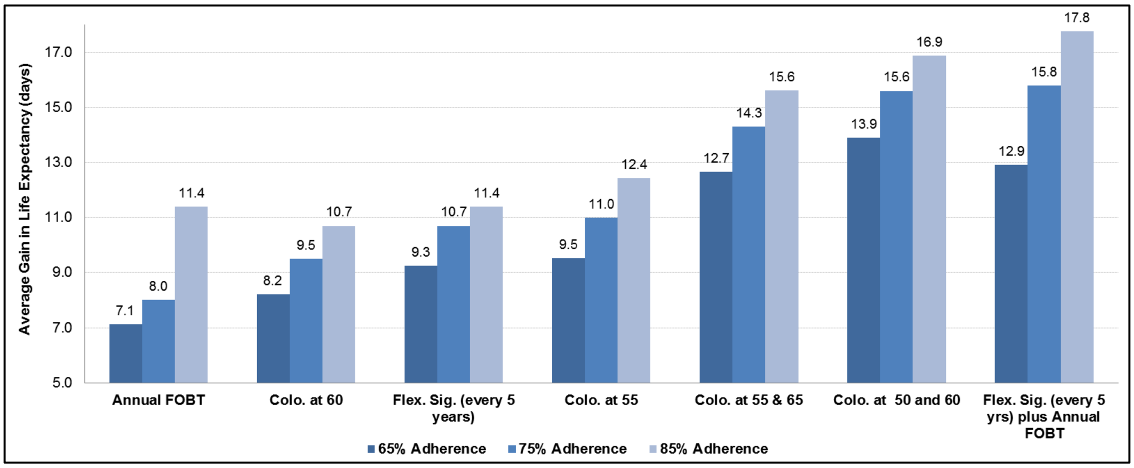

Figure 3: Average gain in life expectancy across seven CRC screening strategies across three categories of patient compliance

Two formulations of incremental cost-effectiveness ratios (ICERs) were calculated. The first involved observing the ICER for CRC strategies after a national overhaul of training programs compared to a patient receiving no treatment at all. This ratio is the same as Vijan et al's except that ours incorporate the cost and improved effectiveness of the national overhaul. The second ICER calculation observes the resulting ICER when compared to the status quo supply of CRC screening strategies (that is, without a national overhaul of training programs). These ICERs represent the incremental improvements that would be expected after introducing a national overhaul of CRC screening residency programs.

Sensitivity analyses were conducted to determine the impact of altering each of the variables we introduced including capital costs, faculty training cost, number of total residents trained per program (over a ten year period), total number of new FMR CRC training programs, percentage of FMR CRC screening 'graduates' who go on to conduct CRC screening in their practices, and patient compliance. We tested each of these variables at 75% and 125% of their base case estimates.

Results

Using all of the baseline estimates, we extrapolate that 71,820 additional colonoscopies or 2,394 newly trained residents could perform 119,700 additional flexible sigmoidoscopies after ten years. We evenly distributed the costs of the training program overhaul across each of the procedures that would be conducted by the graduates of these new programs (either all colonoscopy or all flexible sigmoidoscopy; we did not assume that there would be a mix of training strategies). The average additional cost per procedure was $395 per colonoscopy (assuming colonoscopy-only training) and $130 for flexible sigmoidoscopy (assuming flexible sigmoidoscopy-only training). Even with the additional costs of the national overhaul of CRC screening residency programs, the cost-effectiveness ratio of all seven strategies compared with no screening is under $20,000 per life-year gained.

As a result of the increase in average costs for strategies involving colonoscopy and flexible sigmoidoscopy, significant departures from Vijan et al's (2001) ICERs at the 75 percent compliance level (our baseline) were found. These higher average costs resulted in different ICERs than Vijan et al's (2001) such that fecal occult blood test (FOBT) is no longer dominated, flexible sigmoidoscopy remained dominated by colonoscopy at 55, and colonoscopy at ages 50 and 60 years is now dominated by flexible sigmoidoscopy every five years combined with annual FOBT. Another departure from Vijan et al's (2001) model is that colonoscopy at 60 alone now exceeds a willingness-to-pay threshold of $50,000 and flexible sigmoidoscopy combined with FOBT no longer exceeds the same threshold. The hierarchy of effectiveness for each strategy was also disrupted with FS every five years combined with annual FOBT now serving as the most effective strategy (see Table 2).

We also calculated the incremental cost per life year added against the existing supply of colonoscopists at the 50 percent compliance level. This ICER represents the impact of the graduates of the 38 "upgraded" FMR programs. In this portion of the model, none of the strategies were dominated. The ICER for FS combined with FOBT fell dramatically due to a significant increase (39 percent) in effectiveness as a result of higher compliance.

Table 2: Costs and effectiveness of CRC screening with and without national FMR training overhaul

Program Expansion	Strategy	Average Gain in Life Expectancy (days)	Average Cost ($)	Relative Reduction in Colorectal Cancer Mortality (%)	ICER (No screen as baseline)	ICER (Status quo equivalent as baseline)
No	No Screen	~	1,300	~	~	~
	FOBT	5.8	1,420	32.1	Dominated	~
	Colonoscopy at age 60 years	6.3	1,310	26.3	579	~
	Flexible sigmoidoscopy	7.1	1,590	35.0	Dominated	~
	Colonoscopy at age 55 years	7.3	1,360	23.1	18,250	~
	Flexible sigmoidoscopy + FOBT	8.5	1,570	45.6	Dominated	~
	Colonoscopy at ages 55 and 65 years	10.2	1,380	41.1	2,517	~
	Colonoscopy at ages 50 and 60 years	11.4	1,480	38.4	30,417	~
Yes	FOBT	8.0	1,470	43.4	7,756	8,295
	Colonoscopy at age 60 years	9.5	1,705	39.5	57,177	45,052
	Flexible sigmoidoscopy	10.7	1,859	41.0	Dominated	27,272
	Colonoscopy at age 55 years	11.0	1,785	34.7	19,467	41,923
	Colonoscopy at ages 55 and 65 years	14.3	1,845	56.3	6,636	41,394
	Colonoscopy at ages 50 and 60 years	15.6	1,995	52.7	Dominated	44,754
	Flexible sigmoidoscopy + FOBT	15.8	1,969	61.0	30,176	19,949

Sensitivity Analyses

In one-way sensitivity analyses, strategies attenuated or amplified as one might expect. When minimizing costs to 75 percent of our baseline estimates, colonoscopy at age 60 still exceeded a willingness-to-pay threshold of $50,000 ($51,399). Maximizing costs by 25 percent did not result in any changes in ICERs different from our model's baseline results. Similar results were found for similar changes in the estimated cost of clinical faculty time per hour. We did not alter the number of hours required as this is a national standard set by ASGE, but would expect similar results.

We tested the sensitivity of FMR program output by 25 percent in both directions (see Figure 4). When programs were able to produce 79 residents over ten years, all strategies fell well below a $50,000 willingness-to-pay threshold. However, if resident program output fell to an average of 47 graduates per decade, ICERs for all four strategies involving colonoscopy compared to status quo supply then exceeded a $50,000 willingness to pay threshold. Similar results were found for altering the number of expanded training programs and the percentage of graduates who go on to administer 60 colonoscopies or 100 flexible sigmoidoscopies; most notably, if decreased to only 29 programs nationally or 38 percent practice rate, all four strategies involving colonoscopy exceed the $50,000 willingness to pay threshold. Strategies involving flexible sigmoidoscopy remain well below the same threshold throughout.

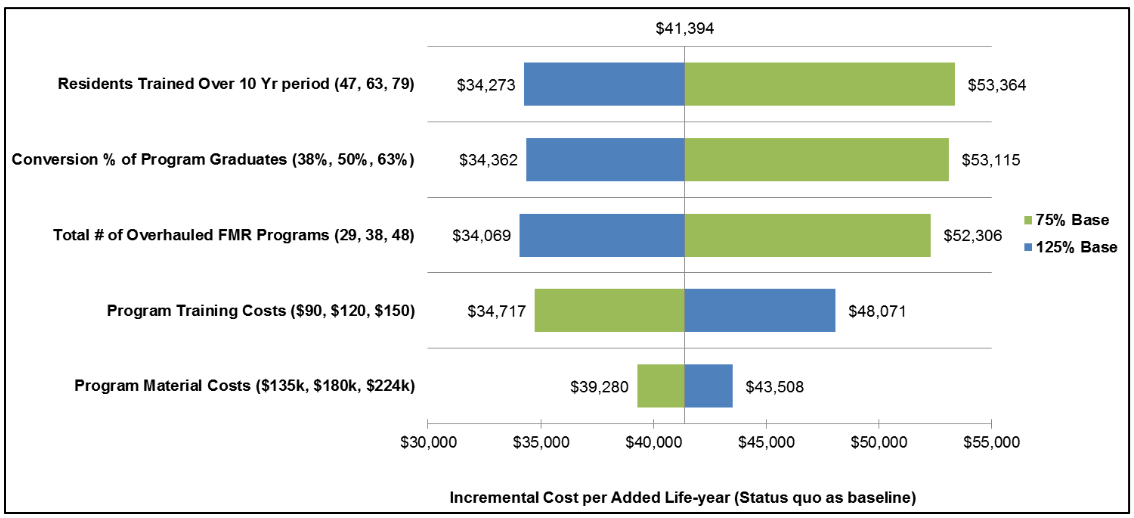

Figure 4: Tornado diagram of univariate sensitivity analysis for colonoscopy at 55 & 65

Finally, if the training overhaul were to only increase national compliance from 50 percent to 65 percent (our baseline assumed an increase to 75 percent), we find all four strategies involving colonoscopy with ICERs above $64,000 (see Table 3). We also observe both strategies that involve flexible sigmoidoscopy to be dominated or exceed the willingness to pay threshold when using 'no screen' as baseline. Conversely, if the training overhaul were to increase national compliance from 50 percent to 85 percent, all strategies fall well below a $50,000 willingness-to-pay threshold when compared to the status quo supply and demand for colonoscopies. When observing ICERs with 'no screen' as baseline, we find that colonoscopy at age 60 is now dominated by FOBTs (which, due to their curvilinear effectiveness, become much more effective at the higher ends of compliance).

Table 3: Univariate sensitivity analysis of patient compliance

Subsequent Patient Adherence	Strategy	Average Gain in Life Expectancy (days)	Average Cost ($)	Relative Reduction in Colorectal Cancer Mortality (%)	ICER (No screen as baseline)	ICER (Status quo equivalent as baseline)
65%	Fecal occult blood test	7.1	1,450	38.9	7,690	8,295
	Colonoscopy at age 60 years	8.2	1,705	34.2	84,605	75,086
	Flexible sigmoidoscopy	9.3	1,803	38.6	Dominated	35,990
	Colonoscopy at age 55 years	9.5	1,773	30.1	19,092	67,899
	Colonoscopy at ages 55 and 65 years	12.7	1,817	50.2	5,115	64,836
	Flexible sigmoidoscopy + FOBT	12.9	1,861	54.8	73,018	24,249
	Colonoscopy at ages 50 and 60 years	13.9	1,947	47.0	30,179	67,637
85%	Colonoscopy at age 60 years	10.7	1,705	44.8	Dominated	32,470
	Fecal occult blood test	11.4	1,502	47.0	1,665	5,345
	Flexible sigmoidoscopy	11.4	1,939	42.2	Dominated	29,486
	Colonoscopy at age 55 years	12.4	1,797	39.3	103,524	31,030
	Colonoscopy at ages 55 and 65 years	15.6	1,881	61.0	9,642	33,737
	Colonoscopy at ages 50 and 60 years	16.9	2,055	57.1	50,405	38,297
	Flexible sigmoidoscopy + FOBT	17.8	2,145	64.4	37,334	22,664

Discussion

Exploring the cost-effectiveness of CRC screening strategies is a well-traveled road. While colonoscopy continually proves to be one of the most effective CRC screening strategies (Frazier, Colditz, Fuchs, & Kuntz, 2000; Khandker et al., 2000; Lansdorp-Vogelaar, Knudsen, & Brenner, 2011; Telford, Levy, Sambrook, Zou, & Enns, 2010) these analyses seldom incorporate true compliance rates and, to our knowledge, none to-date have incorporated the stark imbalance in demand for colonoscopy and supply of colonoscopists (S Vijan et al., 2004). To address this gap, a significant amount of resources would need to be invested in order to increase the supply of trained endoscopists. However, this injection of costs could, in turn, alter the well-established ICERs of numerous CRC screening strategies.

In this paper, we explored how the costs of a national overhaul of family medicine residency programs would interact with existing cost-effectiveness ratios for seven current CRC screening strategies. We contend that this approach—of training family medicine residents—is a lower cost strategy that would likely lead to improved patient compliance (Rogge et al., 1994). Our findings suggest the costs of a national overhaul of FMR training program would affect the ICERs of several strategies. For one, colonoscopy only once at age 60 now exceeds a willingness-to-pay threshold of $50,000. Second, flexible sigmoidoscopy combined with annual FOBTs, which is currently dominated by colonoscopy strategies, is no longer dominated and, in fact, proves to be the most effective of all strategies with an acceptable ICER well below a $50,000 willingness-to-pay threshold. However, one could argue that improving patient adherence for an annual procedure is a steeper hill to climb than improving patient adherence for a procedure that is only required once every 10 years. Thus, improving patient adherence to 85 percent for flexible sigmoidoscopy every five years combined with annual FOBTs would be more difficult to achieve than improving patient adherence for colonoscopy at ages 55 and 65.

Perhaps the most interesting of our findings involved the sensitivity analyses of assumed patient compliance. Our model shows that if a national overhaul of FMR training programs does not result in higher patient compliance by at least 18 percent, the costs of the overhaul undermine the gains in effectiveness, such that all colonoscopy procedures become excessively costly. Fortunately, the model also demonstrates that the converse is also true. If patient compliance were to improve by more than 18 percent, colonoscopy strategies retain their dominance and, for some strategies, even demonstrate improved cost-effectiveness.

These results suggest that careful attention ought to be given to national rates of compliance and how they vary among specialists and primary care physicians. Additional studies to replicate Rogge et al's (1994) findings are warranted. Strategies to improve the rate of trained family medicine residents who go on to consistently administer colonoscopies and flexible sigmoidoscopies in their practices ought to be explored. Studies similar to this one should be conducted to explore alternative methods of addressing the gap between CRC screening demand and the supply of care providers who are able to perform them.

CHAPTER III

THE INFLUENCE OF ORGANIZATION TENURE ON NURSES' PERCEPTIONS OF THREE STUDER GROUP CHANGE INITIATIVES

Introduction

US healthcare organizations are facing changes in their external and internal environments at unprecedented rates. Whether they are in response to policy or market forces, a typical healthcare organization today may have dozens of ongoing system-level change initiatives, ranging from information technology to quality improvement to cost control (Bita A Kash, Aaron Spaulding, Larry Gamm, & Christopher E Johnson, 2013). Most of these initiatives will at least in some way affect the work processes of hospital nurses. This is often by design. Despite the current trend of hospitals employing more of their physicians, nurses continue to be high leverage change recipients; that is, system-level change initiatives can be diffused more efficiently via nurses—who work in networked units, are fully employed by the hospital, and have the highest patient interaction—than any other role in the organization.

However, system-level changes can have unintended, unanticipated impacts that vary greatly among units and among individuals within those units (Mohrman, 1989). Despite the well-traveled path of change management literature—which has identified implementation climate (Helfrich, Weiner, McKinney, & Minasian, 2007), innovation-values fit (Klein & Sorra, 1996), and leadership commitment (Herold, Fedor, Caldwell, & Liu, 2008), among others, as critical success factors—organizational change initiatives continue to fail at staggering rates. By one account, fewer than 12 percent of organizations are successful in managing change on a consistent basis (Tidd & Bessant, 2011).

This fail rate is pushing researchers to alter their approach to evaluating change. Herold and colleagues (2008) point out that managers are either: A) simply not applying what has been identified in the literature or, B) that “the focus on change management practices and processes has obscured other important factors that ultimately shape people's reactions to change.” Researchers who lean towards this latter option have begun to investigate less molar and more molecular factors associated with change-related attitudes and behaviors. This line of individual-level research has discovered associations with self-esteem (Wiesenfeld, Brockner, & Thibault, 2000), voice in decision-making (Brockner et al., 2001), job impact (Fedor, Caldwell, & Herold, 2006), and age (Caldwell, Herold, & Fedor, 2004). The research reported in this article continues in this vein by examining the influence of job tenure at the individual level on nurse perceptions of three process changes—each with varying levels of job disruption.

Organization Tenure and Change

An employee’s relationship with their employer has been traditionally conceptualized to mirror the psychological concept of life stages; that is, birth, development, maturity, and demise (Super, 1957). Just as an individual’s ability, priorities, and outlook evolve over the course of his/her life, so too do the attitudes and behaviors of employees in regards to their work. We should clarify here that the term tenure has been used in the literature with multiple definitions including position tenure (Allen & Meyer, 1993), organization tenure (Jans, 1989), and professional tenure (Lynn, Cao, & Horn, 1996). For this research, we focused on organization tenure, though we also ran our models using professional tenure as we will discuss later. We contend that while none of the definitions are necessarily superior to another, the definition does affect the implications of the results. For example, a negative relationship between change behavior and *position* tenure lends itself to understanding the impacts of promotion (Hoath, Schneider, & Starr, 1998); that is, the relationship could be explained, in part, by frustrated senior position-holders who feel overlooked for promotion or, conversely, who are content and do not seek further promotion. Meanwhile, a negative relationship between change behavior and *professional* tenure might lend itself to understanding career burnout (Reilly & Orsak, 1991). For the purposes of this study *organization* tenure was selected as the principal independent variable as the dependent variables—three process change initiatives—were organization-level initiatives affecting almost all nurses in the organization equally and at the same time, regardless of position or professional tenure. In other words, the process change initiatives were not targeted at any specific nurse position or any particular strata of nurse experience level, but instead to the entire body of nurses in the organization.

With the definition of tenure agreed upon, we then explored prior research that investigated tenure as its own independent variable and not just as a peripheral variable that ought to be controlled for. The latter is commonplace in management research as tenure is habitually used to reduce the confounding effect between more marquee independent and dependent variables (see Wayne, Shore, Bommer, & Tetrick, 2002, for an example). Substantial amounts of research have been conducted linking tenure with a number of psychosocial measures, often times with conflicting results. For example, affective organizational commitment has been shown to both increase with tenure (Mathieu & Zajac, 1990), decrease with tenure (Beck & Wilson, 2000), and exhibit U-shaped trends as well (Morrow & McElroy, 1987). Similar mixed results have been found with regards to tenure and job satisfaction (Kacmar & Ferris, 1989), job performance (Wright & Bonett, 2002), and burnout (Martin & Schinke, 1998).

Very little research though was found that directly examined the relationship between organization tenure and perceptions towards change initiatives. Van Dam and colleagues (2008) found a positive relationship between tenure and change resistance. Similarly, Hornung and Rousseau (2007) found a negative relationship, albeit weak, between tenure and anticipated benefit related to change. Most of the other connections we found in our literature review asserted similar arguments, though through transitive means (Iverson, 1996; Mumford & Smith, 2004).

Finally, when we limited our search to studies only involving *nurses* as the recipients of change we found only two studies that examined the relationship between nurse tenure and reactions to change initiatives. In both cases, researchers found a positive relationship with job tenure and compliance with new safety measures (McGovern et al., 2000; Nichol et al., 2008). These findings are peculiar in that they are in direct opposition to findings from studies discussed earlier, where change recipients with more tenure exhibited behavior less receptive towards change initiatives than their new-to-the-organization counterparts.

This begs the question of whether nurses are perhaps different from non-nurses in their proclivity to change or, alternatively, if reactions to change are simply dependent on the *type* of change being implemented. If it is the former, perhaps nurses (or any professional worker for that matter) with more tenure interpret the likely impact or effectiveness of an intervention differently than those who are newer to the organization. In both McGovern et al's (2000) study and Nichol et al's (2008) study, the authors proposed the positive effect of tenure was likely due to more experienced nurses incorporating personal experiences and judgments into their attitudes and behaviors towards the change initiative. In both studies the change initiatives were safety-related interventions that, the authors argue, would have found higher favor with more senior nurses. As nurses with more years in an organization would have had or witnessed more 'near misses' and preventable events than junior nurses, they would place more value in preventing such events in the future. This observation falls into line with Weick's (1995) concept of sensemaking in organization—where individuals create connections between past interactions and events in order to anticipate trajectories for current decisions.

However, in neither of these two studies did researchers attempt to capture attitudes or behaviors towards distinctly *different* types of interventions. Nichols et al (2008) only looked at use of facial protection. Although McGovern et al (2000) looked at multiple interventions, they were, by design, quite similar (e.g., wearing disposable gloves, eye shields, face masks, etc.) as to allow the researchers to collapse the individual measures into two general safety categories. In order to better understand when a nurse's tenure might work in favor of a change initiative and when it might work against it, one would need to observe nurses' perceptions across multiple, distinctly different change interventions. Doing so would allow us to explore whether nurses within different categories of tenure do, in fact, react differently to a given change initiative. Furthermore, it would allow us to examine if the direction and discrepancy between categories of tenure varies or remains constant across different change initiatives. Finally, it would allow us to begin to understand which types of interventions are more likely to be viewed favorably or unfavorably across categories of organization tenure. The research performed in this article sought to conduct this very type of study.

In addition to evaluating perceptions across different interventions, we also wanted to explore possible sources of discrepancy by tenure within each intervention. Specifically, we were interested in capturing nurses' perceptions of the intervention's impact on patient care, unit work change, and individual job change (more information on these three subscales can be found in the methods section of this paper). We contend this level of granularity will provide additional insight into the variance that has been observed in other similar research (McGovern et al., 2000; Nichol et al., 2008). Finding high variance in one of these subscales but not in another could have significant implications. For example, if senior nurses exhibit no differences than their junior counterparts in their perceptions of an intervention's impact on patient care, but *do* exhibit differences for perceived impact on individual job change, this would guide managers and researchers to further investigate how senior nurses frame their job processes differently than junior nurses. Perhaps the intervention truly *does* impact senior nurses' work processes differently than junior nurses. Such a finding would concede that senior nurses thought just as high (or low) as their junior counterparts of the intervention's impact on patient care. Conversely, if the only discrepancy found is within the patient impact subscale, managers and researchers would need to subsequently examine (or convey) which category of nurses is more accurately predicting the intervention's true impact on patient care (e.g., reduced falls, fewer hospital acquired infections, improved patient satisfaction scores, etc.). It is not likely that both groups are correct in their perceptions.

To examine perceptions across multiple, distinct change interventions we conducted our study in a large, metropolitan, multi-hospital health system that had implemented Studer Group's "Evidence Based Leadership" (EBL) 30 months prior. EBL is designed to be a system wide change intervention that is enacted through a series of behavior-modifying tools (see Table 4). These tools act as agents of standardization across all hospital sites and units, and are expected to be practiced throughout the entire organization. By focusing on behaviors, EBL follows the James-Lange theory of change by focusing on behaviors within organizations rather than values or attitudes (Burke, 2011; Porras & Robertson, 1992).

Given its relative newness to the organizational development (OD) scene, EBL has been evaluated very little by organization change researchers. Vest and Gamm's systematic review (2009) revealed only one empirically-driven publication on EBL, and it focused exclusively on but one EBL tool—nurse rounding on patients (C.M. Meade, A.L. Bursell, & L. Ketelsen, 2006). However, the EBL intervention fit perfectly with our research agenda. First, its multiple “tools” are distinctly different from one another unlike previous research that only evaluated one work process intervention (Nichol et al., 2008) or one set of similar interventions (McGovern et al., 2000). Second, the multiple tools are all implemented in close proximity to one another. This assists our design by minimizing the impact of recall bias. While this form of bias would still be present for us, we would expect for the bias to be relatively equal across all interventions. Finally, all of the interventions are introduced to units by a Studer Group coach who helps train nurse managers and oversees the implementation of each tool. This mitigates at least one type of selection bias—that nurses with different tenure might have received different training or were held to different standards.

Table 4: Definitions for the ten principal work process tools of Studer Group's "EBL"

EBL Tool	Description
AIDET	Communication checklist that all hospital employees utilize when interacting with a patient: Acknowledge, Introduce, Duration, Explanation, Thank You
Discharge Phone Calls	Post-discharge follow up mechanism that allows nurses to inquire about medication adherence, issues with pain, and follow-up appointments
High Medium Low	A simplified human resource rubric that calls for managers to rate their staff and identify areas for improvement. Multiple offense low performers are terminated.
Hourly Rounding on Patients	Nurses check-in on their patients on an hourly basis during awake hours to check on comfort levels
Leader Evaluation Manager	Automated performance evaluation application for mid-level managers
Leadership Development Institute	A quarterly meeting hosted at an offsite location that is attended by all managers, directors, VPs and C-Suite to share best practices, report on outocmes, and meet peers
Monthly Meeting Model	Monthly reporting template for all who report to Vice Presidents or higher
Reward and Recognition	Hand-written notes from managers sent to employee's home to compliment and thank them for their work
Rounding on Employees	Managers check-in regularly on their staff to identify positive outcomes or problem areas that should be addressed or escalated
Rounding on Internal Customers	Interdepartmental evaluation of services and needs

Methods

Sample

Participants were medical-surgery nurses at four hospitals in a large metropolitan, academic health system. Medical-surgery nurses were targeted in an effort to maximize potential sample size within the health system while decreasing inter-role variation that might mask valid associations (type II error). The institutional review boards of the author's institution and the health system approved the survey protocol. Informed consent was obtained from all participants. The survey was sent electronically to 1,593 medical-surgery nurses belonging to 44 distinct hospital units across four system hospitals. The survey was administered approximately 30 months after the initiation of the EBL implementation. Nurses were notified that their participation entered them in a drawing for one of three gift cards worth 50 USD. 427 nurses completed the survey (27 percent response rate). Though low, this rate is within the range of acceptability for similar studies dealing with healthcare professionals (Barlow, Dietz, Klish, & Trowbridge, 2002; Schneider, Gallery, Schafermeyer, & Zwemer, 2003; Shortell et al., 2001). We discuss later an additional argument for why this low response rate in the context of this study is not as serious a threat of selection bias as one might conclude for other studies. Finally, some nurse units were structured so that only one or two nurses in a unit would be responsible for conducting all discharge phone calls within a unit. Therefore, for questions related to discharge phone call, our sample size was further reduced to 204 participants, as we were only interested in results from nurses who personally conducted discharge phone calls. Respondent characteristics are presented in Table 5.

Respondents tenure with the health system were reported as follows: <1 year (15 percent), 1-5 years (47 percent), 6-10 years (23 percent), 11-15 years (8 percent), 16-20 years (2 percent), and >21 years (6 percent). For power issues, tenure was reduced to three categories: <1 year, 1-5 years, and >5 years. Respondents represented 41 distinct hospital units across four of the system's hospitals. Ninety percent of respondents were female. Due to IRB restrictions of the study site, we were unable to attain global characteristics of the organization's medical-surgery nurse population for comparison purposes. In the discussion section we argue why, given our study's design, this is not as serious a threat of selection bias as one might conclude in other studies.

Table 5: Respondent characteristics by dependent variable

	N	% Female	% with <1 Year Tenure	% with 1-5 Years Tenure	% with >5 Years Tenure
AIDET Respondents	401	89	15	47	38
Hourly Rounding Respondents	395	90	15	47	38
Discharge Phone Call Respondents	204	88	17	48	36

Measures

The survey was designed to capture data on nurses' perceptions towards three EBL tools and their impact on patient care, unit work change, and individual work change. To keep the survey length to a minimum, the instrument focused on only three of the ten EBL tools: AIDET, hourly rounding on patients, and discharge phone calls.

The health system's administrators had identified these three tools as being the most disruptive for nurses during an earlier portion of this study (National Science Foundation Grant No. IIP-0832439).

Impact on patient care: Healthcare organization change interventions such as EBL can be multifaceted in their approach, but a likely underlying aim is to improve the patient care experience. Nursing literature is full of examples of nurses discounting personal inconveniences for change interventions that demonstrate obvious improvements in patient care (for a few examples, see Anderson, 2000; Rosenman, Simms, Kay, & Adelman, 1977; L. Walker & Gilson, 2004; Williams, Harris, Randall, Nichols, & Brown, 2003). This observation has also been found in research outside of healthcare where a change intervention's positive impact has been associated with change recipients' positive emotional responses towards the intervention (Choi & Price, 2005; Hartwick & Barki, 1994; Leonard-Barton, 1988). Thus, our first subscale measured nurses' perceptions of the impact of three EBL tools on patient care. Four questions (α = .90, .91, .82 for AIDET, hourly rounding, and DPC, respectively) were adapted from the Job Satisfaction Scale for Nurses (Ng, 1993), a scale that has demonstrated high reliability and construct validity (Van Saane, Sluiter, Verbeek, & Frings-Dresen, 2003). The four items comprising this scale are: "(AIDET, hourly rounding, DPC) has a high impact on patient satisfaction," "(AIDET, hourly rounding, DPC) is useful for gaining information that is helpful in providing care," "(AIDET, hourly rounding, DPC) appears to help reduce patient anxiety," and "(AIDET, hourly rounding, DPC) helps establish relationships with patients' families." Ratings were on a

7-point scale (1 = strongly disagree to 7 = strongly agree), with options for "neutral" and "I do not know."

Impact on unit work change: The consequences of a change intervention at the unit level have been shown to affect employee commitment to the organization (Fedor et al., 2006) and to the change initiative itself (Molinsky, 1999). Organizational justice concepts can be applied in this context to understand how the burden of EBL is dispersed among units during its implementation (procedural justice) and whether the outcomes of EBL are properly attributed back to change agents and recipients (distributive justice). Our second subscale measured nurses' individual perceptions of the impact of the three EBL tools on their collective unit. Two questions (α = .86, .81, .82 for AIDET, hourly rounding, and DPC, respectively) were adapted from Fedor and colleagues' (2006) multilevel investigation of organizational change. The two items comprising this scale are: "I believe that (AIDET, hourly rounding, DPC) has positively contributed to this unit's overall employee satisfaction," and "I believe that (AIDET, hourly rounding, DPC) has positively contributed to this unit's overall quality of care." Ratings were on a 7-point scale (1 = strongly disagree to 7 = strongly agree), with options for "neutral" and "I do not know."

Impact on individual job change: Proximal work impact—that is, a change affecting one's own job requirements (Fedor et al., 2006)—serves as the basis for our third subscale. For the purposes of this subscale, we adopted Cable and DeRue's (2002) approach to measuring individual-level change by parsing "demands-abilities fit." This concept contends that organizations exhibit stability when the demands of the work match with the ability of the worker. In the context of organizational change initiatives, we apply this concept to understand how a change initiative alters the demands placed on nurses and whether those new demands can be addressed with the existing abilities of nurses (Caldwell et al., 2004). Our third subscale measured nurses' perceptions of the impact of the three EBL tools on their individual job change. Three questions ($\alpha = .77$, .74, .64 for AIDET, hourly rounding, and DPC, respectively) were adapted from Caldwell and colleagues' (2004) organizational change and individual differences questionnaire. The three items comprising this scale were "I am comfortable in performing (AIDET, hourly rounding, DPC)," "(AIDET, hourly rounding, DPC) has become a routine part of my job," and "(AIDET, hourly rounding, DPC) improves the efficiency of my work." Ratings were on a 7-point scale (1 = strongly disagree to 7 = strongly agree), with options for "neutral" and "I do not know."

Analysis

Factor scores were calculated for each of the three subscales across the three EBL tools, providing a mean of zero and a standard deviation of one. These scores are weighted canonical composites of all items in the factor analysis (Kalichman, Gueritault-Chalvin, & Demi, 2000; Tabachnick & Fidell, 2001). Promax rotation was used as we believed there to be a possible correlation among the three subscales (Cureton & Mulaik, 1975). A scree test confirmed the presence of three factors in the instrument with expected, satisfactory loadings for all but one item: item #3 in the *individual job change* subscale fell below .5. However, after determining that its presence improved the subscale's alpha, it was decided to leave the item in the factor score calculation.

A MANOVA was first performed for each EBL tool to protect against inflating the Type 1 error rate in the follow-up ANOVAs (Cramer & Bock, 1966). Having satisfied significance thresholds with MANOVA, individual differences among tenure categories were subsequently examined using analysis of variance (ANOVA) and post hoc tests (Scheffe's method).

Results

The MANOVA was performed to test the hypothesis that there would be one or more mean differences between the three tenure categories (<1 year, 1-5 years, & >5 years) and our three subscales (impact on: patient care, unit work change, and individual job change). This was conducted for each of the three EBL tools (see Table 3). Before performing ANOVAs on each of the three subscales, the homogeneity of variance assumption was tested using Bartlett's test for equal variances. Results for all three subscales across all three EBL tools were not conclusive that the homogeneity assumption had been satisfied. Therefore, we simulated the pattern of sample sizes and standard deviations while holding the means constant, to calculate the type I error rate that *would* be expected given this pattern of data (Mitchell, 2008). These simulations revealed favorable p values for all but two of the nine subscale-tool matches (see Table 3) indicating the Bartlett's test scores were reacting to non-normality versus homoscedasticity (Snedecor & Cochran, 1989) and that ANOVA would be robust.

(There were no changes in significance between the non-simulated ANOVAs and the simulated ANOVAs, but the more conservative simulated p values are reported in Table 6.)

Table 6: MANOVA statistics

Dependent Variable	Pillais' Trace	*F*	Significance
AIDET	0.067	4.58	0.0001
Hourly Rounding	0.061	4.08	0.0005
Discharge Phone Calls	0.059	2.03	0.0611

ANOVAS were then performed on each of the three subscales acting as dependent variables for each of the three EBL tools. As can be seen in Table 7, seven of the nine ANOVAs were significant. Effect sizes were calculated (partial η^2) for each ANOVA and ranged from a low of .023 (discharge phone call impact on unit work change) to a high of .052 (AIDET on unit work change).

Lastly, post-hoc analyses were conducted using Scheffe's method to examine individual mean difference comparisons across all three levels of tenure and all three subscales for each EBL tool.

Table 7: Univariate comparisons for variables in the MANOVA

	<1 Year	1-5 Years	>5 Years	F	Significance	Partial Eta2
AIDET - Patient Care	.359 (.67)	**.053 (.89)**	**-.214 (1.05)**	8.93	0.001	0.043
AIDET - Unit Work Change	**.401 (.49)**	**.030 (.77)**	**-.193 (1.03)**	11.41	0.001	0.052
AIDET - Individual Job Change	.262 (.64)	**.086 (.75)**	**-.212 (1.00)**	8.91	0.001	0.042
Hourly Rounding - Patient Care	.307 (.77)	.046 (.94)	**-.181 (1.00)**	6.44	0.001	0.031
Hourly Rounding - Unit Work Change	**.344 (.49)**	.010 (.78)	**-.148 (.96)**	8.19	0.001	0.038
Hourly Rounding - Individual Job Change	.189 (.65)	**.087 (.79)**	**-.187 (.94)**	6.47	0.001	0.031
DPC - Patient Care	.270 (.83)	-.080 (.94)	-.027 (.96)	2.38	0.083	0.018
DPC - Unit Work Change	.276 (.73)	-.015 (.80)	**-.102 (.91)**	3.70	0.026	0.023
DPC - Individual Job Change	.048 (.86)	.036 (.74)	-.066 (.82)	0.44	0.654	0.004

Bold = p < .05 | Column 1: <1 Year vs. 1-5 Years | Column 2: 1-5 Years vs. >5 Years | Column 3: >5 Years vs. <1 Year

AIDET

For AIDET, a statistically significant MANOVA effect was found: Pillais' Trace = .07, F(6, 792) = 4.61 ($p < 0.001$). The multivariate model's effect size was estimated at .07, implying that 7 percent of the variance of the canonical variable for AIDET can be accounted for by organizational tenure. ANOVAS for each of the three subscales were statistically significant. Descending means were found for each subscale indicating novice nurses thought higher of AIDET than intermediate nurses, and intermediate nurses thought higher of AIDET than veteran nurses (see Figure 5). Seven of the nine post-hoc mean comparisons were statistically significant ($p < .05$) as indicated in bold in Table 7. The difference in means between novice nurses' perceptions of impact on patient care and that of intermediate nurses approached significance ($p = .072$). There was not a significant difference found between novice and intermediate nurses' perceptions of individual job change (p = .395).

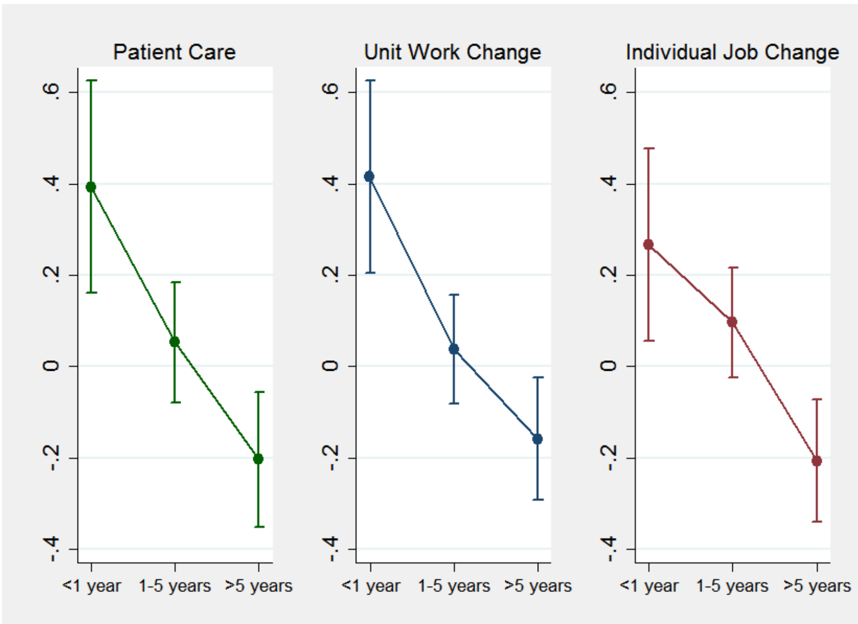

Figure 5: Adjusted 95% confidence interval plot for AIDET

Hourly Rounding

For hourly rounding, a statistically significant MANOVA was found: Pillais' Trace = .061, $F(6, 782) = 4.08$ ($p < 0.001$). The multivariate model's effect size was estimated at .06, implying that 6 percent of the variance of the canonical variable for hourly rounding can be accounted for by organizational tenure. ANOVAS for each of the three subscales were statistically significant. Descending means were found for each subscale indicating novice nurses thought higher of hourly rounding than intermediate nurses, and intermediate nurses thought higher of hourly rounding than veteran nurses (see Figure 6). However, only five of the nine post-hoc mean comparisons were statistically significant ($p < .05$) as indicated in bold in Table 7. For perceived impact on patient care, the only significant means difference was between novice nurses and veteran nurses. Differences between novice and intermediate, and intermediate and veteran were not significant. For perceptions of unit work change, significant differences were found between novice and intermediate, and novice and veteran, however the difference between intermediate and veteran was not significant. Finally, there was not a significant difference found between novice and intermediate nurses' perceptions of individual job change, but significant differences were found between intermediate and veteran, and novice and veteran.

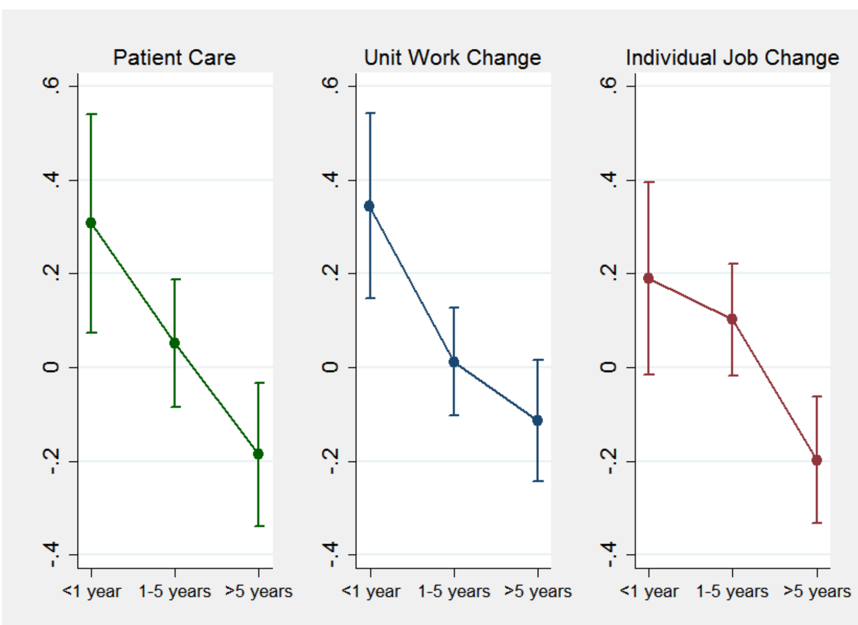

Figure 6: Adjusted 95% confidence interval plot for hourly rounding

Discharge Phone Calls

For discharge phone calls, the MANOVA was found to only approach statistical significance: Pillais' Trace = .059, $F(6, 400) = 2.03$ ($p < 0.061$). ANOVAS for two of the three subscales were also not statistically significant—patient care and individual job change. Only the unit work change ANOVA was statistically significant ($p = .023$). Descending means were not found for each subscale as had occurred with AIDET and hourly rounding (see Figure 7). Only one of the nine post-hoc mean comparisons was statistically significant ($p < .05$) with veteran nurses thinking less positively of discharge phone calls impact on unit work change than novice nurses.

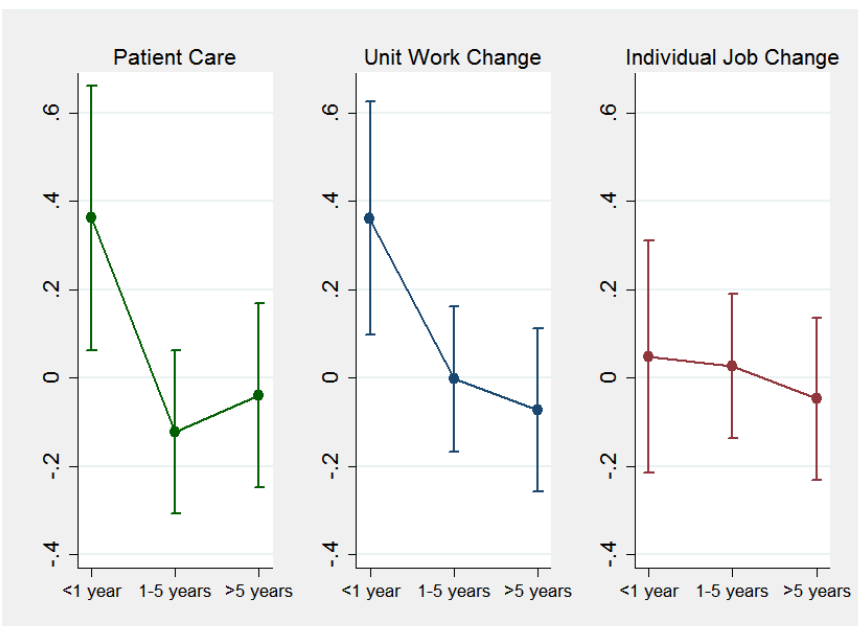

Figure 7: Adjusted 95% confidence interval plot for discharge phone calls

Additional MANOVAs were subsequently performed that included participants' "total years in healthcare" as an independent variable to determine if our three categories of tenure were potentially acting as a proxy for a more global independent variable such as total years of healthcare experience or age. Had this been the case, we would have expected to find equivalent or larger effect sizes in these models. The first follow-up MANOVA used "total years in healthcare" as a lone independent variable. This model, while significant ($p = .001$), produced a smaller effect size (Pillai's Trace = .067) than the tenure only model. A second follow-up MANOVA included both "total years in healthcare" and tenure, and also allowed for an interaction term between the two. However, in this model neither the main effects for either variable, nor the 2-way interaction term was significant ($p = .28$, $p = .21$, $p = .89$, respectively).

Discussion

This research has confirmed that in at least some cases, significant differences in perceptions do exist depending on how long you have been in an organization. However, we have also seen that this rule of thumb does not always hold. While similar findings were also discovered for professional tenure, it appears that organization tenure is a more powerful predictor of nurses' reactions to change.

Looking across the three interventions it does not appear that the senior-most nurses categorically think less of the interventions than their junior counterparts. These mixed results actually support the design of this study. Recall that we previously hypothesized that a likely cause for previous studies' conflicting results (that is, both positive and negative findings associated with increasing tenure) is the nature of the intervention itself. Had we conducted this same study using AIDET as our only dependent variable, our results could have lead us to believe that an almost perfectly linear, negative relationship exists between organization tenure and the belief that AIDET positively impacts patients, nurses, and the units they work in. Conversely, had the study only focused on discharge phone calls as the intervention our results would have been mostly insignificant and we might have concluded that tenure does not in fact play a part in nurses' perceptions towards change interventions. Similar to stepping back from a Seurat, this study's design allowed us to simultaneously view multiple points that, together, tell a different story than had we simply analyzed any one of those points in isolation.

AIDET appears to be the one EBL tool that exhibited a negative, linear relationship with organization tenure, particularly with regards to perceived impact on unit level change. This trend has been identified in other research, although not specific to a communication checklist such as AIDET (Hornung & Rousseau, 2007; Van Dam et al., 2008). Nurses new to the organization expressed the highest mean favorability ratings for AIDET than either hourly rounding or discharge phone calls. Meanwhile nurses with more than five years of experience expressed the lowest mean favorability ratings for AIDET than either hourly rounding or discharge phone calls. This could be attributed to multiple factors. For one, nurses new to the organization might appreciate knowing specifically what is expected of them and thus, not perceive this as a threat to their autonomy but instead as an approved behavior template. Conversely, intermediate and senior nurses, who have been with the organization long enough to know what is expected of them, might perceive this as a threat to their autonomy. Second, there do appear to be conflicting perceptions about the impact of AIDET on patient care. Our findings indicate that long-tenure nurses do not believe that AIDET is as beneficial to patients as their intermediate or junior counterparts. Through the lens of organizational sensemaking (Weick, 1995), it would appear that more tenured nurses have an opposing narrative—shaped by experiences—that lead them to be more skeptical about this particular process change. To address this, researchers might empirically measure AIDET's true impact on patient care (e.g. pre/post design on patient satisfaction scores). Results from such a study would either validate or reject the perceptions of these nurses. However, void of such evidence, it is likely that each category of tenure will instead continue to selectively observe instances of AIDET that align with their personal beliefs (Robert King Merton, 1968).

Hourly rounding on patients produced mixed results across categories of tenure. For perceived impact on patient care, the only significant difference found was between junior nurses and senior nurses. For perceived impact on unit work change, junior nurses stood out in favor of the initiative whereas intermediate and senior nurses exhibited less favorable perceptions that were significantly different than their junior counterparts. When these two results are viewed in tandem it appears that although there is some agreement that hourly rounding has a positive impact on patients, nurses who have been with the organization for more than one year perceive its impact on unit work change less favorably.

Finally, the findings for discharge phone calls, though non-significant, do still provide insight in the context of this study. Whereas AIDET and hourly rounding painted an undesirable picture for change agents having to deal with anyone other than new hires, it appears that with *some* change initiatives, veterans to an organization are not unconditionally opposed to change. This should be reaffirming for change agents and healthcare leaders. While we do not believe that all of the needed changes in healthcare can be neatly packaged into initiatives that are equally favored by new hires and senior employees alike, we do believe that there are more change initiatives out there that, similar to discharge phone calls, can lead to meaningful improvements in care delivery without necessarily being such a "tough pill to swallow." Managers who are aware of these varying perceptions across initiatives can tailor the sequencing of change initiatives to avoid overwhelming those who might be more skeptical.

Limitations

This study is not without its limitations. As discussed earlier, though consistent with similar published studies (Barlow et al., 2002; Schneider et al., 2003; Shortell et al., 2001), this study suffers from poor response rate, which typically presents a threat of selection bias. However, we counter this argument by calling into question the plausible alternative hypothesis—that nurses within categories of tenure self-selected into the survey as a result of some unmeasured confounder (e.g., favorable/unfavorable disposition towards the change initiative). However, at no point was any nurse aware that their categorization of tenure would serve as the principal independent variable.

Thus, we would contend that such a confounder would likely be present across multiple categories of tenure. So if nurses who viewed EBL in a less positive light were more likely to participate in the survey, do we have any reason to believe such a bias would only exist in one category of tenure and not the others? Similarly, our data appear to be skewed female. However, if this skew were impacting our results, we would expect the bias to be affecting the three categories of tenure equally given that the skew was equal across all three categories.

CHAPTER IV

MEASURING THE IMPACT OF ELECTRONIC HEALTH RECORDS ON CHARGE CAPTURE: A SECOND GENERATION EHR RESEARCH APPROACH

Introduction

Recent data indicates healthcare providers are only slowly getting behind the adoption of electronic health records (Charles, King, Patel, & Furukawa, 2013). Despite the federal government's carrot *and* stick approach via the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, providers remain skeptical of the technology. For example as of December 2013, fewer than 14 percent of office-based physicians have adopted EHR systems with the capabilities to support at least 14 Stage Two meaningful use requirements (C. Hsiao & Hing, 2014). Researchers have looked into providers' and allied health professionals' causes for concern and have uncovered a wide range of issues, many of which have further strengthened their recalcitrance. For example, providers and administrators often fear the negative impact of EHR adoption on physician productivity. This fear was recently validated by Huerta and colleagues (2013), who found that hospitals that had recently adopted EHRs exhibited lower productivity gains than hospitals who had not yet adopted the technology. However, Adler-Milstein and Huckman (2013) found the exact opposite to be true in ambulatory settings.

Debate on EHRs and their true impact on care quality also persist. Providers and administrators continually dispute whether or not EHRs actually improve quality of care.

Research on this front has also returned mixed results. For example, Zhou and colleagues (2009) could find no linkages between EHR use and six quality of care composite scores. However, these findings conflict with others who have found weak, but positive linkages between EHR use and improved process compliance (Bardhan & Thouin, 2013; Patterson, Marken, Simon, Hackman, & Schaefer, 2012; T. J. Spaulding & Raghu, 2013), improved patient satisfaction (Kazley, Diana, Ford, & Menachemi, 2012) and reduction in medication errors (Radley et al., 2013).

Still other identified barriers to EHR adoption include new costs to an organization (both upfront capital costs and recurring maintenance fees) (Jha et al., 2009), interoperability with existing systems (Abramson, McGinnis, Moore, & Kaushal, 2014), and inadequate training and onsite technical support (Jamoom, Patel, Furukawa, & King, 2014), though each of these barriers are perceived to be higher by those who have not yet adopted EHRs versus those who already have an EHR in place (Abramson et al., 2014; Jamoom et al., 2014).

This last finding—of varying perceptions between the EHR haves and EHR have-nots—suggests at least two issues that could explain the industry's staccato-like diffusion of EHR adoption. The first is that researchers have possibly been premature in their summative evaluations and too vocal in their formative evaluations. The second is that researchers have been unable to study organizations whose compositions and local environments are similar to the EHR have-nots. Fortunately, both of these issues can be addressed through a more strategic research approach—something we are calling a "second generation of EHR research." In the following section, we briefly discuss these two issues and explain how current and future EHR research can mitigate these problems. This second generation EHR research, we contend, stands to be both statistically stronger and more informative to healthcare decision-makers in organizations who have yet to implement an EHR. For the record, we are not attempting to debase existing EHR research that was conducted on organizations prior to the HITECH Act of 2009. Rather, we contend that because these organizations opted into EHRs *prior* to the policy change, they are likely different in their composition, structure, or culture (or some combination thereof) compared to the organizations that, as of 2014, still do not have EHRs. We conclude with such an example of second generation EHR research by exploring the impact of an EHR adoption on charge capture for a large pediatric physician network.

EHR Research Issue #1: Short Game vs. Long Game

The first issue we explore surrounding the discrepancies between the EHR haves and the EHR have-nots is how and why *perceived* barriers to EHR adoption are not as menacing as their *realized* counterparts, yet persist nonetheless (Abramson et al., 2014; Jamoom et al., 2014). We propose that one source of this discrepancy is that EHR-wary organizations have simply heard too many EHR "horror stories" and have entered a wait-and-see hibernation. Indeed, the literature is full of examples of healthcare organizations spending millions of dollars on botched EHR implementations (for a small sampling see Blumenthal & Glaser, 2007; Connolly, 2005; Kemper, Uren, & Clark, 2006; Kumar & Aldrich, 2010). However, this initial surge of bad press ought to have been expected. We would *expect* to encounter more failures than success stories in the first few months and years immediately after the HITECH Act. A doomed EHR implementation is much easier and quicker to spot (and publish) than an incremental improvement in cost, quality, or access. The former could become apparent within weeks of an EHR go-live. The latter might not be detectable for months or possibly even years.

The existing body of EHR implementation literature—what we will refer to as first generation EHR research—ought to be additionally scrutinized when we consider how few organizations have actually *fully* implemented and exploited their EHR. Jha and colleagues (2009) found that while nearly one quarter of US hospitals report having a *basic* EHR in place, only 1.5 percent meet the criteria of having a *comprehensive* EHR system—that is, a system that leverages all four clinical components (computerized physician order entry (CPOE), decision support, imaging, and interorganizational health information exchange capacity) *and* is present in all clinical units in the organization. Similar results were found for office-based physicians with more than half reporting the presence of an EHR, but only one-third of those also reported consistent use of "basic features" such as patient demographics, laboratory and imaging results, problem lists, clinical notes, or computerized prescription ordering (Decker, Jamoom, & Sisk, 2012). This astoundingly low percentage should alarm consumers of EHR research. If we were to audit the entire body of first generation EHR research, what percentage of those studies were likely conducted on organizations with a mere shell of an EHR? Is that fair to the EHR?

Regardless, it is understandable why so many healthcare organizations are still in a wait-and-see mode. If we were to anthropomorphize an organization, all of these negative, oftentimes sensational anecdotes would surely rouse an organization's amygdala more so than any marginally positive anecdote or investigation (Kensinger, 2007). As a result, a sluggish diffusion of EHRs is a perfectly logical outcome. This phenomenon would at least partially explain the discrepancy between perceived versus realized barriers to EHR adoption.

Fortunately, researchers have the tools and the ability to now lead a second generation of EHR research that is statistically stronger and focuses more on the "long game" of an EHR versus the "short game". The most important variable that will differentiate the second generation of EHR research from the first generation is time. Though simplistic, researchers are now gaining access to longitudinal EHR datasets that will greatly improve the internal validity of their research. Although robust longitudinal datasets did exist prior to 2009, they would have belonged to historically progressive, technology-focused organizations with decades of experience in health information technology (Tang & McDonald, 2006). (The issue of generalizability of first generation EHR research is a separate issue we will discuss in the following section). More often, first generation EHR researchers were limited to only one or a few cross-sectional 'snapshots' of post-implementation data. In some cases, these snapshots did not include pre-intervention data since many organizations were now tracking some variables for the first time in their history (Burton, Anderson, & Kues, 2004). Even when researchers *did* have pre/post data, they likely had fewer post-intervention data points due to the recentness of the EHR implementation. Furthermore, many of these post-implementation data were likely for an organization with a mere shell of an EHR in place rather than a comprehensive EHR being used uniformly across the organization (Jha et al., 2009).

Given the nature of these first generation data sources, researchers likely had much higher threats to internal validity (Shadish, Cook, & Campbell, 2002) including: regression toward the mean (e.g., too few post-intervention data points prevented researchers from observing an eventual return to the mean, whether that might have been beneficial or not to the EHR), history (e.g., other concurrent organizational change initiatives or environmental shocks were also contributing to observed deltas but too few post-intervention data points prevented researchers from acknowledging or controlling for the concurrent event), or even Borg's (1984) notion of resentful demoralization (e.g., providers who were adamantly opposed to the EHR—a well-documented phenomena (Doolan & Bates, 2002; Ludwick & Doucette, 2009; Sassen, 2009)—deliberately opposed the EHR in its infancy in an effort to negatively affect its impacts and postpone its adoption. More post-intervention data points in this scenario would have either: A) revealed that these providers eventually "came around" to the EHR, or, B) ruled out this threat altogether by demonstrating that provider recalcitrance remained constant across an extended period of time).

Having the added benefit of time as an independent variable, second generation EHR research can now transition away from cross-sectional and low-observation count repeated measures designs and move towards high-observation count longitudinal designs—a superior approach in the hierarchy of research design. Such longitudinal studies with both pre- and post-intervention data afford researchers the opportunity "for controlled and uniform measurement of exposure history and other factors related to outcomes" (Ware, 1985). This opportunity is precisely how second generation EHR data analysis can generate more reliable results. By focusing on the "long game" of EHR adoption, this research will inform practitioners not only of the initial impacts of the technology, but also its intermediate and long-term outcomes.

EHR Research Issue #2: The Downside of Evaluating Pioneers

A second likely factor contributing to the disparate perceptions between the EHR haves and have-nots is that perhaps researchers have been unable to study the 'everyman' of healthcare organizations. As we discussed in the previous section, first generation EHR researchers had little choice but to look to the progressive EHR "pioneers" of the US healthcare industry for a sufficiently powered longitudinal dataset. However these organizations were structurally and culturally unique. Sociology and diffusion of innovation research has argued that atypicality is a key differentiator for successful innovators, or in our case, EHR pioneers (Granovetter, 1973; Rogers, 2010). This is problematic for researchers. While study of such pioneer organizations may be intriguing for fellow researchers and policy-makers, it is not necessarily actionable for non-EHR-using providers and administrators. For example, EHR success stories from Veterans Health Administration carry little weight for an independent long-term care facility that is on the market for its first EHR. Similarly, demonstrating cost-savings through EHR use at Intermountain Healthcare or Mayo Clinic—both of which are historically progressive, technology-oriented integrated care systems (Tang & McDonald, 2006)—is not necessarily generalizable to an independent, three-provider primary care practice in south Texas.

This notion is supported by research on the perceived barriers of EHR adoption. For example, Kemper and colleagues (2006) found that 32 percent of large pediatric practices had an EHR in 2005 whereas only 3.5 percent of solo practices had an EHR. Obviously the financial risk for EHR adoption is significantly higher for a solo practitioner. However, little to no research exists that demonstrates if an EHR's expected return on investment (ROI) holds across varying practice sizes (Menachemi & Brooks, 2006). Therefore solo practitioners have scant evidence to push them beyond the initial sticker shock. Another example by Pizzi and colleagues (2005) found that EHR users were more likely to be generalists, to work in academic medical centers, and were slightly younger. However, we have no evidence that EHRs are more beneficial for providers *with* these characteristics than for providers *without* (Menachemi & Brooks, 2006). It appears then that EHR adoption is being driven less by a strong evidence base of the technology's true impact and more by financial trepidation (Do we want to invest that much?), structural considerations (Are we the 'type' of organization to adopt an EHR?), and social norms (Won't our providers reject an EHR?).

So how will second generation EHR researchers grow the evidence base with more generalizable and actionable knowledge? We contend that they can do so now by transitioning their focus away from EHR pioneer organizations and focus instead on EHR early adopters—in our case, the organizations that adopted the technology in anticipation of or response to the HITECH Act of 2009. We argue that these organizations are more similar in their composition and local environments to current EHR have-nots. This notion is supported by innovation research that posits "early adopters are a more integrated part of the local social system than the innovators" (Rogers, 2010, p. 309). By focusing on early adopters, EHR researchers will be conducting evaluations on organizations that are only a few steps removed from the 'everyman' organizations that still lack the technology. Of course, this second expectation must not trump the requirements of our first research issue: targeted early adopters must still possess robust longitudinal datasets to protect against the threats to internal validity we discussed earlier. However, should both of these criteria be fulfilled we would expect the results from such research to be both statistically stronger and more actionable for the majority of healthcare organizations that continue to operate without comprehensive EHRs.

Measuring the Financial Impact of EHRs: A Second Generation Approach

As we discussed at the outset, researchers continue to produce mixed results in regards to an EHR's impact on productivity and quality. However, there appears to be less disagreement about the financial impact of EHRs. From a conceptual level, EHRs are expected to increase revenue through enhanced charge capture (Menachemi & Brooks, 2006). This is made possible by the EHR's ability to more accurately prompt and document care (Häyrinen, Saranto, & Nykänen, 2008). This capability applies to pre-service (e.g. prompting providers to schedule appointments with overdue patients), point-of-service (e.g. alerting providers of non-Medicare-covered procedures), and post-service (e.g. allowing providers and patients to manage prescription refills). We could find no publications in MEDLINE (PubMed) that argued against this notion at a conceptual level.

At the applied level, very little research exists that demonstrates the actual financial gains related to EHR implementation and most of the studies pertain to hospitals versus ambulatory care. The literature that does exist often bears the marks of first generation EHR research—that is, it either suffers from too few post-intervention data points or the study relates to an EHR pioneer organization. For example, in their review of 256 health information technology articles, Shekelle and colleagues (2006) found only nine articles that quantitatively assessed the economic value of comprehensive EHR use. Only two of those nine articles investigated variables related to charge capture, with the remaining seven selecting other indirect 'benefit' variables such as savings from chart pulling, reduced pharmacy costs, and prevention of adverse drug events. Notably, both of these two studies used historically progressive, technology-oriented healthcare organization—Partners HealthCare System (Wang et al., 2003) and Virginia Mason Medical Center (Schmitt & Wofford, 2002)—as their data sources, thereby strengthening our argument for a second generation approach to this same research question. In the ambulatory setting, only a few studies exist that address EHR implementation and financial measures and each have produced somewhat mixed results. MGMA's national study (Gans, 2010) revealed increased revenue whereas a study of Cornell Weill's implementation produced a neutral impact on billing (Grieger, Cohen, & Krusch, 2007). We should note however that both of these studies involved practitioners who had implemented an EHR prior to 2009, thus not meeting our definition of second generation EHR research. A more recent study that does meet the definition of second generation EHR research revealed negative impacts on revenue in the short term (Fleming et al., 2014).

In the following section we conduct a financial impact study but with an approach that meets both criteria of second generation EHR research. In responding to EHR Research Issue #1, our study includes 24 pre-intervention observation months and 35 post-intervention observation months. This allows for ample post-intervention observation to strengthen our case against the aforementioned threats to internal validity. In responding to EHR research Issue #2, our study is conducted on an organization that implemented an enterprise EHR (Epic Systems (Verona, Wisconsin)) in the fall of 2010 in response to the HITECH Act's 2011 incentive requirement. Lending further credibility to this organization, they were transitioning from a paper-based health record system to an EHR—yet another similarity with current EHR have-nots.

Methods

Sample, Data, and Measures

We analyzed financial panel data from a large, metropolitan integrated pediatric primary care (PPC) network comprised of 372 providers across 42 practices. This PPC network implemented EPIC electronic health record system in the fall of 2010. Monthly encounter, charge, and collection data were collected from October of 2008 through

September of 2013 for each provider. This range provided us with approximately two years of pre-implementation data and three years of post-implementation data. Our data included monthly productivity measures at the physician level. Average monthly encounters, charges, and collections for the network's physicians were 477, $89,174, and $64,217 respectively. We gathered data from the network's billing and practice management software, which had been implemented in the fall of 2008—allowing us to obtain this financial data prior to the EHR's implementation.

Charge Capture

As mentioned earlier, the measure of charge capture has been used before in EHR economic evaluations, albeit in the context of first generation EHR research (Schmitt & Wofford, 2002; Shekelle et al., 2006; Wang et al., 2003). Charge capture is commonly described as ability to properly ensure that billable services are recorded and reported for payment. Improving charge capture ties back to the notion that physicians can offer a wide array of services during a patient visit but are only paid for those services that are both properly documented and deemed appropriate by third party payers. Conceptually, EHRs ought to improve charge capture through automation and enhanced coding capability. We measured charge capture by using the monthly ratio of charges-to-collections at the provider level. Using three provider-level variables available to us via the organization's practice management system derived this ratio: monthly encounters, charges, and collections (lagged so that collections were apportioned back to the month of the originating charge). Using these three variables, we calculated a monthly average per-patient charge, collection, and charge-to-collection ratio for each physician. All three variables appeared to be normally distributed (see Figure 1). Therefore, for ease of interpretation we used untransformed versions. We performed separate analyses for each of our three dependent variables.

EHR

To capture the presence of EHR, a binary variable was created where all pre-implementation observation months were coded '0' and all post-implementation observation months coded '1'. Network administrators had divided all of the practices into four implementation groups. The four implementation 'go-live' dates included one in August, two in September, and one in November of 2010.

Payer Mix

We classified providers into four groups according to their average annual payer mix. Theoretically this classification should increase intra-group homogeneity as payer mix is highly correlated with the types of patients seen by a physician (Glied & Zivin, 2002). Specifically, we calculated a bi-modal public-to-private-pay ratio (PPPR) for annual charges for each provider. The "public pay" portion of the figure combined Medicaid, Children's Health Insurance Program (CHIP), and Medicare. After calculating this ratio for providers, we examined them for any natural break points that would allow for a meaningful classification without creating a subset with too few providers. The final sorting called for four groups:

1) Providers with a PPPR of less than 10 percent (n=26)

2) Providers with a PPPR between 10 and 25 percent (n=14)

3) Providers with PPPR between 25 and 100 percent (n=9)

4) Providers with a PPPR in excess of 100 percent (n=8).

Year

We added a control variable for calendar year in an attempt to control for any macro-level shifts in the environment such as changes in Medicaid reimbursement, implications related to the Affordable Care Act, and inflation.

Analysis

The dataset was initially examined for missing and anomaly values (e.g. average monthly per patient collection of $1,215). Providers with missing observations or months with fewer than ten patient encounters were subsequently dropped from consideration. Providers who were not employed prior to the EHR implementation were also dropped. These two inclusion requirements allowed us to avoid using any imputation. Locum providers were dropped due to low encounters and a high variance of payer mix across years. A total of 57 providers across 32 practices met all of the inclusion requirements.

We estimated the following two-level fixed effects model:

$$Y_{it} = \beta_1{}^{*}EHR\text{-}Use_{\mathrm{j(i,t)i}} + \beta_2{}^{*}PayerMixGroup_{\mathrm{i}} + \beta_3{}^{*}Year_{\mathrm{j(i,t)i}} + \psi_{j(i,t)} + \alpha_{\mathrm{i}} + u_{\mathrm{it}}$$

where index *j(i,t)* denotes the practice of physician *i* during time *t*, Y_{it} is the dependent variable (average monthly per patient *charges* by physician in model one, average monthly per patient *collections* by physician in model two, and average monthly per patient *charge-to-collection ratio* by physician in model three) for physician *i* in month *t* as a function of the time-varying practice-level variable EHR implementation, $EHR\text{-}Use_{j(i,t)i}$, the time-invariant physician payer mix group, $PayerMixGroup_{i}$. We also included a time-varying practice-level year indicator, $Year_{j(i,t)i}$ in addition to a separate mean for each practice, $\psi_{j(i,t)}$, a fixed effects at the physician level α_i to control for practice-specific, time-invariant factors that might affect our three separately run dependent variables, and finally a mean zero error term u_{it} (McCaffrey, Lockwood, Mihaly, & Sass, 2010).

By selecting a fixed effects model we argue that our errors are correlated with the regressors; that is, we assume that something within the physician, their practice, or their payer mix group may bias the predictor variables, the outcome variable, or both. We also assume that these time-invariant characteristics are unique to the physician and that each practice's error term and constant (aggregates from individual physician characteristics) are not correlated with one another (Stock & Watson, 2012). A Hausman test was run to test correlation between the regressor and error terms using a random effects model and was rejected ($p<0.001$). We also verified that our fixed effects model was consistent (that is, x_{it} and α_i are correlated, but pooled ordinary least squares (OLS) was not ($p<0.001$)).

In addition to meeting the assumptions for fixed effects modelling stated above, we would like to further highlight some of the additional merits of this approach. When EHR researchers use traditional OLS regression, they would select a dependent variable similar to ours, a key predictor variable such as “EHR use”, and a slew of other available control variables. However, this approach is susceptible to omitted variable bias. A number of important variables exist in EHR research but are difficult to obtain and to measure reliably. For example, a providers’ attitude toward technology has been shown to vary significantly yet heavily influence behavior (Morton & Wiedenbeck, 2010). Similar variance has been found among physicians and their perceived computer literacy and disruption in workflow (Menachemi, 2006). However, these types of variables can only be collected through primary data collection, which typically suffers from a low response rate (both of the previous two studies had a response rate below 30 percent) and dramatically increase the cost of the study. As a result, these variables are rarely included in studies such as this one that rely on secondary EHR and practice management data. We argue that these variables are correlated with physician productivity (which is a function of charges and, subsequently, collections) and EHR use. If this is the case then the coefficient on EHR use will be biased. Fortunately, fixed effects modelling controls for both observable and unobservable differences among physicians and practices, thereby reducing the threat of omitted variable bias (Stock & Watson, 2012).

Finally, fixed effects modelling presented a good fit with our dataset. Propensity score matching was not permissible since all physicians within the network received the

EHR "dose" within a 45-day window. ARIMA modeling was not possible due to too few pre-intervention data points (McCleary & Hay, 1980).

To compare how our three DVs changed over time, we calculated mean values at selected annual intervals across our four payer mix groups. Differences in mean values between our first and last observation months were analyzed with *t* tests for a broad illustration of the direction of the data. We also graphically traced the evolution of our three DVs across the four payer mix groups. Our fixed effects regression models are presented as a series of nested models (Macinko, Guanais, & de Souza, 2006). Akaike information criterion (AIC) was used to improve model selection.

Results

Table 8 presents the descriptive statistics for mean provider monthly encounters as well as mean per patient charges, collections, and charge-to-collection ratio grouped across our four categories of payer mix. We also present monthly means graphically in Figures 8-11. Encounters and charge-to-collection ratios fluctuate across all six years and exhibit seasonal trends—most notably with high points during the 'back-to-school season' and low points during the summer. Recall that these figures are normalized by patient encounters, which is implies more procedures, more expensive procedures, or a combination of both are driving the seasonal trends. General trends of increased charges, increased collections, and decreased charge-to-collection ratios appear to exist, but become more clearly defined with providers who see more public pay patients (see Figures 9-11). Significant increases in per patient charges and per patient collections from 2008 to 2013 were found for three of the four payer mix categories. Only physicians in the highest public-to-private pay ratio category exhibited significant improvements in their charge-to-collection ratio (that is, a decrease in the ratio implies the physician is collecting on a higher percentage of submitted charges).

Table 8: Summary statistics for 57 providers by payer mix group (selected intervals 08/08 – 09/13)

Payer Mix Group	Mean Provider Monthly Encounters	Mean Per Patient Monthly Charges ($)	Mean Per Patient Monthly Collections ($)	Mean Per Patient Monthly Charge-to-Collection Ratio
Pub/Priv Ratio <10% (n=26)				
Oct 2008	476	198.60	150.49	1.34
Oct 2009	583	197.02	161.22	1.23
Oct 2010	466	207.42	145.78	1.47
Oct 2011	478	205.57	148.29	1.45
Oct 2012	437	205.36	155.85	1.75
Sep 2013	393	232.44	180.74	1.39
Change 08/08-09/13	-83.58 (42.82)	33.84 (26.99)	30.25 (24.56)	.0462 (.0796)
Pub/Priv Ratio 10-25% (n=14)				
Oct 2008	494	191.85	131.02	1.58
Oct 2009	607	182.15	144.30	1.27
Oct 2010	495	190.49	136.84	1.45
Oct 2011	468	196.21	141.22	1.55
Oct 2012	516	205.46	155.77	1.55
Sep 2013	436	219.54	170.71	1.34
Change 08/08-09/13	-57.64 (54.15)	27.68 (10.09)**	39.69 (14.90)**	-.2455 (.1603)
Pub/Priv Ratio 25-100% (n=9)				
Oct 2008	379	170.99	119.88	1.42
Oct 2009	469	170.35	137.13	1.29
Oct 2010	388	192.48	140.40	1.47
Oct 2011	400	188.83	133.49	1.53
Oct 2012	556	200.80	165.68	1.26
Sep 2013	481	217.79	185.95	1.24
Change 08/08-09/13	101.44 (66.68)	46.80 (13.80)**	66.06 (18.92)**	-.1802 (.1076)
Pub/Priv Ratio >100% (n=8)				
Oct 2008	400	141.87	65.49	2.42
Oct 2009	465	142.33	79.21	1.90
Oct 2010	429	177.27	119.13	1.60
Oct 2011	481	186.43	123.88	1.59
Oct 2012	490	199.51	139.72	1.58
Sep 2013	409	223.70	170.60	1.47
Change 08/08-09/13	8.14 (132.05)	81.83 (30.97)*	105.11 (32.88)**	-.9512 (.3638)*

*Standard errors in parentheses. *(p<0.05); **(p<0.01).*

Tables 9-11 present the results of the two-level fixed effects modelling for all three dependent variables. Model 1 presents the simple bivariate relationship between the DV and the implementation of the EHR. The introduction of the EHR is associated with a significant increase in charges and collections. EHR does not appear to have a significant impact on charge-to-collection ratio. Model 2 introduces our payer mix categories and only slightly alters the impact of EHR compared to Model 1, but improves our R^2 and provides a smaller AIC indicating a stronger model. The results for the payer mix categories can be interpreted as follows: ceteris paribus, as providers see a higher percentage of public pay patients, their mean charges and collections decrease and their charge-to-collection ratios increase. Finally, Model 3 introduces our calendar year control variable and significantly alters the impact of EHR on our DVs compared to Models 1 and 2, while also improving our R^2, decreasing AIC and decreasing the standard error for all other IVs.

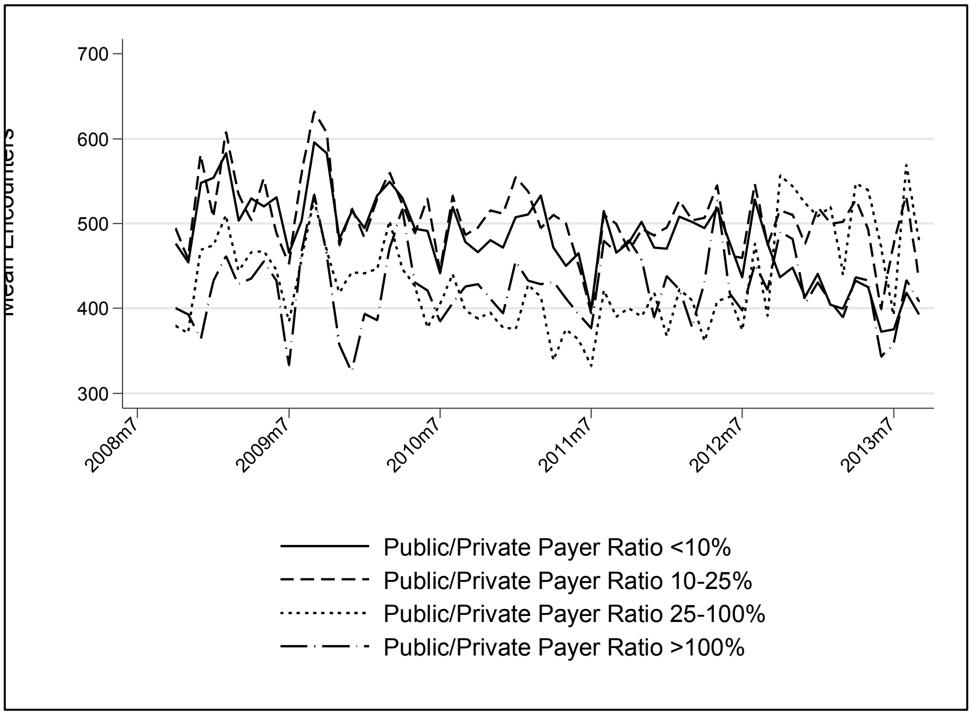

Figure 8: Mean encounters over time by payer mix group

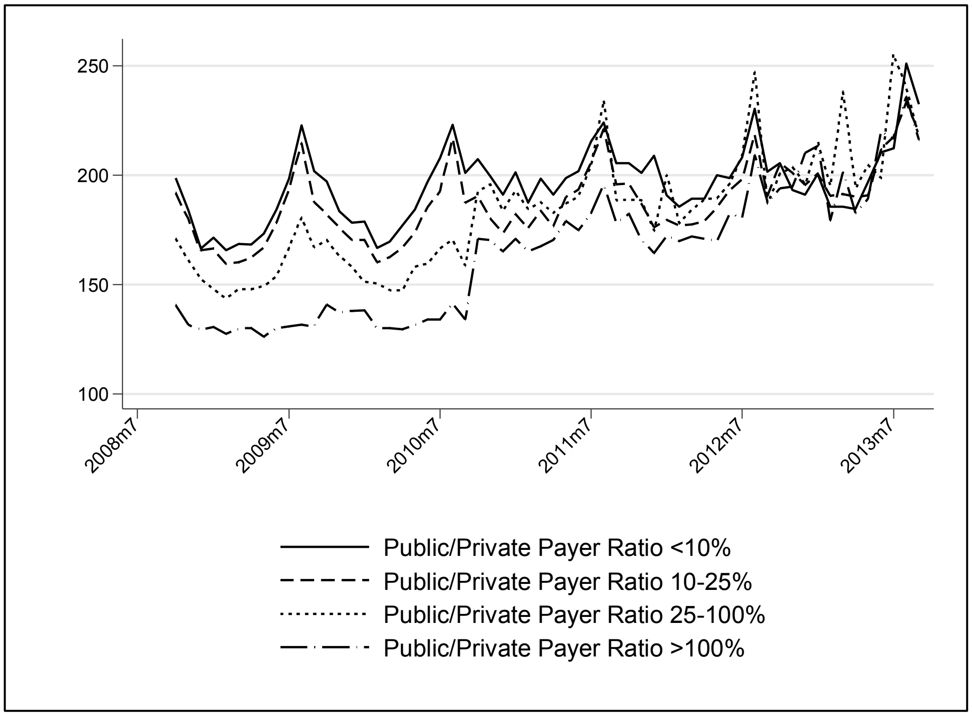

Figure 9: Mean per patient charges over time by payer mix group

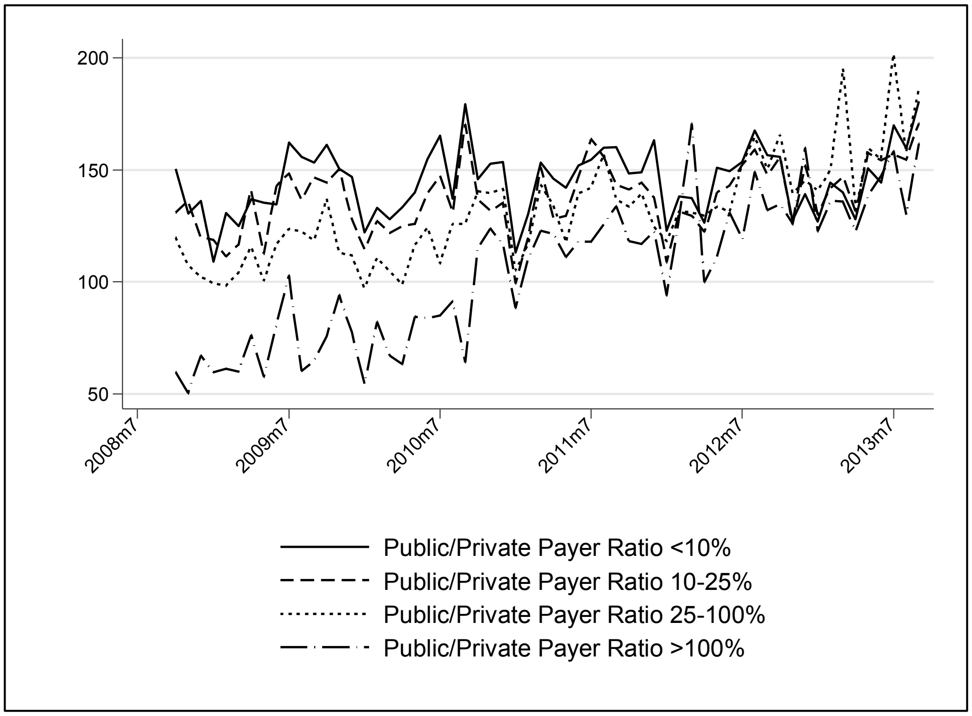

Figure 10: Mean per patient collections over time by payer mix group

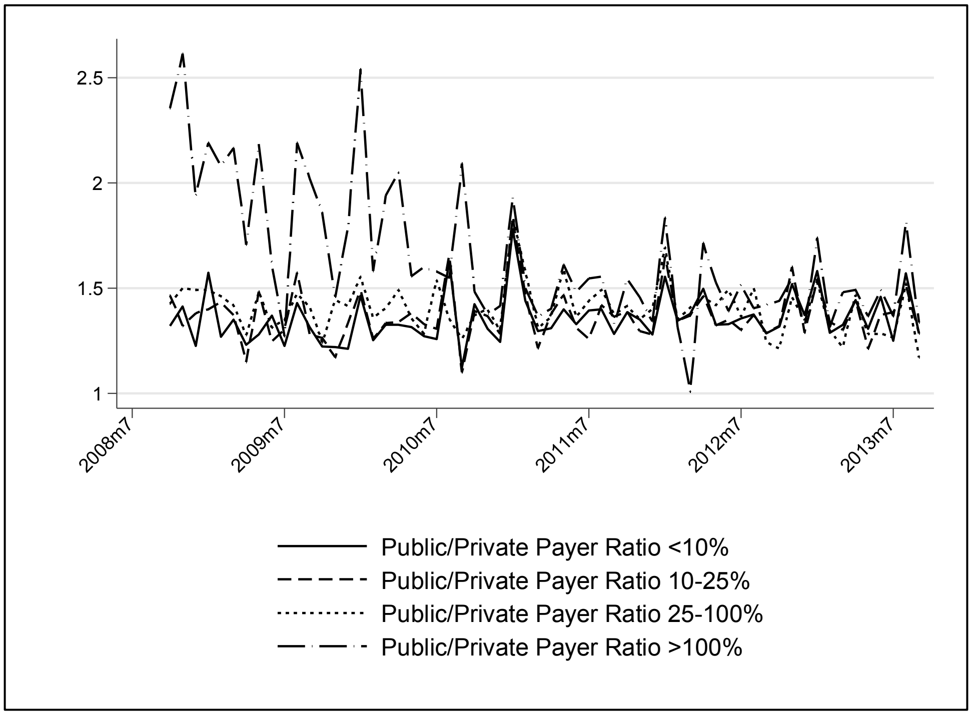

Figure 11: Mean charges-to-collections ratio over time by payer mix group

Table 9: Fixed effects model output for EHR impact on per patient charges

Variable	Model 1	Model 2	Model 3
EHR	27.05** (1.58)	27.05** (1.57)	11.09** (2.49)
Payer Mix Group			
Pub/Priv Ratio <10%	-	Ref	Ref
Pub/Priv Ratio 10-25%	-	-4.21 (3.83)	-4.21 (3.77)
Pub/Priv Ratio 25-100%	-	-20.92** (5.97)	-20.92** (5.88)
Pub/Priv Ratio >100%	-	-58.93** (8.51)	-58.93** (8.37)
Year			
2008	-	-	Ref
2009	-	-	-0.83 (3.25)
2010	-	-	3.52 (3.30)
2011	-	-	14.48** (3.75)
2012	-	-	14.84** (3.75)
2013	-	-	27.84** (3.84)
Constant	175.78** (0.97)	187.56** (2.73)	184.30** (3.85)
Observations	3360	3360	3360
Number of Practices	32	32	32
R^2 (within)	0.0811	0.0958	0.1254
AIC	34057.33	34009.29	33907.21

Standard errors in parentheses. Month & practice fixed effects not shown.
**(p<0.05); ** (p<0.01).*

Table 10: Fixed effects model output for EHR impact on per patient collections

Variable	Model 1	Model 2	Model 3
EHR	18.91** (1.71)	18.91** (1.70)	11.49** (2.72)
Payer Mix Group			
Pub/Priv Ratio <10%	-	Ref	Ref
Pub/Priv Ratio 10-25%	-	-1.45 (4.15)	-1.45 (4.13)
Pub/Priv Ratio 25-100%	-	-16.60** (6.47)	-16.60** (6.44)
Pub/Priv Ratio >100%	-	-64.69** (9.22)	-64.69** (9.17)
Year			
2008	-	-	Ref
2009	-	-	4.31 (3.56)
2010	-	-	6.32 (3.62)
2011	-	-	9.06* (4.11)
2012	-	-	10.27* (4.11)
2013	-	-	20.12** (4.21)
Constant	127.95** (1.07)	139.07** (2.96)	133.46** (4.21)
Observations	3360	3360	3360
Number of Practices	32	32	32
R^2 (within)	0.0354	0.0533	0.0639
AIC	34604.78	34547.57	34520.01

Standard errors in parentheses. Month & practice fixed effects not shown.
**(p<0.05); **(p<0.01).*

Table 11: Fixed effects model output for EHR impact on per patient charge-to-collection ratio

Variable	Model 1	Model 2	Model 3
EHR	.0009 (.0167)	.0009 (.0167)	-.0776** (.027)
Payer Mix Group			
Pub/Priv Ratio <10%	-	Ref	Ref
Pub/Priv Ratio 10-25%	-	-.0143 (.0408)	-.0143 (.0407)
Pub/Priv Ratio 25-100%	-	.0383 (.0636)	.0383 (.0634)
Pub/Priv Ratio >100%	-	.3102** (.0906)	.3102** (.0903)
Year			
2008	-	-	Ref
2009	-	-	-.0820* (.0351)
2010	-	-	-.0731* (.0356)
2011	-	-	.0252 (.0404)
2012	-	-	.0353 (.0404)
2013	-	-	-.0092 (.0414)
Constant	1.464** (.010)	1.422** (.0291)	1.478** (.0414)
Observations	3360	3360	3360
Number of Practices	32	32	32
R^2 (within)	0.0015	0.0057	0.0135
AIC	3496.541	3483.339	3466.831

*Standard errors in parentheses. Month & practice fixed effects not shown. *(p<0.05); **(p<0.01).*

Discussion

This study suggests that the introduction of an EMR to a pediatric care network is independently associated with an \$11.09 increase in average per patient charges, an \$11.49 increase in average per patient collections, and an improvement in physicians charge-to-collection ratio, controlling for other variables. These findings align with the conceptual expectations set forth by early EHR advocates (Häyrinen et al., 2008; Menachemi & Brooks, 2006) and add an additional financial measurement factor for earlier empirical studies that relied on projected "costs averted" as the revenue-related benefit of the EHR (Schmitt & Wofford, 2002; Wang et al., 2003). We believe this is the first study of its kind to evaluate the impact of EHR on charge capture in a fee-for-service model. Almost all previous, similar studies we could find had been conducted on EHR pioneer organizations and networks. Unlike those HIT-advanced organizations, our study was conducted on an organization that, prior to the HITECH Act and as recent as 2010, was a paper-based organization. As a result, we believe our findings are more generalizable to the remaining EHR have-nots who are still paper-based.

Our finding of significant relationships between EHR implementations and charges, collections, and charge-to-collection ratios is informative for both researchers and practitioners. Our findings suggest that despite the varying starting points (intercepts in our model) of different payer mix affiliations, EHRs benefit all physician types. It does appear, though, that physicians who principally serve public pay patients stand to benefit more given their lower pre-implementation means. This was illustrated through our non-estimation based *t* tests and visual scanning of our longitudinal data (Figures 8-11). It also appears that the EHR acted as a leveling mechanism across the organization, creating greater parity for charges, collections, and charge-to-collection ratios across payer mix groups.

This study generates a few very important questions. First: Are EHRs enabling providers to deliver higher quality, in-office care that is resulting in the $11 increase in charges? Or, is the EHR merely improving providers' charting processes that subsequently allow their organizations to increase charges by $11? This is a valuable question but with an expensive answer. The simplest option would be to examine patient records by physician to see if the quantity or appropriateness of procedures improved after the EHR implementation. Unfortunately, since this was a paper-based organization this would require a very resource-intense data capture effort. Second: If EHRs really are just improving charting and not producing higher quality, in-office care, is $11 per patient encounter a fair price for the potential downstream benefits of having the EHR (e.g., reduced adverse drug events, improved coordination as a child transitions to adult care, convenience in prescription refills, etc.)? Finally: How different would these results have been in a capitated environment? If physicians are not operating under fee-for-service parameters, perhaps they would be less likely to utilize an EHRs capacity to prompt and warn? Perhaps in answering this second question we could also answer the first question posed in this paragraph.

Fortunately, some research is already beginning to investigate these issues. On the adverse side, there are emerging cases of practices purposively abusing an EHR's capacity to upcode. Verges (2012) estimated that upcoding may have cost Medicare $100 million in 2010. On the positive side, Zhang and colleagues (2013) ruled out that 'copy-paste' charting was associated with inflated charges. As we have stated above, more research is warranted to better understand the implications of EHRs and how providers and administrators respond to the technology.

Limitations

Although our results align with previous research and also demonstrate strong face validity among the pediatric network administrators, there are a few limitations worth mentioning. First, given the nature of the data set, we have very few variables to hold constant, therefore increasing our likelihood for omitted variable bias. Indeed, our low R^2 values in all three models suggest we are not doing the best at explaining the variation in our dependent variables. Second, although we attempted to incorporate a proxy regressor—calendar year—to account for external shocks to the system, our model does not incorporate more granular, contextual trends of less than 12 months that might confound charges, collections, or charge-to-collection ratios (e.g. employment trends, trends unique to the networks MSA, etc.). Finally, as our data set was from a single organization, albeit an early adopter and by no means an EHR pioneer, our findings cannot be generalized to all pediatric care networks nor to other non-pediatric healthcare organizations.

CHAPTER V

CONCLUSION: APPLICATION OF THE SECOND ORDER IMPACTS OF INNOVATION RESEARCH MODEL

Introduction

In this final chapter we will explore the implications of each of the three preceding chapter's results in light of our second order impact (SOI) research model (see Figure 12 below for a recap of the SOI conceptual model). In doing so, we aim to highlight how these three studies both elaborate and support our conceptual model. We will also address how these three particular innovations fit within the industry's general need for transformation. Finally, we will conclude with a broader discussion of how SOI and, thus, our model are relevant not only to individuals inside of the organization, but also to stakeholders outside the organization.

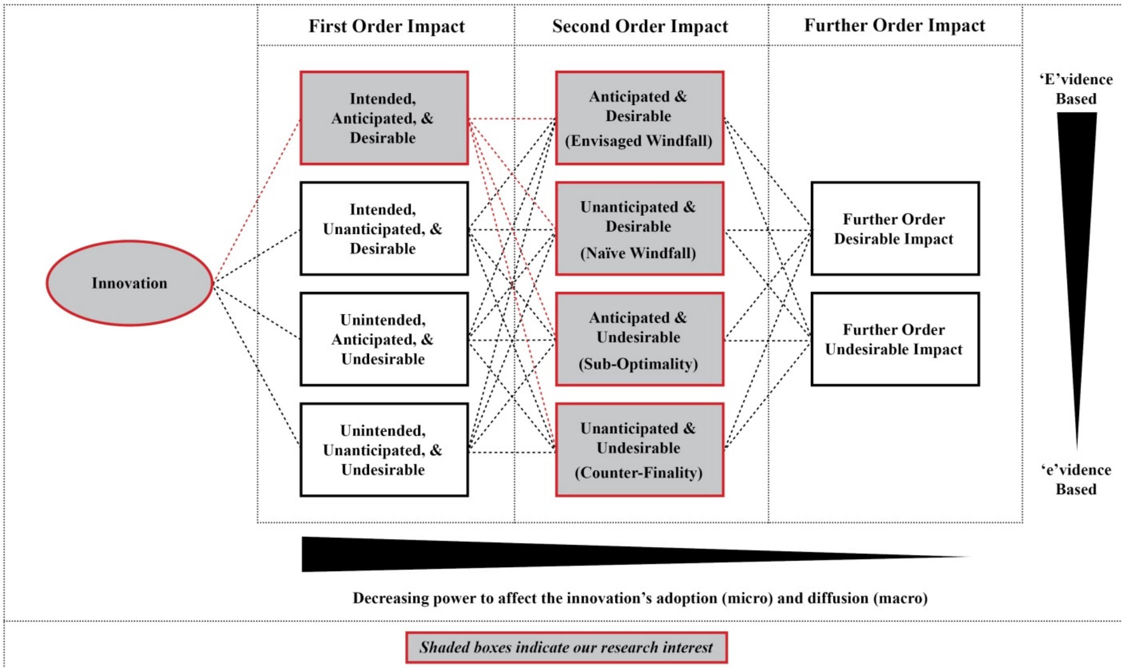

Figure 12: SOI in relation to innovation. Adapted from Baert (1991), Rogers (2010), and Sveiby et al. (2009)

Paper 1: Cost-Effectiveness of Colorectal Cancer Screening

Enabling primary care physicians (PCPs) to serve as trained endoscopists is a safe, sustainable method for improving patient access to colorectal cancer (CRC) screening. This first order relationship has been established by multiple studies (O'Malley et al., 2004; Roge et al., 1994; E. G. Stone, 2002; Wilkins et al., 2009). Our study examined the unintended impacts of CRC screening training in family medicine residency programs. Specifically, by examining the training program's impact on cost and clinical effectiveness, we found that not only do CRC screening strategies remain below commonly accepted willingness-to-pay (WTP) thresholds, but that the relative rankings of the strategies was also disrupted.

With regards to our conceptual model, these results fall into the category of naïve windfall. The results are desirable and complementary for the original innovation—enabling primary care physicians to perform CRC screening. These results demonstrate that the additional costs required to train PCPs do not push any of the CRC strategies above WTP thresholds. The innovation achieves this by improving patient adherence. The study demonstrated that as long as patient adherence can be improved from 55 percent to at least 68 percent the innovation will produce a positive return on investment.

This study's findings are classified as naïve windfall and not envisaged windfall due to the complexity of the program costs. This evaluation was for a first-of-its kind overhaul for family medicine residency programs. As such, it is unlikely that anyone could have anticipated the total per resident cost that was calculated as a result of this study. Indeed, we (the research team) were unsure of the how the results would lean prior to conducting the analysis. At one point we were even wary of the funding agency's reaction had the results reflected poorly on the residency program's costs. Thus, we classify these findings as naïve windfall as they are desirable, but unanticipated.

In regards to our vertical "E"vidence based management (EBM) axis, these findings further elevate the innovation as an empirically vetted policy. That is, we believe that our results further strengthen the case for enabling PCPs to perform CRC screening though family medicine residency training. We also believe that our study's design further enhanced its generalizability. First, the clinical effectiveness data were derived from a meta-analysis of clinical trials data. Second, though our cost data were derived from a single test site, the process behind the capital acquisition required that we obtain nationwide vendor quotes, thus improving the likelihood that these costs could be replicated at other family medicine residency programs. When combined with the previously mentioned first order impacts (FOI) studies (which demonstrated PCP's ability to perform safe, efficient in-office CRC screening) this policy is one step further along on its journey to what Rousseau (2006) would refer to as "Big 'E' Evidence."

Finally, in regards to our horizontal adoption/diffusion axis, we believe these findings will exhibit an intermediate affect power. That is, this SOI will support the innovation in its continued adoption and diffusion, but at neither a high nor a low degree of impact. Recall that in Chapter 1 we argued that second order impacts with high observability and low latency possess more power to affect the innovation's diffusion. We contend that our study's desirable results will ultimately be critical for decision-makers who might otherwise balk at the initial high cost of the innovation, thus supporting its diffusion. However, because the impact of the innovation (an increase in patient adherence and a decrease in colorectal cancer) will not be realized for years or possibly even a decade, this study suffers from high latency. As a result, we expect these findings to exhibit an intermediate affect power on the innovation's continued diffusion.

Paper 2: Organization Tenure and Nurses' Perceptions of Change Initiatives

System-level cultural change initiatives such as Studer Group's 'Evidence Based Leadership' (EBL) are being widely adopted by acute care hospitals in an effort to improve patient satisfaction scores and organizational accountability. Though little research has been conducted on EBL as a whole (Vest & Gamm, 2009), studies have been conducted that demonstrate the desirable, intended FOI of AIDET (L.-f. Zhang et al., 2013), hourly rounding (Christine M Meade, Amy L Bursell, & Lyn Ketelsen, 2006), and discharge phone calls (Kennedy, Craig, Wetsel, Reimels, & Wright, 2013; Setia & Meade, 2009). Our study examined the unintended impacts of these three change initiatives on the nurses responsible for implementing them. Specifically, by examining how long a nurse had worked for the organization and his/her perceptions of the three initiatives, we found that in some, but not all cases, significant differences in perceptions do exist depending on how long one has been in an organization. Our results indicate the mechanics and disruptiveness of each individual intervention moderates a nurse's perceptions.

These mixed results provide a unique opportunity to demonstrate the breadth and versatility of our SOI model. Within the context of this study, we can categorize the results across tenure strata and for each of the three change initiatives. So, whereas in Study 1 where the results could be neatly placed into a single category of SOI, results from Study 2 will fall into multiple categories depending on the perspective taken and the specific results for each change initiative.

For example with regards to discharge phone calls (DPC), the non-significant differences across categories of tenure, taken in tandem with overall favorability, produce a SOI that we would classify as naïve windfall. These results are desirable for the innovation in that they complement the innovation's intended impact. That is, not only can discharge phone calls improve patient satisfaction scores and patient quality of care (Kennedy et al., 2013; Setia & Meade, 2009), it also appears to be an intervention that is well-received by the nurses who adopt the innovation, irrespective of organization tenure. We classify this as naïve versus envisaged as it contrasts with earlier literature that found positive relationships between nurse tenure and safety related change initiatives (McGovern et al., 2000; Nichol et al., 2008). In regards to our vertical EBM axis, these results further elevate DPC as being an empirically vetted innovation, but only marginally. Given the nature of the data—cross sectional from a single health system—we cannot infer strong generalizability, thus preventing any significant leaps on our vertical EBM axis. In regards to our horizontal adoption/diffusion axis, we believe these findings will further support DPC in its continued adoption and diffusion.

Meanwhile, when we consider the results for AIDET and hourly rounding (though less so for the latter), we find ourselves in an undesirable category of our model: counter-finality. Specifically, the results here indicate that the more senior a nurse is, the less favorably he/she perceives these two innovations. These results contrast and could possibly even counteract the two innovations' desirable, intended first order impacts (Christine M Meade et al., 2006; L.-f. Zhang et al., 2013). We know from the literature that senior nurses are better positioned to serve as 'change champions' as they possess more sway over their junior counterparts in sustaining a change intervention (Scalzi, Evans, Barstow, & Hostvedt, 2006). Thus, we could expect the innovation to diffuse more slowly or eventually fail all together, despite the high favorability among novice nurses.

We classify this as anticipated versus unanticipated, though accurate classification would depend on the knowledge of the change agent. As we discussed in the introduction section of Study 2, the literature has produced mixed results with both positive and negative relationships between organization tenure and change initiative favorability. If the change agent had expected more senior nurses to be *more* hostile to the innovation, this would be a case of counter-finality. Conversely, if the change agent had expected more senior nurses to be *less* hostile to the innovation, this would be a case of sub-optimality.

With regard to our vertical EBM axis, while these results do not necessarily negate any previous desirable relationships between the innovation and a first order outcome variable, they do call into question the long-term sustainability of these two innovations. Should one or both of the innovations fail to “stick” in the organization, they would meet the criteria of having performed as a “little ‘e’” evidence based practice that failed in spite of its desirable FOI.

Finally, in regards to our horizontal adoption/diffusion axis, we believe these less-than-ideal findings will slow, if not halt AIDET and hourly rounding in their continued adoption and diffusion. Which impact ultimately ‘wins’ is likely a function of subsequent events. As we alluded to earlier, the ability of a SOI to affect an innovation’s long-term payoff is seldom clean or quick. Instead we should expect the two opposing levels of impact to interact in a metaphorical war of attrition. Each ‘side’ can be reinforced by action or inaction on the part of the change agent. For example, continued top-level and managerial support for the innovation (both financial and social) would reinforce the desirable FOI, thus reducing the affect power of our undesirable second order impacts. However, abandoning the innovation or too quickly introducing yet another innovation would reinforce the undesirable second order impacts and increase their affect power.

Paper 3: EHR Impact on Charge Capture

A high hope for electronic health record (EHR) adoption and diffusion in the US was to improve the quality of care (Menachemi & Brooks, 2006). Fortunately, FOI research has demonstrated positive (albeit weak) linkages between EHR use and improved process compliance (Bardhan & Thouin, 2013; Patterson et al., 2012; T. J. Spaulding & Raghu, 2013), improved patient satisfaction (Kazley et al., 2012) and reduction in medication errors (Radley et al., 2013). Our study examined the unintended impacts of EHR adoption on charge capture. Specifically, by estimating a fixed effects model of the impact of EHR implementation on charges, collections, and a charge-to-collection ratio, we found the introduction of an EMR to a pediatric care network is independently associated with an $11.09 increase in average per patient charges, an $11.49 increase in average per patient collections, and an improvement in a physician's charge-to-collection ratio, controlling for other variables.

With regards to our conceptual model, similar to Study 2, these results will fall into multiple categories depending on the perspective taken. From the perspective of the pediatric network, these results fall into the category of envisaged windfall. From this perspective, the results complement the original, intended first order impact of improved quality care. We classify this as envisaged versus naïve windfall as there was an abundance of conceptual expectations set forth by early EHR advocates (Häyrinen et al., 2008; Menachemi & Brooks, 2006) and with earlier empirical studies that relied on projected costs averted as the revenue-related benefit of the EHR (Schmitt & Wofford, 2002; Wang et al., 2003). In regards to our vertical EBM axis, these results further elevate EHR as being an empirically vetted innovation. Given the nature of our study design (that is, second generation EHR research), we can infer improved generalizability compared to that of first generation EHR research that would have relied on EHR pioneers and organizations who were structurally and culturally different than most typical healthcare organizations. Our generalizability is further supported by the wide array of patient-payer mix present in our dataset. In regards to our horizontal adoption/diffusion axis, we believe these findings will strongly support EHR diffusion in the industry.

Meanwhile, when we consider the perspective of either society or payers, we find ourselves yet again in the *un*desirable category of SOI. As we mentioned above, that so much literature had predicted this likely outcome, we contend that this was a known likely outcome to national policy-makers who went ahead with the innovation regardless. Thus, from the societal perspective we would classify this as counter-finality. This pessimistic interpretation of the results projects that charges and collections are increasing, but with little evidence that those increases are resulting from a change in the type of care delivered. Instead, physicians could be delivering the exact same care they did prior to the EHR, only now with a much improved automated documentation process. In this bleak outlook, only the organization is benefitting while society is simply paying $11.49 more per visit for the same level of care.

Interestingly, despite this negative SOI for society we would expect organizations to continue to adopt EHRs (a dialectic tension we will discuss in the following section on public versus private consequence). This provides a keen example of our horizontal adoption/diffusion axis in action. Although the SOI in this particular case is undesirable for society, this study will do little to slow the diffusion of EHR use.

Public Consequence vs. Private Consequence

Finally, we would be remiss to partake in such a lengthy discussion on innovation and its primary and second order impacts and not discuss whom ultimately benefits. Sociologists have argued that an innovation yields consequences of the public variety, private variety, and in many cases, both (Mazzarol, 2011; Wejnert, 2002). Public consequences are realized when an innovation's chief recipient is a collective actor such as a country, region, or a subset of the population. The advent of the diagnosis-related group (DRG) classification system is an example of such an innovation. DRGs were enacted to shift hospitals away from the existing unrestrained cost reimbursement system (W. C. Hsiao, Sapolsky, Dunn, & Weiner, 1986). The consequences of this innovation were controlled costs for payers (both public and private) and a decrease in practice variance. These consequences were of immediate benefit to the public.

Private consequences on the other hand are realized when an innovation's chief recipient is either an individual or a small collective such as an organization or a peer group. Any innovation that is enacted with the goal of improving an organization's market share or productivity is an example of an innovation with private consequence. The actor purposively protects such an innovation in an effort to protract their time before competitors can imitate the innovation and thereby remove the competitive advantage (Barney, 1991).

To be clear, both varieties of consequence can benefit society. Management scholars have argued that to truly maximize growth of the firm an organization must "develop new and innovative goods and services that generate economic growth while delivering important benefits to society" (Ahlstrom, 2010, p. 11). Pharmaceutical companies that invest billions into research and development are doing so principally to drive profits and appease stockholders. However, society benefits when drugs are developed that cure disease and improve quality of life. The same can be said for agriculture (How can we grow more food faster and cheaper?), transportation (How can we travel faster, safer, and more efficiently?) and energy (How can we produce cheaper, safer, sustainable energy?). In these non-dichotomous cases, Wejnert (2002) argues that innovations can "reflect direct (manifested function) and indirect (latent function) consequences." Whereas FOI research focuses mostly on the manifested function, we contend that SOI research is critical in highlighting the latent functions. As a result, SOI research becomes not only relevant to the innovating organization (the private consequence) but also to stakeholders outside of the innovating organization (the public consequence).

For the innovating organization, SOI research can provide additional insight into the public consequences of the innovation. In the event the public consequences are desirable, the organization can exploit these findings to demonstrate the value of the innovation both internally (vision alignment) and externally (marketing and/or fulfillment of community need). Such is the case with Chapter 2. That colonoscopies performed by primary care physicians can actually improve the cost-effectiveness of the strategy while simultaneously improving patient accessibility is a finding that ought to be insightful and encouraging for primary care physicians who are contemplating the innovation. Primary care physicians could also exploit these findings as they market the new service line and lobby for additional support among third party payers. Conversely, in the event the public consequences be less than desirable, the organization can strategically posture itself to mitigate criticism. As discussed earlier, one could argue that results from Chapter 4 are neutral or even negative from a societal perspective. Critics could contend that EHRs are increasing healthcare costs at a time when healthcare innovations ought to be focusing on achieving the opposite. However, knowledge of this information (specifically that charges increased by $11.09 and collections increased by $11.49) can inform EHR-adopting organizations of the amount of additional cost savings they would need to demonstrate to counter critics' arguments.

For stakeholders outside of the innovating organization, SOI research can inform them where they ought to stand in regard to the organization-level innovation. Should the public consequences be desirable, collective entities such as the government, private payers, and patient advocacy groups ought to support the innovation's diffusion throughout the industry. Such is the case with the colonoscopy study from Chapter 2. Given the results the study, Medicare, Medicaid, and private health plans ought to incentivize additional family medicine residency programs to add colorectal cancer screening training. In the likely event that specialists such as gastroenterologists could view this innovation as professional encroachment by primary care physician, one can witness here an illustration recognized as "disruptive innovation" for CRC services and providers (Hwang & Christensen, 2008). Conversely, should the public consequences be undesirable as they were in Chapter 4, the collective entities ought to conduct counter-operations to slow its diffusion or negate its impact. We witnessed such a reaction from public and private payers in 2012 when it was revealed that EHR-using organizations were dramatically increasing their reimbursements, due in part to more efficient billing documentation afforded by EHRs (Abelson, Creswell, & Palmer, 2012). The US Department of Health and Human Services and the US Department of Justice responded by issuing a warning letter about the illegality of encounter "cloning" and improper upcoding (Lowes, 2012). Similarly, private payers launched a series of targeted audits to "ensure that medical records do not contain inaccurate information that may indicate that the provider documented more work than he/she actually did or needed to do" (Independence Blue Cross, 2013, p. 1).

Conclusion

In summary, we have highlighted how SOI research can augment its pervasive first order brethren by focusing on the latent functions of an innovation. Our SOI model encourages both practitioners and researchers to observe the long game of an innovation instead of just the 'low hanging fruit' of FOI. Our model also calls attention to the dearth of research on the unintended, oftentimes undesirable impacts of innovation, commonly referred to as the research community's "pro-innovation bias" (Sveiby et al., 2009). Avoiding the myopia of FOI-only research can help practitioners avoid many of the common pitfalls of innovation implementation that are pervasive across all industries. It can also help them identify opportunities for leveraging an innovation to spur additional growth and capacity for change.

Whether the SOI produces results that are supportive of or contrary to the innovation's FOI, we have argued that such research is immediately relevant to both the innovating organization and also to stakeholders outside the innovating organization. This concept feeds back into our horizontal adoption/diffusion axis from Chapter 1. Recall that we argued SOI research could either accelerate or slow an innovation's adoption and diffusion. Through our proposals of internal marketing and increased public funding or our real-life examples of DHHS warning letters and directed audits we have provided concrete examples of how SOI research can affect an innovation's rate of adoption and diffusion. We contend that with additional SOI research we are equipping decision makers with the decision support they need to pursue changes that will truly transform healthcare.

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