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ABSTRACT

This paper uses employee and patient survey data from a large, integrated healthcare provider to assess the moderating role that employee involvement (EI) plays in the effectiveness of a patient scheduling module that is part of an electronic health record (EHR) system. The author finds that while the module facilitated the appointment-making process, its effects were greater in those clinics that sought input from frontline workers and made use of worker peers trained as system "super-users." This case of workplace technological change begins to explain the elusiveness of the EI-performance link in received studies by suggesting an alternative avenue by which EI can improve organizational performance. Moreover, this study presents the first empirical evidence of EI's potential to enhance the effectiveness of health IT, findings that should inform policymakers and sectoral actors as they allocate substantial resources toward the healthcare industry's transition from paper-based to electronic recordkeeping.

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Newcomers to the study of work and employment might be surprised to learn of the elusiveness of the link between employee involvement (EI) and organizational performance. In fact, despite the long-term interest of scholars of organizational behavior (OB), human resources (HR), and employment relations (ER), among other fields, the connection between EI and performance is far from universal. At the same time, the widespread diffusion of information technology (IT) over the last two decades has heightened our need to understand how human and technological capital interface in production. Since it has been shown, for example, that many of the benefits once assumed to arise from IT actually arise through the interplay of IT and features of the employment relationship (Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson, Hitt, and Yang 2002), could the converse be true—that the productivity gains anticipated of EI are actually channeled through the effective implementation of new technologies?

The extent to which EI in the implementation of IT tightens the link between each of these inputs and measures of productivity has immediate implications for both policy and research. From a policy perspective, nowhere is the need to answer this question more acute than in the healthcare sector. There is near universal agreement that the industry requires major reform and that diffusion of health IT is critical to improving efficiency and service quality—a belief backed up by billions of dollars in government incentives to those adopting electronic health records (EHRs). For example, the Health Information Technology for Economic and Clinical Health (HITECH) Act allocated $46 billion of economic stimulus funds towards advancing EHR technologies. Reformers justify the allocation of these resources by blaming the slow diffusion of health IT for the poor performance of the healthcare industry, marked by skyrocketing costs and poor quality outcomes relative to other countries (Kaiser Family Foundation 2007). The Obama administration, citing a RAND Corporation study (Hillestad et al. 2005), points to a projected annual savings of $81 billion from the effective deployment of health IT systems.

However, to date policymakers have little or no empirical evidence to support their optimistic expectations or data on the organizational or employment conditions needed to translate these new technologies into improved performance outcomes. Yet, if results from studies of investments in technologies in other industries (Batt 1999; MacDuffie and Krafcik 1992) generalize to healthcare, there is reason to question whether a "technology alone" strategy will realize policymakers' expectations. Instead, these studies have demonstrated that technological investments need to be complemented with employment and organizational practices to achieve their desired results.

Likewise, if the theorized complementarity obtains, the results could help piece-together what has been a theoretical and empirical puzzle by revealing a common situation in which EI can be a positive driver of performance. This would explain why managers maintain this belief and continue to rely on EI despite the dearth of empirical evidence in its favor (Freeman and Kleiner 2000). That is, beneficial effects of EI may come through the implementation of new technologies. This makes sense if EI structures and processes allow for two-way communication between the strategic and workplace levels as well as for frontline involvement in training and optimization around the new technology. Therefore, the extent to which employee involvement in the implementation of a new IT system moderates the effectiveness of the technology is a question with immediate consequences in both the research and policy realms.

This paper begins to address this issue by testing for the performance effects of a specific type of health IT at varying levels of EI. It does so by examining the implementation of one piece of an EHR system, a scheduling module, across a single region of Kaiser Permanente, the nation's largest, not-for-profit health plan. I first draw on qualitative, observational data to develop an understanding of the processes by which the scheduling module facilitates the work of frontline employees. This stage of data-gathering also allows me to identify performance measures most directly tied to the effective use of this particular technology, outcomes that are of interest to the organization itself and that are measured reliably across clinics over time. Furthermore, I determine the specific ways in which workers and union representatives are involved in the development, deployment, and use of the IT, particularly those forms of EI that the organization believes will improve the effectiveness of the scheduling module. This qualitative evidence is then used to develop context-specific measures of the EI practices and IT in-use and to conduct a longitudinal analysis of the individual and joint effects of IT and EI on performance across multiple healthcare clinics.

The study offers a number of advantages over existing ones. It allows us to hold constant many of the unobservable contextual factors that remain unaccounted for in national, cross-industry studies of IT's performance effects (e.g., Brynjolfsson, Hitt, and Yang 2002; Caroli and van Reenan 2001). In particular, it leverages the strength of a case study approach, studying a very specific, well-defined technological change—something that cannot be done in national studies where IT is frequently defined rather vaguely (Brown and Campbell 2002) and has yet to be done even in more-grounded studies of EI and IT (Mirvis, Sales, and Hackett 1991). Likewise, rather than relying on measures of revenue or profit, it relies on a contextually-appropriate, homogenous performance measure as suggested by Ichniowski, Shaw, and Prennushi (1997) and MacDuffie (1995). The paper also supplements more-grounded examinations of employment practices and IT developed largely in manufacturing rather than in the service sector.

Employee Involvement and Technological Change

Employee Involvement in Human Resources and Organizational Behavior

The fields of Human Resources (HR) and Organizational Behavior (OB) offer a far-reaching literature on EI, theorizing the effects of "participation" largely through a psychological or motivational lens. In the US, empirical analyses date at least as far back as the Hawthorne (Roethlisberger and Dickson 1939) and Harwood (Coch and French 1948) studies. These foundational pieces from the "human relations" school first came to symbolize the benefits attendant to participation, but were later (and famously) maligned for their methodological shortcomings. Subsequent and more careful analyses of EI yield a much more cautious view of its instrumentality over organizational performance. Motivated by anecdotal and ideological accounts of the importance of EI, Locke and Schweiger's (1979) extensive review concluded that while participation may drive job satisfaction, it does not reliably influence productivity.

In the absence of evidence of a universal relationship, HR and OB theorists have at least sought to answer two overarching questions. Contingency theories (e.g., Vroom and Yetton 1973) attempted to explain *when* or under what organizational conditions EI should be used to boost performance. Though contingency models examining employee-level traits and the appropriateness of different types of decisions find little support in the data (Miller and Monge 1986), more organizationally-grounded approaches, indeed, find support for a link between EI and performance. Kanter's (1983) empirical work, for example, suggested that EI was appropriate for frontline staff if they had knowledge or expertise—tacit or explicit—not available at higher ranks within the organization, results that have since been replicated and generalized (Latham, Winters, and Locke 1994; McCaffrey, Faerman, and Hart 1995; Scully, Kirkpatrick, and Locke 1995). Aside from asking when EI might boost performance, HR and

OB research has examined *how* EI should be implemented to promote its performance benefits. That is, ascribing Locke and Schweiger's (1979) "non-results" to a unitary conceptualization of participation, research sought to determine what institutional forms of EI might strengthen the link between EI and performance. The findings suggested that self-directed teams in which EI centers around everyday work are much more likely to drive performance than are weaker forms of participation, such as offline problem-solving groups or quality circles (Cotton, Vollrath, Froggatt, Lengnick-Hall, and Jennings 1988; Cotton 1993). However, even this seemingly safe conclusion has been called into question on methodological grounds (Leana, Locke, and Schweiger 1990).

The HR and OB literatures diverge with respect to their treatment of technology. The work of Edmondson and colleagues exemplifies OB's nuanced examination of the role of technology in organizations. Channeling Kanter's conceptualization of frontline worker knowledge, they explain the effectiveness of new technologies as a consequence of the form of worker knowledge—tacit or codified—required to more-fully leverage new technologies (2001). In a related, qualitative study, they examine the collective learning process of those responsible for implementing the same technology, arguing that the deep entrenchment of routines developed around old technologies can limit the success of new ones (2003). The need to realign workflows around new technologies certainly applies to the technological change to be examined in this paper. However, in Edmondson, Winslow, Bohmer, and Pisano (2003), the resistance stems from the deep-seated nature of hierarchical relations in an organization, hospitals in this case, and the high level of task interdependence required for the effective use of the technology under study.

Interestingly, while OB, in particular, cares a great deal about the role of technology in organizations generally, neither HR nor OB reserves a place for technology in theory linking HR practices to organizational performance (Becker and Huselid 1998; Becker and Huselid 2010). One notable exception on the HR side is Mirvis, Sales, and Hackett's (1991) comparison of two very different technologies—computerized machinery in a metal fabrication factory and word processing technology in a publishing company. They concluded that a top-down deployment strategy like that used in the factory appeared less effective than the more participatory, training-focused strategy employed in the publishing house. However, their findings are undermined by an "apples to oranges" research design, and more widely-cited contributions to the HR literature are much more likely to treat technology solely as a source of measurement error (Huselid and Becker 1996; Locke and Schweiger 1979) rather than as an appropriate object of study. As a result, despite a wealth of theoretical and empirical work linking EI to performance, HR and OB research has yet to fully examine EI and IT in tandem. That is, it has yet to explicitly and carefully consider the possibility that EI's empirically elusive performance effects may come through its moderation of the technology-performance link.

Employee Involvement and Technological Change in Employment Relations

Scholars of work and employment, on the other hand, have an abiding interest in what Dunlop (1958 [1993]) labeled the "technological context." Marxists, of course, portray new technologies and the technological change process as a deliberate strategy on the part of managers to tighten control over workers and the labor process through de-skilling (Braverman 1974; Marx 1849 [1978]). This point-of-view though has been widely criticized as deterministic, charting at least two paths on which to advance theory. Science and technology studies (STS), though more focused on "technologies of consumption" rather than the realm of production (cf. Noble 1984; Oudshoorn and Pinch 2007, p.556), counters deterministic approaches by examining the ways that actual users of technology as well as the social environment more broadly shape characteristics of new technologies, implying that emergent manifestations of IT and the impact of new hardware and software, for example, depends on early-stage "negotiations" between the relevant actors.

In contrast to this focus on agency in technological change, pluralist industrial relations, i.e., employment relations, adopts more of an institutional perspective, paying very close attention to the interplay of technology and EI in production. Over the past three decades, ER research has delivered a growing body of evidence on the effects of technology and workplace practices, motivated in part by the highly visible and widely reported early experiences of General Motors (GM) and others in the auto industry with investments in automation. Case study research documented that in the 1980s, GM invested billions of dollars in automation technology—$650 million in one GM factory alone (Kochan 1988)—but did not achieve the expected performance improvements or achieve the levels of performance observed in Japanese plants in North America or in Japan (Krafcik 1988). Instead, follow-up case study and quantitative analyses demonstrated that it was the combination of new technologies and innovative employment practices that positioned shop floor workers to "give wisdom to the machine" (MacDuffie and Krafcik 1992; MacDuffie 1995) that delivered these levels of performance. This evidence suggested that a "bundle" of innovative employment practices, inclusive of opportunities for worker involvement in problem solving, moderated the return on investments in new technologies.[1]

These results have subsequently been replicated in other manufacturing settings and even a few service industries. Kelley (1996), for example, shows that increased computerization in the machined products sector drives larger productivity gains in firms that involve workers through participatory structures. Batt (1999) found that telecommunications sales representatives with access to new technology outperformed those not using IT, and that the size of the performance increment was greater for those workers reporting high levels of involvement in problem-solving and participation.

Interestingly, ER research focused on EI and performance to the exclusion of technology have been unable to establish a conclusive link between EI and economic performance (Cappelli and Neumark 2001; Freeman and Kleiner 2000; Kleiner, Leonard, and Pilarski 2001). Appelbaum and Batt (1994) suggest that measurement error may be the problem, as neither researchers nor practitioners have a single, shared understanding of the meaning of EI or how it actually occurs in workplaces. Instead, the dominant finding in the literature on high-performance work systems (HPWS) has identified "bundles" or clusters of employment practices as opposed to individual practices as significant drivers of economic performance (e.g., Becker and Huselid 1998; Ichniowski, Shaw, and Prennushi 1997; MacDuffie 1995). Of course, the instrumentality of EI-inclusive bundles of employment practices also stands on firm theoretical ground. It is now widely accepted that workers will only share their valuable, often tacit, production-related information if they are invited to do so, have the appropriate skills to do so, and are given the appropriate incentives (Appelbaum, Bailey, Berg, and Kalleberg 2000; Becker and Huselid 1998; MacDuffie 1995). Furthermore, consistent with aforementioned findings from HR and OB (Cotton, Vollrath, Froggatt, Lengnick-Hall, and Jennings 1988; Cotton 1993), it also appears that not all forms of EI "pack the same performance punch." That is, purely consultative, offline forms of EI such as the "quality circles" popularized in the 1980s and 1990s, generally yield weak performance improvements, if any (Levine and Tyson 1990).

[1] Interestingly, MacDuffie's (1995) groundbreaking empirical study measured technology very carefully in an effort to isolate the performance effects of employment practice bundles. However, it did not focus on the ways that certain employment practices managed to "unlock" new technologies.

This study proffers an alternative explanation for the empirical elusiveness of the EI-performance link. It theorizes that the implementation of new technologies, IT in particular, offers one avenue by which EI positively influences performance, thereby filling a gap in the management literature left by scholars of ER, HR, and OB. Taking an employment relations approach—characterized by organizational and phenomenological groundedness—it suggests that the deployment of an IT system offers opportunities for EI, and that those workplaces that successfully include workers in the deployment will show larger gains from the use of the new system than workplaces taking a more traditional, top-down approach—a process suggested by Mirvis, Sales, and Hackett (1991). By drawing on what we already know about the ways employment practices complement new technologies, the theory begins to clarify the ambiguity of the EI-performance link in employment relations research. Furthermore, the argument allows for a critique of the HR and OB literature's very narrow framing of the technology construct, suggesting an additional contingency thus far largely ignored by these fields. In particular, the questions of "when" and "how" to implement EI can be answered by taking more serious consideration of workplace technologies and technological change. It appears that technology has not only been under-theorized by these fields, but that its omission has itself clouded attempts to link worker participation to performance measures.

Technological and Organizational Context

This study integrates technology and technological change into research on EI to show that the EI surrounding the deployment of a new IT system does, indeed, drive organizational performance. One can think of EI as complementing IT in the production and delivery of healthcare services, which equates to EI moderating the relationship between IT and organizational performance. Establishing this relationship reliably requires a deep understanding of the technology and of the organization and its workflows, something that existing studies of the effects of EI and IT on performance have been criticized for failing to do (e.g., Brown and Campbell 2002; Ichniowski, Kochan, Levine, Olson, and Strauss 1996). Consequently, I describe the EHR and EI systems and the Kaiser Permanente labor management partnership (LMP) in considerable detail here in order to provide the context needed to interpret the quantitative results that follow.

Employee Involvement at Kaiser Permanente

Kaiser Permanente, the integrated health insurer and healthcare provider, was chosen for this study because it has been a forerunner in healthcare's conversion from paper-based to electronic recordkeeping and has a history of promoting EI as part of an overall labor management partnership (Kochan, Eaton, McKersie, and Adler 2009). Kaiser's EHR system, KP HealthConnect, once fully-deployed, will include a full complement of interoperable administrative and clinical health IT applications. One of these, which I refer to as the "scheduling module," is used for scheduling office visits, procedures, and lab tests in each region's outpatient or "ambulatory" clinics—essentially, large-scale doctors' offices.

The LMP is a cooperative arrangement between Kaiser Permanente and thirty union locals representing workers in seven of its eight regions (Kochan, Eaton, McKersie, and Adler 2009). As of 2008, the Coalition of Kaiser Permanente Unions (CKPU) and thus, the LMP, covers about 86,000 Kaiser employees. The configuration of the CKPU replicates that of its management-side counterparts, creating labor-management "partners" at every level in every region in which the CKPU represents workers. At the apex of the LMP in its Oakland-based office sits a representative from Kaiser—a senior vice president reporting directly to Kaiser's COO—alongside the CKPU's director.

[—Insert Table 1 about here.—]

The LMP funds a full-time KP HealthConnect union coordinator at the national level to represent the interests of the CKPU with respect to KP HealthConnect's development, deployment, and ongoing use. It also negotiated and now administers a national KP HealthConnect "Effects Bargain" agreement governing job and wage protections for workers as they relate to the KP HealthConnect initiative (See Table 1.). Together, these provisions and personnel assignments establish the importance of labor to the KP HealthConnect initiative and seek to assure that KP HealthConnect will advance the interests of the workforce as it advances Kaiser's goals. Further, the agreement underlines the need for flexibility at all levels in processes and workflows and for the active involvement of labor representatives and frontline workers in developing and implementing KP HealthConnect. In exchange, the document creates and funds regional KP HealthConnect union representatives to represent labor alongside IT and operations leads at the top of each region's KP HealthConnect project team. Among other protections, it makes guarantees with respect to training and preparation as well as a commitment to mitigating the effects of staffing challenges that would inevitably occur in the run-up to implementation.

The Effects Bargain established the creation of at least one, full-time, KP HealthConnect labor coordinator to serve on each regional KP HealthConnect leadership team. Since the labor coordinator was charged with monitoring KP HealthConnect-related service process and workflow change experiments and pilots, he or she also assumed responsibility for identifying and responding to demands for frontline worker involvement arising in the course of the initiative. In the aggregate, Kaiser expected labor's active involvement in configuring, implementing, and eventually, encouraging optimal use of KP HealthConnect.

One of Kaiser's regional operations, Kaiser Permanente of the Northwest, signaled its commitment to both the Partnership and to KP HealthConnect by funding two employees to serve as KP HealthConnect labor coordinators, each pulled directly from the bargaining unit. With clinical functionality largely in-place, the region turned to one of KP HealthConnect's non-clinical applications, the scheduling module. The labor coordinators assumed their positions on the local configuration team, alongside IT and operations leaders as well as programmers and application specialists. They also began assembling a cadre of bargaining unit members to serve as "super-users."

Super-users were support staff end-users drawn from throughout the region. At any one time, there were approximately 15-20 active super-users. They were the first to learn how to use the scheduling module and served as liaisons between frontline support staff and the regional configuration team. As the region grew closer to implementing the system in the spring and summer of 2005, super-users were temporarily transferred on a full-time basis from their regular roles on the front lines, allowing them to travel the region answering questions and facilitating the training of other bargaining unit members. Much of what the super-users did was informal. However, there were four main channels by which their participation—and by extension, the participation of all those frontline workers whom they touched—served to make the scheduling module more effective.

First, during their travels throughout the region, they sought suggestions on how to improve the system or its rollout. Through weekly meetings, they relayed this information to the labor coordinators, who ensured it was integrated into the planning being done by the regional leadership team. It was through this process that frontline staff pointed out that the transition between scheduling systems could not be done in waves—by clinic, by department, or by any way other than what would eventually be labeled a "big bang." This is because Kaiser patients, while assigned to a specific provider in a specific clinic, draw on services from many departments and often multiple facilities. Aside from communicating this up to management through their labor coordinators, the super-users also made a related case with respect to training, also voiced at the strategic level by the regional labor coordinators: as a consequence of the decision to go with a "big bang" rollout, all end-users would have to be trained before "go-live."

Training was, in fact, the second area where super-users played a key role in the deployment of the scheduling module. They worked with regional trainers to develop and lead sessions for their frontline co-workers. This introductory training occurred mainly at the regional training facility, but called upon the super-users to scope out opportunities within the clinics to make sure staff were up and running on the technology. Later on in the process, they played a similar dual role in follow-up or "optimization" training.

Super-users were also charged with communicating information downward from regional leadership to those on the frontlines, a responsibility that often included as much justification as communication. For example, management's recognition that staff from all clinics would have to be trained before the rollout reinforced the need for some extra flexibility from the rank-and-file. In particular, the short time frame meant that some training would have to occur in the evenings and on weekends, a decision that was not welcomed by the workforce.

Finally, super-users provided ongoing, "just-in-time" support for co-workers not only around the time of the deployment, but thereafter as well. These experts would eventually return to their jobs able to serve as their workplace's de facto leaders and "go-to" people for all matters technological and work-related pertaining to the KP HealthConnect scheduling module. Indeed, super-users played just as vital a role in the initiative when they returned fulltime to their regular positions. Managers and frontline staff report their being in-demand as KP HealthConnect resource people in their clinics, providing co-workers with quick answers to the sorts of "just-in-time" questions that arose as those who were already formally-trained became everyday users.

Despite the sturdy structure supporting the mandate for workforce participation, interviews with frontline staff in many clinics across multiple Kaiser regions revealed a great deal of variation in just how involved workers felt they were in the project. This deviation between stated policies and their impact on the ground is actually quite common in studies linking employment practices to performance (e.g., Bartel 2004; Jones, Kalmi, and Kauhanen 2009). However, within well-defined regional boundaries, there was little or no variation in attributes of the IT module itself—including when it "went live." Likewise, a host of contextual variables can be reasonably assumed not to vary within a single region. This study exploits these advantageous, quasi-experimental conditions to undertake a more careful analysis of EI's role in IT implementation than that permitted by the research designs employed in earlier studies (e.g., Mirvis, Sales, and Hackett 1991).

Technology and Workflow at Kaiser Permanente

Through interviews with managers and labor leaders in Kaiser's national headquarters as well as those in multiple regions, the Northwest region's scheduling module emerged as one with clear and measurable performance improvement expectations. Furthermore, it was implemented in organizational units doing the same work and that were similar enough on other dimensions to provide for suitable comparisons. Headquartered in the suburbs of Portland, Oregon, the region employs 880 physicians and 8,900 employees to serve just over 480,000 "members" (i.e., patients). The region spans the greater metropolitan Portland and Vancouver, Washington areas. It offers "ambulatory" care through 27 outpatient medical office buildings, 15 of which serve as hubs for primary care—family practice, pediatrics, and internal medicine.[2] The study focused on these primary care clinics, in part, because so many of the performance outcomes of interest to Kaiser are shaped by the member's experience with his or her primary care physician (PCP). Bounding the sample in this way also allowed the researcher to spend time in all of the clinics, accounting for or assuring the non-variation in contextual characteristics. For example, including appointment-making procedures beyond primary care would introduce variation across specialties and ancillary services.

The scheduling module addressed a very concrete set of organizational challenges—inefficiencies and patient dissatisfaction with the appointment-setting process. Among other challenges, those support staff charged with setting patient appointments using the legacy scheduling applications frequently found themselves asking even long-term Kaiser members for data that should be permanently linked to a member's health record number (HRN), namely

[2] The term "outpatient" is often used to describe those patients expected to check-in and out of the hospital on the same day. However, since this study does not address anything related to "inpatients" or hospital care, I use the adjectives "ambulatory" and "outpatient" interchangeably.

contact information. The legacy system also made it difficult to schedule regularly recurring appointments and often lacked up-to-date information on providers' availability vis-à-vis vacation scheduling, "panel support" time, or the use of planned or unplanned leave.

To understand how this would have a negative impact on economic performance, consider the process by which members make a primary care appointment by phone. They dial their clinic's appointments line. The call is received by a member intake specialist (MIS). The MIS opens the schedule corresponding to the member's PCP and searches for the first available appointment time or the first available time slot amenable to the member. This only disposed of about 40 percent of cases. More frequently, large sections of a provider's schedule would be blocked as "unavailable" for one of the reasons listed above. The MIS would then transfer the member to the medical assistant (MA) supporting the appropriate provider. If the MA picked up, she could override or correct the schedule. If instead the MA were unavailable or serving another patient in-person, the patient calling could leave a message. If the patient ever called again, possibly returning a call from the MA, they would start all over again at the clinic's call center, where the MIS would again try to make an appointment and would likely run into the same complication.

The end result was that 75-80 percent of members initially denied an appointment would ultimately be given one within an acceptable time frame. However, this chain of events came at the great expense of patient satisfaction with the appointment-making process. Furthermore, appointment-setting required 4-5 "touches" from more highly-paid MAs in addition to MISs, rather than the single touch of one MIS. Effective use of the new scheduling module was expected to address this issue and the patient dissatisfaction that arose from it.

Complementarity Between Employee Involvement and Information Technology

At Kaiser, the new IT—the scheduling module—served as a tool for workers, providing them real-time, up-to-date information that facilitated their ability to better meet a strategic goal. Therefore, one might expect that just turning the technology on—which occurred at the same time across all clinics examined—would boost performance. While there was no inter-clinic variation in when the IT "went-live," there was variation in the levels of EI achieved in each clinic. At some clinics, workers reported the frequent presence of and reliance upon so-called super-users. However, at other clinics, workers claimed not to have had their ideas or concerns solicited or considered or reported being trained not by a fellow frontline worker in the form of a super-user, but rather by a manager or regional IT staffer. This inter-clinic variation in EI is what enables the identification of the theorized complementarity between EI and IT. While the IT might boost performance across-the-board, these improvements should be measurably larger under higher levels of EI. Finally, as alluded to above, these quasi-experimental conditions allow for an unprecedented, "apples to apples" comparison of before-and-after effects in very similar organizational sub-units doing identical work and using the same new technology (cf. Mirvis, Sales, and Hackett 1991). Furthermore, relative to the organizational processes examined by Edmondson et al. (2001; 2003), the simple nature of the work and the focus on two, relatively lateral jobs in the organizational hierarchy—MISs and MAs—minimizes the likelihood that shifting power dynamics have any influence on observed outcomes.

Methods

For it to be true that EI facilitated the deployment of the scheduling module, it must be shown that variation in EI drives variation in performance. This analysis does so by measuring the performance impact of the same technology—the scheduling module—in 16 clinics in the same regional operations of the same organization over a 35-month period beginning in October 2004 and ending August 2007. Measures of IT "go-live" were constructed from interviews, archival data, and clinic observations. Performance is measured using Kaiser's Patient Satisfaction Survey, and EI is assessed using a new survey of employees designed specifically for this study. Table 2 details all of the variables used in the quantitative analyses.

[—Insert Table 2 about here.—]

The analysis leverages the multi-method nature of the research in numerous ways. It uses the rich qualitative information to understand the processes that generated the data and, more directly, to construct temporal variables, e.g., when the technology was "switched on." This allows for a number of methodological benefits. For example, qualitative research revealed why the scheduling module was such an attractive choice for in-depth study—its direct connection to a well-measured outcome of great interest to Kaiser managers. Whether or not the new system was effective could be measured by patients' perceptions of the appointment-making process. Indeed, Kaiser had for many years collected patient-level data on the appointment-setting process as part of a mailed paper-and-pencil Patient Satisfaction Survey sent shortly after an appointment. Though the use of these types of "localized" performance measures poses a challenge for generalizability, a number of researchers have argued for their use on reliability grounds (e.g., Hunter and Pil 1995), claiming that they provide a more direct causal link than do financial performance measures. Some researchers have chosen to use such measures even when more generalizable dollar figures could have been easily imputed (e.g., Bartel, Ichniowski, and Shaw 2007; Ichniowski, Shaw, and Prennushi 1997; MacDuffie 1995).

Due largely to the newness of the technology, Kaiser's human resource records did not contain reliable measures of the flavor of EI examined here. Though Kaiser conducts an annual poll of its employees, the instrument had only recently been augmented with a single and very broad question about the health IT system. Therefore, the best option was to develop a new employee survey specifically for this study, ensuring that the EI measures were not about some broad EI construct, but about EI in the context of the deployment of this specific IT module. There are a number of advantages to surveying employees directly, and then aggregating these data to the clinic (i.e., establishment) level. First, EI measures cannot be biased by individual, clinic-level managers wanting to offer an idealized account of EI (Jones, Kalmi, and Kauhanen 2009). Second, Huber and Power (1985) suggest that single-response bias be tackled by asking survey questions of the "most-informed respondent" in the establishment. In this case, only those employees expected to use the scheduling module in the course of their everyday work are included in the analysis. This technique also avoids "frame of reference" problems (Hunter and Pil 1995) by asking frontline workers the very EI-related questions that they should know the answers to—not questions about a broad EI construct. Furthermore, Gerhart, Wright, MacMahan, and Snell (2000) suggest that drawing on multiple respondents from each establishment disposes of inter-rater reliability issues, though they also note that research designs bounded to a small number of clinics and a homogenous group of workers rarely suffer from this problem anyway. Finally, perhaps the most significant methodological challenge to studies linking employment practice "inputs" to performance "outputs" occurs when the same instrument is used to collect both. In this way, so-called "common method bias" generates artificially-inflated correlations between EI, IT use, and performance (Podsakoff, MacKenzie, Lee, and Podsakoff 2003). However, the research design here circumvents the causes of common method bias with its collection of the independent and dependent variables from completely separate and unrelated sources—one long in existence for organizational use and another conceived of and administered years later purely for the purposes of this research.

Having described and justified key methodological choices, I will next briefly explain the variables constructed from qualitative research—those picking up when the technology was turned on and those intended to control for random performance movements around the time the technology was turned on. Likewise, there are variables to capture the trending of the performance variables, allowing for the separation of trend from the changes engendered by the use of the scheduling module. Then, I describe in detail the Patient Satisfaction Survey and the employee survey and explain how relevant variables were constructed from questionnaire items. I will then explain each of two separate estimation strategies that rely on these data, focusing on how these methods allow for two different paths toward identifying the moderating effects of EI on the effectiveness of the new technology.

Performance Trends, Transition to the New Technology, and Module-in-Use

The period of observation represented in the archival data is October 2004 to August 2007—35 months. It is important that the influence of trend over this period be controlled for in order to meaningfully identify the effects of the new technology. Thus, the first linear time trend ("Time Trend") begins with October 2004 and ends with August 2007. The next step toward identifying the theorized effects is to identify the discontinuity in performance associated with turning the new technology on. The scheduling module went live across all clinics observed at the end of July 2005. Therefore, if we were using a single dummy variable to capture the discontinuity, then all months from August 2005 onward would be set to equal one. However, in order to control for performance gyrations around "go-live," the analysis presented here allows for June 2005, July 2005, August 2005 to be labeled "transition months." That decision gets operationalized with the binary variable "Transition Period," which equals zero for all months except June, July, and August 2005. Therefore, "Module-in-Use" does not begin to take on the value of one until September 2005, just after the period of transition. This was a conservative choice, since it potentially "dummies out" the benefits that would accrue from the IT being in use in July and August. Changes in the number of transition months allowed for almost no difference at all in any of the subsequent estimates. A second linear time trend—"Time Since 'Go-Live'"—captures the month-to-month changes (as opposed to the structural break) associated with "go-live." Therefore, it carries a value of zero until September

2005. In September 2005, the second linear time trend begins at one and increments up to 24 for August 2007. Thus, as operationalized in the paper, there are 8 pre-"go-live" months, 3 transition months, and 24 post "go-live" months.[3]

Patient Satisfaction and Ease of Scheduling

This study uses two items from the Patient Satisfaction Survey. One question asks, "Were you able to get the appointment scheduled by talking to just one person?". Another asks respondents to rate on a nine-point Likert-type scale their satisfaction "with the length of time spent on the phone to schedule the appointment." These variables were strongly related. Those who answered "yes" for the binary performance item were, on average, more satisfied with the length of time required to make their the appointment ($t = 74.4$, $p < .001$), providing evidence of convergent validity for these performance measures (Furr and Bacharach 2008; Schwab 2005). However, the difference in discreteness allows for two, separate paths towards statistical substantiation, to be explained below.

With approximately 43,000 patient responses, the response rate for the survey was 35%, which stacks up favorably to comparable customer surveys administered by mail (Kaplowitz, Hadlock, and Levine 2004). Though management could not provide the necessary data dismissing the possibility of response bias, this bias should be consistent over the time period studied. Furthermore, the marketing literature suggests that disgruntled or dissatisfied patients may be more likely than others to respond to such surveys (Richins 1983). To the extent that this is true and that the use of the technology dissatisfies patients, it only serves to make the statistical estimates more conservative, i.e., biased away from theorized results.

Employee Involvement in IT Deployment

As alluded to above, measures of EI were developed from an author-administered employee survey of MAs and MISs. Responses to eight survey items were summed to construct the EI index. The first four, items are: 1.) My suggestions relating to the design and improvement of [the scheduling module] have been valued., 2.) My issues or complaints about it have been ignored., 3.) There is at least one bargaining unit member in my office who helps me be a better user of [the scheduling module], and 4.) Before it was rolled out, the people

[3] However, since the panel is unbalanced, the total number of observations is not simply equal to 16 clinics × 35 months.

whose work would be affected were asked for guidance. Each was answered using a seven-point, Likert-type scale in which 7 represented strong agreement. The second item was reverse-coded. The remaining four items were binary in nature. Respondents answered questions on whether or not a fellow member of the bargaining unit introduced them to the scheduling module, provided them with their follow-up training on the module, or otherwise served as an on-site expert or "super-user" for the scheduling module. Respondents also answered yes or no as to whether they provided any specific recommendations on additional ways that the system could be used to meet its strategic goals. As a further reliability check, the survey included an open-ended question asking workers to document a specific suggestion that they had made. This step provided additional confidence that respondents understood exactly the kinds of EI they were being asked about (Hunter and Pil 1995).

As noted above, the employee survey included questions derived from the author's observations and interviews to measure EI relevant to employees in this particular organizational setting, similar to the methodological approach adopted by Bidwell (2009). According to Jarvis, Mackenzie, and Podsakoff (2003), the construction of formative indicators such as these rather than more traditional "reflective" measures makes sense when indicators "define" different aspects or dimensions of the construct and when indicators need not be interchangeable. In Kaiser's case, there were multiple ways in which workers might have participated in the IT initiative, and any one of them could effectively substitute for any other. For example, a worker may have been directly canvassed for their thoughts on effective system use. Alternatively, they may have relied frequently on guidance from a super-user. Summing answers into a composite measure therefore captures the overall level of EI in this context, even though there is no *a priori* reason to expect a high correlation between items (Bidwell 2009).[4]

The survey was piloted on frontline workers in addition to union and management leaders, and then administered electronically through the organization's intranet in Fall 2007—shortly after the end of the constructed data series. Organizational constraints prevented the survey from being run earlier or multiple times. The survey achieved a response rate of 58 percent—268 MAs and 128 MISs that use the technology in the course of their everyday work. Analyses confirmed that those MISs who responded had about the same average age and job

[4] This scale proves only marginally reliable by conventional standards ($\alpha = .58$). Nonetheless, a low alpha does not indicate low reliability in the case of formative measures like that employed for EI (Bidwell 2009; Bollen and Lennox 1991; Jarvis, Mackenzie, and Podsakoff 2003).

tenure as those who did not. The MA respondants had the same average tenures as their non-responding colleagues. However, those MAs who responded were marginally older, on average, than those that did not respond—41.8 years vs. 39.3 years ($t = 2.44$, $p < .01$).[5] Not surprisingly, the number of responses from each clinic—ranging from eight to 43—was mainly driven by clinic size.[6]

Estimation Strategies

I employ a two-prong approach to show that the use of the IT is associated with performance increases at the clinic level and that these effects are greater in those clinics with higher mean levels of EI. The most straightforward way to demonstrate the moderating role of EI would be to collapse the data into a dataset of clinic-months, and then to regress each performance measure on a vector of independent variables. These variables would include controls, namely for trend, but also main effects for IT "go-live" and for EI. The focal explanatory variable would be the two-way, multiplicative interaction term crossing IT "go-live" (i.e., "Module-in-Use") with EI, and a statistically significant, positive coefficient estimate on this term would support the theory. Indeed, with some modifications to account for the dependency structure of the data and performance gyrations right around the "go-live" month, this is essentially how the paper tests the impact of EI and IT on the *continuous* performance measure described above. The findings would be more robust, however, if one could then replicate the analysis using the *binary* performance variable. However, the key partial slope estimate is attached to the interaction term, and two-way, multiplicative coefficient estimates are inconsistent in the context of functional forms necessary for estimating binary dependent variables (Ai and Norton 2003; Jaccard 2001). Therefore, the paper offers an alternative method—a plotting procedure—for testing the theory on the binary variable.[7]

Multilevel models. As noted above, the most straightforward way to test the theory on the continuous variable is to create a dataset of clinic-months, and then to regress the continuous performance measure—patient satisfaction with the length of time required to make

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[5] I could not test for randomness with respect to sex. However, nearly all of the MAs and MISs sampled were women.

[6] As noted earlier, the work of Gerhart and colleagues (2000) suggests that even a very small number of respondents should be enough to ensure reliability in studies like this one.

[7] One can run the plotting procedure on the continuous dependent variable, and the resulting scatterplot is qualitatively similar to the one that emerges when using the binary dependent variable.

an appointment—on a vector of independent variables. This requires melding patients' responses to the Patient Satisfaction Survey—the dependent variable—with employee responses to the employee survey—the independent variable. Calculating the mean EI index for each clinic is straightforward. Given that workers were only surveyed once, this measure is time-constant. Aggregating the patient satisfaction data is only slightly more complicated. About 43,000 patient observations were linked to the specific PCP with whom the patient-respondent made the appointment, and then these data were crossed with archival managerial data placing physicians into specific clinics over time. Following Jones, Kalmi, and Kauhanen (2009) and Bartel (2004), I do this by taking the average of patient satisfaction responses by clinic by month, standardized—a method that further strengthens the reliability of these specific performance measures (Harter, Schmidt, and Hayes 2002). The models include on the right-hand side the variables to capture trend ("Time Trend" and "Time Since Go-Live") and transition ("Transition Period") as well as the main effect of the new technology being in-use ("Module-in-Use"). Finally, the focal independent variable is the two-way, multiplicative interaction of "Module-in-Use" with EI. Whereas the point estimate on "Module-in-Use" will establish the influence of the scheduling module on performance, the estimate for the two-way interaction establishes the moderating impact of EI.

Given the dependence structure of the data, the usual assumptions required of OLS do not hold. In particular, one would expect that the error terms would be systematically correlated at the clinic level. Accommodating this data structure requires a longitudinal model, multilevel in the sense that individual observations are of clinic-months "clustered" in clinics. Therefore, the models estimated here instead partition the variance term into a random effect at the clinic level in addition to the usual zero-expectation error term. That is, the observations can be assumed independent conditional on the random effect, and the estimates can be interpreted with the same ease as typical OLS coefficients (Skrondal and Rabe-Hesketh 2004).[8]

Scatterplot. As noted above, the analysis seeks additional evidence by examining the longitudinal data on a binary performance measure—whether or not a patient respondent to the Patient Satisfaction Survey is able to schedule their appointment by speaking to just one person, an event that is theorized to be more likely to occur when the scheduling module is in-place and being used effectively. This is accomplished by running 14 separate logistic

[8] The time-constant nature of the EI measure unfortunately precludes the estimation of clinic-level fixed effects with these data.

regressions—one for each clinic—using patient-level responses to the Patient Satisfaction Survey as the unit-of-observation.[9] These regressions include just four independent variables—the two time trends ("Time Trend" and "Time Since 'Go-Live'") and the two IT-related dummies ("Module-in-Use" and "Transition Period").

Each of these regressions yields a point estimate for "Module-in-Use" that can be interpreted as the clinic-specific performance effect of the scheduling module. These point estimates are then plotted as a function of each clinic's mean EI score, the same one used in the multilevel estimates above. Support for the theory here takes the form of a scatterplot in which each dot represents one of the actual clinics under study. There should be a discernible and obvious positive relationship between a clinic's mean EI score and the size of the performance gain it achieves when the scheduling module gets turned on, even after having controlled for trend and transition.

Results

Table 3 presents summary statistics from the survey of the Northwest's support staff. Recall that means are calculated using only responses from those MAs and MISs expected to use the scheduling module in the course of their work. The first set of variables represents the four continuous items contributing to the EI scale. Notice how in all four cases, means hover near the neutral response (4 = "neither agree nor disagree"), albeit with significant variation about the mean. Overall, only 11 percent of respondents claimed that they were first introduced to the technology by a fellow member of the bargaining unit (as opposed to a manager or an IT staffer), though 18 percent asserted that they had, in fact, received follow-up training from a co-worker. About 40 percent noted the importance of "super-users"—fellow members of the bargaining unit pulled from their regular, frontline positions to assist in the development and deployment of the system—to their successful use of the scheduling module. Interestingly, about 15 percent of respondents have made specific recommendations of ways that the system could be used more effectively, the details of which were validated with the responses to a free-form text field included in the survey. For example, some workers suggested the need for "write" privileges in addition to "read-only" privileges at certain screens. Others pointed out the need to make sure that a patient's contact details remain on-screen

[9] While there are 16 clinics under study, the estimates sometimes include only 14 or 15 clinics, depending on the particular model. This is because the Peterson clinic closed prior to the collection of quantitative measures of EI, and the Ulrich clinic opened too late in the observation period to provide pre-"go-live" observations.

throughout the appointment-setting process or the need to allow the home phone number field to be left empty for those patients having only a cell phone. Others had suggested the creation of shortcuts for frequently-used "bundles" of mouse clicks, like those required to make certain, regularly-occurring types of office visit appointments.

[—Insert Table 3 about here.—]

Table 4 breaks out the dependent variables for each (de-indentified and relabeled) clinic, derived from patient-level data. The first three columns focus on the binary dependent variable—whether or not the patient was able to make an appointment with the first person he or she spoke to on the telephone. In the Bruford clinic, for example, of 3,911 patient responses to the question over the observation period (October 2004 to August 2007), 78 percent answered affirmatively. Note that most of the clinics average around 80 percent for this variable over the period of observation. The one exception appears to be Collins, which only managed to schedule appointments with one "touch" 73 percent of the time. The next three columns repeat the exercise for the continuous dependent variable—patient's satisfaction with the length of the phone call required to make the appointment. In this case, the variable was standardized such that the mean was equal to zero and the standard deviation equal to one. Therefore, each clinic's mean for the variable as reported in Table 4 is relative to the overall sample average. The Fleetwood clinic averaged .2 standard deviations above the sample mean, the highest of all the clinics. The clinic labeled Mullen achieved the lowest performance and the widest variation on this metric over the sample period.

[—Insert Table 4 about here.—]

Table 5 displays the multilevel models estimated on the dataset of clinic-months, beginning with a simple model considering only the effects of a linear time trend. The first model shows a small, but statistically significant month-to-month increase in the dependent variable between October 2004 and August 2007. Once a separate, post-implementation trend is added on the right-hand side (in the second model), the estimated partial slope on the original time trend turns negative and remains so for the remaining models to be estimated. The post-implementation time trend ("Time Since 'Go-Live'"), however, that first appears in the second model reveals a positive association between the use of the scheduling module and the performance measure it was intended to influence. Despite the negative, month-to-month effect of the overall time trend ("Time Trend"), the post-implementation time trend is actually positive and remains so for all subsequent estimates. Consistent with anecdotal accounts, customer service was suffering prior to the implementation of the scheduling module, a trend that reversed itself with the transition to the new system. Moreover, without the new technology, it appears that month-to-month performance would have continued to decline. The next model adds two dummy variables capturing transition to ("Transition Period") and deployment of the scheduling module ("Module-in-Use"). Both estimates are positive and statistically significant in this and the remaining models. Also note the point estimate on the post-implementation time trend doubles. That means that once one accounts for a structural break in the time series, one can see evidence of a large (.44 standard deviations), one-time jump in performance as well as a steady, sizable (.06 standard deviations) month-to-month performance increase associated with the scheduling module, despite what would otherwise be a declining performance function (-.05 standard deviations each month) over time. These effects are not sensitive to changes in the way the transition period is operationalized, e.g., one month or two months on either side of the transition from legacy systems to the new IT.

[—Insert Table 5 about here.—]

The last two models in Table 5 incorporate the effects of EI on the effectiveness of the technology. Model 4 incorporates only a main effect for EI. Interestingly, this predictor has an estimated performance effect that is insignificantly different from zero, suggesting that the impact of EI comes not through an engaged workforce *per se*, but from the moderating impact of EI with respect to the scheduling module initiative. It is also worth noting that the inclusion of the EI variable in the fourth model does virtually nothing to the point estimates of all those variables carried over from the three versions of the equation previously estimated. The fifth and final model in Table 4 adds the two-way interaction to directly capture the incremental, moderating effect of EI on the IT-performance link. Controlling for all of the other effects, an increase of one standard deviation in the EI index increases the effectiveness of the technology by .27 standard deviations. Interestingly, the estimate for the main EI measure turns negative, further demonstrating that EI's performance impact appears to come through its moderation of the scheduling module's effect on performance. The results are also robust to many different ways of operationalizing the EI measure.

The second bit of evidence comes from the scatterplot. Figure 1 projects the point estimates for "Module-in-Use" for each clinic—derived from the 14 separate logit estimates—on a scatterplot as a function each clinic's mean EI score. First, notice that accounting for trend and transition, none of the clinics witnessed a performance decrement arising from the technology, and three of them increased their performance by at least one standard deviation. More important, the figure reveals a positive association between workers' involvement in the IT effort and the size of performance improvements: those clinics whose workers reported greater mean EI levels with respect to the technology saw greater performance improvements arising from the technology than those clinics with lower mean EI scores. Once again, the shape of the point cloud—revealing the positive association between the size of a clinic's IT-engendered performance gain and its mean level of EI—is robust to different operationalizations of EI. That is, similar point clouds emerge when the same exercise is performed with the individual variables that make up the EI index.

[—Insert Figure 1 about here.—]

Discussion and Conclusions

Though employment relations has long acknowledged the role of technology in its theory-building (e.g., Dunlop 1958 [1993]; Slichter 1941; Slichter, Healy, and Livernash 1960), that focus has been largely limited to trade union responses to new technologies that were intended to serve as substitutes for labor. This oversight is particularly interesting given the attention that industrial relations theory has long given to the "technological context" for employment relations. As IT and other new technologies become even more ubiquitous, employment relations scholars would do well to look within both the IT and EI processes at work to better understand how and why they interact to affect performance outcomes. Inasmuch as this study illustrates the ways that a union-management-negotiated agreement and participatory employment practices enable workers to use IT more effectively, it focuses explicitly on the ways that employment practices influence the effectiveness of new technologies intended to make workers more productive. Moreover, it does so by leveraging the multi-method, organizationally-grounded approach indicative of employment relations to show how one healthcare organization used EI to achieve larger returns from newly-deployed IT. Therefore, it sheds light on the moderating role that aspects of the employment relationship play in linking technology to performance.

The design of the study allows for a clean separation of the technology inputs from the EI inputs that management theory suggests complement one another in production. The great benefit of IT is that it makes more information available to frontline workers (Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson and Mendelson 1993). However, pushing information downward and outward—in this case, up-to-date information on patients and on physician availability—will do much less to influence performance if those workers who will need to use the technology cannot shape how it is used and are not "brought on board" with clear communication from managers and union representatives. For example, with respect to the scheduling module at Kaiser, aspects of the technology and of the organization necessitated that some training had to occur outside of regular working hours, and the labor coordinators and the super-users played a key role in justifying this unpopular decision to the region's workforce.

More specifically, Kaiser Permanente's deployment of its scheduling module, one component of its much larger EHR system, was associated with clinic-level performance improvements. However, these improvements were more than 50% greater in those clinics in which workers scored one standard deviation greater than average on a contextual measure of EI. It appears that while the scheduling module provided workers across all the clinics additional, real-time information on provider availability and patient information, employees made better use of that information when they understood management's strategic rationale for the system, when they were able to communicate their own ideas and concerns back up to the strategic level, and, most critically, when they were availed fellow frontline workers who could ease them through the deployment process.

As a result of this study, we know that EI in implementation moderates the performance effects of IT. While earlier empirical work suggested the importance of EI in this way (Mirvis, Sales, and Hackett 1991), the relationship had yet to be demonstrated by looking at the effectiveness of identical technology, with people doing the same work, in nearly identical workplaces, over time, under varying levels of employee involvement.

Scholars of OB should welcome these findings. They offer a much-needed explanation for the persistence of EI structures and processes despite a lack of empirical evidence in their favor (Locke and Schweiger 1979). Rather than proposing a contingency along the lines of those already considered such as characteristics of the workers themselves (e.g., Miller and Monge 1986) or aspects of the type of knowledge required to do the work (Latham, Winters, and Locke 1994; McCaffrey, Faerman, and Hart 1995; Scully, Kirkpatrick, and Locke 1995), this paper suggests that the new technology is itself a channel through which EI influences performance. Therefore, these findings fold into an emerging stream of the OB literature considering the ways that social structure, organizational attributes, or attributes of the work itself moderate the link between new technologies and organizational performance (Edmondson, Bohmer, and Pisano 2001; Edmondson, Winslow, Bohmer, and Pisano 2003). In this case however, the grounded nature of the research suggests that social structure and aspects of the work itself are not the factors driving IT's effectiveness. Rather, it is variation in EI around implementation that moderated the IT-performance link.

While this result informs any management-related discipline with an interest in EI, it should perhaps raise the biggest alarm for the HR literature. As noted earlier, despite a deep interest in EI, HR as a field practically ignores technology as an object of study (cf. Batt 1999). This study shows that technology must be examined in-depth as an avenue through which EI can drive organizational performance. Recall from the last two columns of Table 5 that the direct effects of EI on performance are insignificantly different from zero, particularly in the fourth model, the one that does not include the two-way interaction term. Had the subsequent model never been estimated, the "non-results" would be broadly consistent with findings to date regarding EI. That is, the performance effects of EI in this context would be nil, consistent the direction of empirical work to date (e.g., Cappelli and Neumark 2001; Freeman and Kleiner 2000). However, after estimating the final model, the penultimate model appears to suffer from measurement error, effectively averaging the direct effect of EI on performance with the influence of EI that occurs through the effective implementation of the new system. Once both effects are accounted for, the direct effect of EI becomes only slightly more precise, and interestingly, negative—though not at conventional levels of statistical significance. Those positive performance effects resulting from EI appeared to arise entirely through the interaction of the IT variable and the EI measure.

One might challenge these results on a number of grounds. The issues of reliability and construct validity are the most critical, in part because both the EI and performance measures were developed or chosen specifically for this study rather than taken from previously validated instruments. The resulting EI measures were those that emerged as important to the effective use of this technology in this setting. Likewise, the performance measures were chosen for their tight coupling with the effective use of the scheduling module. With respect to endogeneity, one might argue that those clinics that were "ready" for the technology based on observed measures of EI or some other unobserved factors, not surprisingly, were able to use the technology more effectively. With respect to these issues, reliance on qualitative investigation in addition to the statistical estimates offers some assurance of the findings' overall validity. For example, it was the deliberative, pre-statistical investigative process that determined that the "go-live" date was set at the regional level and was not chosen clinic-by-clinic based on each clinic's readiness. Finally, given the unique features of the Kaiser labor management partnership, further work is needed to determine if similar effects are observed in more traditional, unionized settings and/or in nonunion settings that provide other employee voice arrangements. However, it is reasonable to believe that even nonunion workplaces can identify and select frontline workers to support an implementation effort like the one described here. In fact, such workplaces have clearly become the drivers of employment practice innovations, including the growth of various forms of EI (e.g., Bryson, Gomez, Kretschmer, and Willman 2007; Osterman 1994; Osterman 2000). Broadening or redirecting these programs to encompass IT implementations should be something that could be done at relatively low cost, a result with obvious implications for managers as well as for future research.

This study sheds some much-needed light on IT and EI in the service sector and outside of manufacturing, the sector that has been the focus of most of the empirical work to date on the employment practice correlates of organizational performance. Therefore, not only do the results offer a lens into the service sector and "service processes" (as opposed to manufacturing's "production processes") more broadly, but they also inform the fastest growing sector of the US economy—healthcare.

The immediate implication for both policymakers and healthcare administrators is that health IT can improve organizational outcomes. Therefore, it makes sense that the government should promote the diffusion of EHRs and related technologies, and it makes sense for practices and physicians to respond accordingly to those incentives. However, policies that seek only to encourage the adoption of health IT as opposed to the adoption of both the technology and the employment practices that more-fully "unlock" it are, at best, incomplete. Such costly mandates—like those that appear in the 2009 stimulus package—should also include language to encourage the adoption of employment involvement structures and processes along the lines of those taken up in the case presented above.

REFERENCES

Ai, Chunrong, and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters*, Vol. 80, No. 1, pp. 123-129.

Appelbaum, Eileen, Thomas Bailey, Peter Berg, and Arne Kalleberg. 2000. *Manufacturing Advantage: Why High-Performance Work Systems Pay Off*. Ithaca: ILR.

Appelbaum, Eileen, and Rosemary L. Batt. 1994. *The New American Workplace: Transforming Work Systems in the United States*. Ithaca: ILR.

Bartel, Ann P. 2004. "Human Resource Management and Organizational Performance: Evidence from Retail Banking." *Industrial and Labor Relations Review*, Vol. 57, No. 2, pp. 181-203.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw. 2007. "How Does Information Technology Really Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement and Worker Skills." *Quarterly Journal of Economics*, Vol. 122, No. 4, pp. 1721-1758.

Batt, Rosemary L. 1999. "Work Organization, Technology, and Performance in Customer Service and Sales." *Industrial and Labor Relations Review*, Vol. 52, No. 4, pp. 539-564.

Becker, Brian E., and Huselid, Mark A. 2010. "Strategic Human Resources Management: Where do we Go from here?" In Adrian Wilkinson, Nicolas Bacon, Tom Redman and Scott Snell, eds., *The SAGE Handbook of Human Resource Management*. London: SAGE, pp. 351-376.

Becker, Brian E., and Huselid, Mark A. 1998. "High Performance Work Systems and Firm Performance: A Synthesis of Research and Managerial Implications." In Gerald Ferris, ed., *Research in Personnel and Human Resources Management*. Greenwich, CT: JAI, pp. 53-101.

Bidwell, Matthew. 2009. "Do Peripheral Workers Do Peripheral Work? Comparing the Use of Highly-Skilled Contractors and Regular Employees." *Industrial and Labor Relations Review*, Vol. 62, No. 2, pp. 200-225.

Bollen, Kenneth, and Richard Lennox. 1991. "Conventional Wisdom on Measurement: A Structural Equation Perspective." *Psychological Bulletin*, Vol. 110, No. 2, pp. 305-314.

Braverman, Harry. 1974. *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. New York: Monthly Review.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. 2002. "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm Level Evidence." *Quarterly Journal of Economics*, Vol. 117, No. 1, pp. 339-376.

Brown, Clair, and Benjamin A. Campbell. 2002. "The Impact of Technological Change on Work and Wages." *Industrial Relations*, Vol. 41, pp. 1-33.

Brynjolfsson, Erik, Lorin M. Hitt, and Shinkyu Yang. 2002. "Intangible Assets: Computers and Organizational Capital." *Brookings Papers on Economic Activity*, Vol. 2002, No. 1, pp. 137-181.

Brynjolfsson, Erik, and Haim Mendelson. 1993. "Information Systems and the Organization of Modern Enterprise." *Journal of Organizational Computing*, Vol. 3, No. 3, pp. 245-255.

Bryson, Alex, Rafael Gomez, Tobias Kretschmer, and Paul Willman. 2007. "The Diffusion of Workplace Voice and High-Commitment Human Resource Management Practices in Britain, 1984–1998." *Industrial and Corporate Change*, Vol. 16, No. 3, pp. 395-426.

Cappelli, Peter, and David Neumark. 2001. "Do 'High-Performance' Work Practices Improve Establishment-Level Outcomes?" *Industrial and Labor Relations Review*, Vol. 54, No. 4, pp. 737-775.

Caroli, Eve, and John van Reenan. 2001. "Skill-Biased Organizational Change? Evidence from a Panel of British and French Establishments." *Quarterly Journal of Economics*, Vol. 116, No. 4, pp. 1449-1492.

Coch, Lester, and John R. P. French Jr. 1948. "Overcoming Resistance to Change." *Human Relations*, Vol. 1, No. 4, pp. 512-532.

Cotton, John L. 1993. *Employee Involvment: Methods for Improving Performance and Work Attitudes.* Newbury Park, CA: SAGE.

Cotton, John L., David A. Vollrath, Kirk L. Froggatt, Mark L. Lengnick-Hall, and Kenneth R. Jennings. 1988. "Employee Participation: Diverse Forms and Different Outcomes." *Academy of Management Journal*, Vol. 13, No. 1, pp. 8-22.

Dunlop, John T. 1958 [1993]. *Industrial Relations Systems.* Boston: Harvard Business School.

Edmondson, Amy C., Richard M. Bohmer, and Gary P. Pisano. 2001. "Disrupted Routines: Team Learning and New Technology Implementation in Hospitals." *Administrative Science Quarterly*, Vol. 46, No. 4, pp. 685-716.

Edmondson, Amy C., Ann B. Winslow, Richard M. J. Bohmer, and Gary P. Pisano. 2003. "Learning How and Learning What: Effects of Tacit and Codified Knowledge on Performance Improvement Following Technology Adoption." *Decision Sciences*, Vol. 34, No. 2, pp. 197.

Freeman, Richard B., and Morris M. Kleiner. 2000. "Who Benefits Most from Employee Involvement: Firms or Workers?" *American Economic Review Papers and Proceedings*, Vol. 90, No. 2, pp. 219-223.

Furr, R. Michael, and Verne R. Bacharach. 2008. *Psychometrics: An Introduction.* Thousand Oaks, CA: SAGE.

Gerhart, Barry, Patrick M. Wright, Gary C. MacMahan, and Scott A. Snell. 2000. "Measurement Error in Research on Human Resources and Firm Performance: How Much Error Is There and How Does It Influence Effect Size Estimates?" *Personnel Psychology*, Vol. 53, No. 4, pp. 803-834.

Harter, James K., Frank L. Schmidt, and Theodore L. Hayes. 2002. "Business-Unit-Level Relationship Between Employee Satisfaction, Employee Engagement, and Business Outcomes: A Meta-Analysis." *Journal of Applied Psychology*, Vol. 87, No. 2, pp. 268-279.

Hillestad, Richard, James Bigelow, Anthony Bower, Federico Girosi, Robin Meili, Richard Scoville, and Roger Taylor. 2005. "Can Electronic Medical Record Systems Transform Health Care?: Potential Health Benefits, Savings, and Costs." *Health Affairs*, Vol. 24, No. 5, pp. 1103-1117.

Huber, George P., and Daniel J. Power. 1985. "Retrospective Reports of Strategic-Level Managers: Guidelines for Increasing Their Accuracy." *Strategic Management Journal*, Vol. 6, No. 2, pp. 171-180.

Hunter, Larry W., and Pil, Frits K. 1995. "How do You Survey Firms?" In Paula B. Voos, ed., *Proceedings of the 47th Annual Meeting of the Industrial Relations Research Association*. Madison: IRRA, pp. 152-162.

Huselid, Mark A., and Brian E. Becker. 1996. "Methodological Issues in Cross-Sectional and Panel Estimates of the Human Resource-Firm Performance Link." *Industrial Relations*, Vol. 35, No. 3, pp. 400-422.

Ichniowski, Casey, Thomas A. Kochan, David Levine, Craig Olson, and George Strauss. 1996. "What Works at Work: Overview and Assessment." *Industrial Relations*, Vol. 35, No. 3, pp. 299-333.

Ichniowski, Casey, Kathryn Shaw, and Giovanna Prennushi. 1997. "The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines." *American Economic Review*, Vol. 87, No. 3, pp. 291-313.

Jaccard, James. 2001. *Interaction Effects in Logistic Regression*. Thousand Oaks, CA: SAGE.

Jarvis, Cheryl Burke, Scott B. Mackenzie, and Philip M. Podsakoff. 2003. "A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research." *Journal of Consumer Research*, Vol. 30, No. 2, pp. 199-218.

Jones, Derek C., Panu Kalmi, and Antti Kauhanen. 2009. "How Does Employee Involvement Stack Up? The Effects of Human Resource Management Policies in a Retail Firm." *Industrial Relations*, Vol. 49, No. 1, pp. 1-21.

Kaiser Family Foundation. 2007. *Employee Health Benefits: 2007 Annual Survey*. Washington, DC: KFF.

Kanter, Rosabeth Moss. 1983. *The Change Masters: Innovation and Enterpreneurship in the American Corporation*. New York: Simon and Schuster.

Kaplowitz, Michael D., Timothy D. Hadlock, and Ralph Levine. 2004. "A Comparison of Web and Mail Survey Response Rates." *Public Opinion Quarterly*, Vol. 68, No. 1, pp. 94.

Kelley, Maryellen R. 1996. "Participative Bureaucracy and Productivity in the Machined Products Sector." *Industrial Relations*, Vol. 35, No. 3, pp. 374-399.

Kleiner, Morris M., Jonathan S. Leonard, and Adam M. Pilarski. 2001. "How Industrial Relations Affects Plant Performance: The Case of Commercial Aircraft Manufacturing." *Industrial and Labor Relations Review*, Vol. 55, pp. 195.

Kochan, Thomas A. 1988. "On the Human Side of Technology." *ICL Technical Journal*, Vol. 6, No. 2, pp. 391-400.

Kochan, Thomas A., Adrienne E. Eaton, Robert B. McKersie, and Paul S. Adler. 2009. *Healing Together: The Labor-Management Partnership at Kaiser Permanente*. Ithaca: ILR.

Krafcik, J. F. 1988. Comparative Analysis of Performance Indicators at World Auto Assembly Plants. Unpublished master's thesis, MIT/Sloan School.

Latham, Gary P., Dawn C. Winters, and Edwin A. Locke. 1994. "Cognitive and Motivational Effects of Participation: A Mediator Study." *Journal of Organizational Behavior*, Vol. 15, No. 1, pp. 49-63.

Leana, Carrie R., Edwin A. Locke, and David M. Schweiger. 1990. "Fact and Fiction in Analyzing Research on Participative Decision Making: A Critique of Cotton, Vollrath, Froggatt, Lengnick-Hall, and Jennings." *Academy of Management Review*, Vol. 15, No. 1, pp. 137-146.

Levine, David I., and Tyson, Laura D'Andrea. 1990. "Participation, Productivity, and the Firm's Environment." In Alan S. Blinder, ed., *Paying for Productivity: A Look at the Evidence.* Washington, DC: Brookings, pp. 183-243.

Locke, Edwin A., and David M. Schweiger. 1979. "Participation in Decision-Making: One More Look." *Research in Organizational Behavior*, Vol. 1, pp. 265-339.

MacDuffie, John Paul. 1995. "Human-Resource Bundles and Manufacturing Performance: Organizational Logic and Flexible Production Systems in the World Auto Industry." *Industrial and Labor Relations Review*, Vol. 48, No. 2, pp. 197-221.

MacDuffie, John Paul, and Krafcik, John F. 1992. "Integrating Technology and Human Resources for High-Performance Manufacturing: Evidence from the International Auto Industry." In Thomas A. Kochan and Michael Useem, eds., *Transforming Organizations.* New York: Oxford University, pp. 209-226.

Marx, Karl. 1849 [1978]. "Wage Labor and Capital." In Robert C. Tucker, ed., *The Marx-Engels Reader*. New York: W.W. Norton & Company, pp. 203-217.

McCaffrey, David P., Sue R. Faerman, and David W. Hart. 1995. "The Appeal and Difficulties of Participative Systems." *Organization Science*, Vol. 6, No. 6, pp. 603-627.

Miller, Katherine I., and Peter R. Monge. 1986. "Participation, Satisfaction, and Productivity: A Meta-Analytic Review." *Academy of Management Journal*, Vol. 29, No. 4, pp. 727-753.

Mirvis, Philip H., Amy L. Sales, and Edward J. Hackett. 1991. "The Implementation and Adoption of New Technology in Organizations: The Impact on Work, People, and Culture." *Human Resource Management*, Vol. 30, No. 1, pp. 113-139.

Noble, David F. 1984. *Forces of Production: A Social History of Industrial Automation.* New York: Knopf.

Osterman, Paul. 2000. "Work Reorganization in an Era of Restructuring: Trends in Diffusion and Effects on Employee Welfare." *Industrial and Labor Relations Review*, Vol. 53, No. 2, pp. 179-196.

Osterman, Paul. 1994. "How Common Is Workplace Transformation and Who Adopts It?" *Industrial and Labor Relations Review*, Vol. 47, No. 2, pp. 173-188.

Oudshoorn, Nelly, and Pinch, Trevor. 2007. "User-Technology Relationships: Some Recent Developments." In Edward J. Hackett, Michael Lynch and Judy Wajcman, eds., *Handbook of Science and Technology Studies.* Cambridge, MA: MIT, pp. 541-565.

Podsakoff, Philip M., Scott B. MacKenzie, Jeong-Yeon Lee, and Nathan P. Podsakoff. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology*, Vol. 88, No. 5, pp. 879-903.

Richins, Marsha L. 1983. "Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study." *Journal of Marketing*, Vol. 47, No. 1, pp. 68-78.

Roethlisberger, Fritz J., and William J. Dickson. 1939. *Management and the Worker: An Account of a Research Program Conducted by the Western Electric Company, Hawthorne Works, Chicago.* Cambridge, MA: Harvard.

Schwab, Donald P. 2005. *Research Methods for Organizational Studies.* Mahwah, NJ: Lawrence Erlbaum Associates.

Scully, Judith A., Shelley A. Kirkpatrick, and Edwin A. Locke. 1995. “Locus of Knowledge as a Determinant of the Effects of Participation on Performance, Affect and Perceptions.” *Organizational Behavior and Human Decision Processes*, Vol. 91, No. 3, pp. 276-288.

Skrondal, Anders, and Sophia Rabe-Hesketh. 2004. *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models*. Boca Raton: Chapman and Hall/CRC.

Slichter, Sumner H. 1941. *Union Policies and Industrial Management*. Washington, DC: Brookings Institution.

Slichter, Sumner H., James Joseph Healy, and E. Robert Livernash. 1960. *The Impact of Collective Bargaining on Management*. Washington, DC: Brookings Institution.

Vroom, Victor H., and Philip W. Yetton. 1973. *Leadership and Decision-Making*. Pittsburgh: University of Pittsburgh.

Table 1. Highlights of the KP HealthConnect Effects Bargaining Agreement Between Kaiser Permanente and the Coalition of Kaiser Permanente Unions.

Coalition agrees to:		**Kaiser agrees to:**
• commit to the "successful implementation of KP HealthConnect and the full realization of its benefits."		• extend existing language on flexibility and job and wage security to changes engendered by new technology.
• engage in development, implementation, and continuous improvement efforts at each stage, regionally and nationally.	Joint commitment to create "an environment where all staff…freely engage in the transformation effort."	• follow a process for incorporating into the bargaining unit new jobs created by the technology.
		• fund KP HealthConnect labor coordinators in each region and for release, backfill, and training demands arising from the initiative.

Source: KP HealthConnect Effects Bargain, effective April 5th, 2005.

Table 2. Definitions of Variables.

Variable	*Description*	*Source*
Employee Involvement index	sum of responses to 8 survey items (listed below)	employees
suggestions have been valued	answered on a 7-point Likert-type scale in which 1 = "strongly disagree" and 7 = "strongly agree", and then standardized	employees
issues have been ignored	answered on a 7-point Likert-type scale in which 1 = "strongly disagree" and 7 = "strongly agree", and then standardized, with coding subsequently reversed	employees
unionized super-user improves my use	answered on a 7-point Likert-type scale in which 1 = "strongly disagree" and 7 = "strongly agree", and then standardized	employees
affected staff were asked for guidance	answered on a 7-point Likert-type scale in which 1 = "strongly disagree" and 7 = "strongly agree", and then standardized	employees
introduced to technology by a union member	binary variable created from a question allowing respondents to choose between a fellow union member, a member of the IT staff, or a manager	employees
received follow-up training from a union member	binary variable created from a question allowing respondents to choose between a fellow union member, a member of the IT staff, or a manager	employees
relies on a "super-user" in their clinic	binary created from a yes-or-no question	employees
made specific recommendations for effective use	binary created from a yes-or-no question	employees
made appointment with first person spoken to	binary created from a yes-or-no question	patients
satisfaction with length of phone call required to make appointment	answered on a 9-point Likert-type scale in which 1 = "extremely dissatisfied" and 9 = "extremely satisfied", and then standardized	patients
Time Trend	linear time trend beginning with the first month of data, i.e., October 2004 = 1, November 2004 = 2, …, August 2007 = 35	interviews, archival records, and clinic observation
Transition Period	dummy variable to capture performance fluctuations around the time of "Go-Live"; set to 0 for all months except June, July, and August 2005	interviews, archival records, and clinic observation
Module-in-Use	dummy variable to capture the effects of "Go-Live"; set to 0 until September 2005, and then set to 1 for all months until the end of the observation period	interviews, archival records, and clinic observation
Time Since "Go-Live"	linear time trend beginning with the first month in which September 2005 = 1, October 2005 = 2, …, August 2007 = 24	interviews, archival records, and clinic observation

Table 3. Descriptive Statistics for Worker-Level Variables Included in the Employee Involvement Index.

Variable		*Mean*	*Std. Dev.*
suggestions have been valued		3.99	1.53
issues have been ignored		3.57	1.65
unionized super-user improves my use		4.01	1.77
affected staff were asked for guidance		3.77	1.52
introduced to technology by a union member		0.11	0.31
received follow-up training from a union member		0.18	0.39
relies on a "super-user" in their clinic		0.39	0.49
made specific recommendations for effective use		0.15	0.36

Notes: Values based on responses from those medical assistants (MAs) and member intake specialists (MISs) reporting expected use of the system (n = 396). The first four components of the EI index were answered on a seven-point, Likert-type scale in which 1 = "strongly disagree" and 7 = "strongly agree", though the values for the second item have been reversed for ease of comparison. The remaining four items are binary.

Table 4. Descriptive Statistics for Dependent Variables, by Clinic.

		made appointment with first person spoken to				satisfaction with length of phone call required to make appointment		
Clinic Name		*Mean*	*Std. Dev.*	*n*		*Mean*	*Std. Dev.*	*n*
Bruford		0.78	0.41	3,911		-0.07	1.01	4,051
Collins		0.73	0.44	1,992		0.01	1.00	2,078
Copeland		0.81	0.40	2,755		0.004	0.99	2,864
Dolenz		0.79	0.41	3,898		0.04	0.96	4,056
Escovedo		0.80	0.40	2,925		0.09	0.97	3,016
Fleetwood		0.80	0.40	2,948		0.20	0.93	3,046
Henley		0.80	0.40	3,237		0.09	0.97	3,371
Mullen		0.78	0.41	992		-0.10	1.05	1,028
Peart		0.77	0.42	2,967		-0.02	0.97	3,084
Peterson		0.79	0.40	932		-0.04	1.04	976
Schock		0.80	0.40	2,771		-0.05	1.02	2,898
Slichter		0.79	0.41	2,825		-0.08	1.02	2,921
Starkey		0.79	0.40	2,884		-0.07	1.04	3,018
Torres		0.77	0.42	2,829		-0.03	1.01	2,992
Ulrich		0.82	0.38	245		0.08	0.90	255
Watts		0.80	0.40	3,070		-0.07	1.04	3,194

Notes: Values based on responses to Patient Satisfaction Survey. The first variable—"made appointment with first person spoken to"—is binary. The second variable—"satisfaction with length of phone call required to make appointment"—is standardized at mean zero and a standard deviation of one. Survey responses were collected over a 35 month period from October 2004 to August 2007.

Table 5. IT and Employee Involvement as Determinants of Patient Satisfaction with Length of Phone Call Required to Make an Appointment for an Office Visit.

Variables	*1*	*2*	*3*	*4*	*5*
Time Trend	0.01***	-0.01**	-0.05***	-0.05***	-0.05***
	(6.98)	(-2.73)	(-5.21)	(-4.87)	(-5.03)
Time Since "Go-Live"		0.03***	0.06***	0.06***	0.06***
		(4.97)	(5.65)	(5.30)	(5.46)
Transition Period			0.15*	0.15*	0.15*
			(2.26)	(2.25)	(2.36)
Module-in-Use			0.44***	0.43***	0.42***
			(6.31)	(5.87)	(6.02)
Employee Involvement				0.03	-0.14
				(0.43)	(-1.89)
Module-in-Use × Employee Involvement					0.27***
					(4.06)
n	496	496	496	468	468
clusters	16	16	16	15	15
R^2	.11	.16	.26	.25	.28

Notes: Multilevel random effects regression with significance tests performed using robust standard errors. Dependent variable is mean patient satisfaction with the length of time it took to make an appointment by telephone for each clinic in a given month. Since n represents clinic-months and "clusters" is the number of distinct clinics included in each estimate, their quotient represents the mean number of months of data supplied by each clinic. In the first model, for example, each clinic contributes, on average, 31 months of data.

Key: * $p<.05$, ** $p<.01$, *** $p<.001$.

Figure 1. Scatterplot of Performance Gain at Scheduling Module "Go-Live" as a Function of Each Clinic's Mean Score on the Employee Involvement Index.