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RESEARCH ARTICLE

WORK HARDER OR WORK SMARTER? INFORMATION TECHNOLOGY AND RESOURCE ALLOCATION IN HEALTHCARE PROCESSES[1]

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While the impacts of health information technology (HIT) are widely studied, prior research presents mixed findings. In this study, a granular examination of the impact of HIT systems on how resources are allocated to healthcare tasks and processes was undertaken. A longitudinal field study that combined interview, archival, observation, and survey data was conducted. The effects of telemedicine on the input allocative efficiency of the healthcare process through the reallocation of organizational resources was evaluated and an assessment of whether gains in allocative efficiency resulted in improvements in organizational outcomes, such as lower hospitalization rates and lower uncertainty in patient wait time, was conducted. Applying the theory of swift and even flow, our findings suggest that the gains in allocative efficiency for some processes are associated with improved organizational outcomes.

Keywords: Healthcare, IT, telemedicine, stochastic frontier analysis, resource allocations

Introduction

The healthcare industry continues to face chronic challenges of rising costs and increased workload for healthcare workers (Kohli and Kettinger 2004; Porter and Teisberg 2006). Healthcare information technologies (HITs) are often touted as one of the solutions to these problems. While some studies on healthcare and HIT have found that IT investments and use, in general, have led to lower medical errors, mortality rates, and increased financial performance (Amarasingham et al. 2009; Devaraj and Kohli 2000, 2003; Kohli and Kettinger 2004; Porter and Teisberg 2006), these positive HIT impact findings are not consistently true as other studies have highlighted cases of HIT issues and failures. Part of the confusion and equivocality regarding HIT impact findings is due to the fact that many HIT studies were based on cross-sectional data and were ambiguous regarding the type of HIT they were studying (Agarwal et al. 2010). Others point to the complications in measuring the benefits of HIT as healthcare work is highly complex (Cuellar and Gertler 2005; Davidson and Chiasson 2005; Leviss 2010). Put together, even as HIT impact research continues to evolve, more research is needed to explain how HIT use could help manage rising costs of healthcare and improve productivity.

Early research on IT impacts has identified how IT (in general) could directly change the level of output, usually at the aggregate level, so as to bring about improved organization performance (Hitt and Brynjolfsson 1996; Hitt et al. 2002). Following from this stream of research, most HIT

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impact studies have focused on the *direct productivity impacts* of HIT. However, this direct approach is problematic as studies of HIT use have found that many aspects of healthcare work are hard to enhance and automate since this type of work requires ongoing human interactions (Berg 1998; Davidson and Chismar 2007). Furthermore, it is common for healthcare medical personnel to put in long hours at work, thus any possible gains in productivity may be less likely to be derived from working harder.

Recent research, especially in the use of telemedicine, has shown that HIT use may indirectly impact work processes and improve healthcare processes (Hui et al. 2001; Singh et al. 2011). Building on a small but growing stream of IS research that provides an enhanced and holistic understanding of HIT value (Devaraj and Kohli 2002; Devaraj et al. 2013; Menon et al. 2009), our research study focuses on how a specific HIT—telemedicine—impacts healthcare processes and how that, in turn, leads to improved organizational outcomes. In this study, we used the concept of input allocative efficiency and the theory of swift and even flow (TSEF) perspective to explicate how HIT may affect relevant healthcare outcomes.

Our study analyzed the impact of telemedicine use on patient, physician, and healthcare process outputs in the geriatric department of an acute-care hospital. We evaluated the effect of telemedicine on the input allocative efficiency of healthcare process through the reallocation of organizational resources and assessed whether gains in allocative efficiency resulted in improvements in organizational outcomes. Input allocative efficiency (or in short allocative efficiency) refers to the *choice of inputs (resources) mix* to produce the outputs while minimizing production cost (Kumbhakar and Lovell 2000; Menon et al. 2000). The allocative efficiency approach allows us to understand how HIT use could improve the assignment of resources to different tasks for efficiency gains (Leibenstein 1966; Menon and Lee 2000; Menon et al. 2000). In our study, we chose to focus on the impacts of applying a telemedicine system to the geriatric care process. We conducted a longitudinal field study that combined interview, archival, observation, and survey data to measure the performance before and after the implementation and use of a telemedicine system in the geriatric specialist clinic.

Our study found that the use of telemedicine and the process changes that accompanied the system had, overall, a positive impact on allocative efficiency for some processes. We observed that applying telemedicine with business process redesign enabled greater visibility of the patient information resulting in patients (tasks) being better assigned to the appropriate physicians (resources). Further, using TSEF principles, we show that the improved allocative efficiency achieved through the new telemedicine process or clinical pathway reduced variance of patient wait-time in the specialist clinic and provided better care to nursing home patients. By tracing the process and mechanisms through which HIT indirectly impact on organizational outcomes via the reallocation of resources and tasks, our study potentially "enhances our understanding of the various positive manifestations of IT" by providing a more holistic perspective of HIT value (Kohli and Grover 2008, p. 33).

The rest of the paper is organized as follows. First, we discuss the research setting and present the theoretical review and our hypotheses. Next, we describe the empirical methods and model. We then present the findings of this study and robustness checks for the analysis. The final section discusses the implications, limitations, and conclusions of our study.

Research Setting

The context of our study is a publicly funded hospital (Karehealth[2]) that serves the medical needs of the local community located within a developed Commonwealth country. Karehealth is an acute-care hospital with more than 2,600 staff members and operates around 500 beds (Karehealth's annual report of 2011). Although Karehealth is wholly owned by the government and is under the Health Department, it is an autonomous entity as it determines its own strategic directions as well as recruitment and remuneration policies. Thus all clinical and auxiliary care, and administrative staff, are employed directly by Karehealth and are paid monthly salaries based on their expertise and seniority. However, Karehealth's fee structure is under the Health Department's oversight as it is part of the government's provider network. Karehealth services are heavily subsidized by the government, albeit patients are typically required to provide copayment, either through their insurance plans or through their government pension funds.

Karehealth Geriatric Department (KGD) caters to elderly patients within the community. In addition to taking care of two specialized inpatient wards in Karehealth, KGD also runs a specialist clinic. The specialist clinic treats geriatric patients for a range of general geriatric conditions. Although there are fixed schedules in the specialist clinic, they do change over time depending on the workload of the physicians. Patients are usually assigned to a geriatric physician after the initial specialist clinic visit, albeit reassignment of physician is possible. The clinic is usually staffed by senior consultants and

[2]Karehealth is a pseudonym. The names of the organizations, projects, and individuals are disguised to protect confidentiality.

consultants.[3] Registrars are sometimes assigned to clinic cases as part of their training.

KGD's nursing home outreach program was initiated in the middle of 2010 by KGD's senior consultants as part of the government's project for integrated care. As such, the physical on-site visits to the nursing homes are conducted by the senior consultants. The nursing home outreach program involves one or two nursing homes and the on-site visits are limited to once a month. Although these nursing home visits are over and above the physician's existing duties and workload, they are not compensated for assisting with these visits. For the most part, KGD's physicians are not situated in the nursing home. If a nursing home patient develops medical problems or requires a follow-up, the nursing home staff will usually arrange appointments for the patients by calling up the Karehealth call center. If the case is uncertain, the nursing home will arrange for an ambulance to send the patient to Karehealth's emergency department.

KGD implemented telemedicine for its nursing home geriatric patients in January 2011 with the aim of better managing costs. The goal of KGD's telemedicine program is to "improve the matching of resources to patients' needs thus leading to greater efficiency and reduced cost for the healthcare system" (Karehealth Telemedicine Report). This technology is mainly used to support geriatric patients who reside in nursing homes within its health cluster. KGD's telemedicine system was based on the Polycom™ videoconference system linked by a commercial broadband Internet network.

Notably, KGD's telemedicine implementation project is well suited to study the impacts of HIT on resource allocations in healthcare processes as it represents a natural field study whereby we were able to collect granular cost data and qualitative data before and after the use of a HIT system. This allowed us to detect if there were any changes of cost and resource use between pre- and post-technology use and to understand the reasons behind the changes.

[3]Physicians are classified into various occupational grades under UK and Commonwealth standards depending on their level of experience and expertise. Senior consultants are regarded as the most senior physicians followed by consultants (similar to attending physicians in the United States) and registrars who are physicians training to be specialized in a particular field (similar to residents in the United States). Naturally, there is an ordinal variation in wage levels depending on the classification.

Theory

Telemedicine and its Impact on Productivity and Cost Efficiency

Our research study is focused on the impact of a specific class of HIT—telemedicine—on the geriatric care process. Telemedicine is formally defined by the American Telemedicine Association as "the use of medical information exchanged from one site to another via electronic communications to improve a patient's clinical health status" (American Telemedicine Association 2012). In terms of technology, telemedicine is a HIT system that involves a large variety of applications and telecommunications technology. Such systems have been applied to a variety of clinical and specialist settings such as cardiology, dermatology, neurology, ophthalmology, and radiology, as well as geriatric care.

Early concerns over the efficacy and satisfaction of patients and healthcare workers with the telemedicine system have gradually been reduced given recent advances in interactive video and remote monitoring systems that have greatly improved physician–patient interactions (Hailey et al. 2004; Paré et al. 2007; Tulu and Chatterjee 2008). While practitioner literature has noted such technological advances in telemedicine (Hailey et al. 2004; Hailey et al. 2002), there has not been much research into the impact of telemedicine on productivity in healthcare processes (Hailey et al. 2004).

Drawing from the substantial stream of IT impact and value research, one would argue that information technology, such as telemedicine, could intuitively assist to increase productivity by impacting the cost efficiency of healthcare processes. Specifically, cost efficiency is defined as establishing the minimum cost associated with producing a set of outputs. Cost efficiency can be achieved through technical efficiency and allocative efficiency simultaneously (Kumbhakar and Lovell 2000; Menon et al. 2000).

$$\text{Cost Efficiency} = \text{Technical Efficiency} \bullet \text{Allocative Efficiency} \quad (1)$$

Technical efficiency: Telemedicine potentially could assist to *maximize the level* of output quantity for a fixed level of input (i.e., increase technical efficiency or, in layman's terms, by helping a constant number of healthcare workers "work harder" to consult more patients). Existing literature on IT impacts (predominantly in the manufacturing industry) have shown that the application of IT could enable greater outputs by improving the technical efficiency of the production process and thereby raise the productivity of these processes (Hitt and Brynjolfsson 1996; Hitt et al. 2002; Lee and Barua 1999). There have been studies in healthcare and telemedicine that showed that the use of telemedicine increased the number of patients processed (in emergency departments) (Brennan et al. 1999; Giovas et al. 1998).

However, these few studies—they were pilot trials and not ongoing routine use of telemedicine—are not the norm (Hailey et al. 2004). Within the healthcare setting, we find that there are many cases of HIT failures that highlight the challenges of integrating HIT systems with existing medical workflows (Cuellar and Gertler 2005; Davidson and Chiasson 2005; Leviss 2010). Workplace studies in the healthcare settings have shown that many aspects of existing healthcare work require ongoing human interactions and specialized skills that may not lend themselves well to IT automation and hence fail to realize the benefits of improved productivity (Berg et al. 1998; Strauss et al. 1985). For example, post-implementation of electronic medical record (EMR) system studies found that physicians reverted back to non-EMR processes due to the lack of improvement in the productivity of EMR-enabled practices (Ornstein 2003; Wachter 2006; Yeow and Faraj 2008).

Even when IT-enabled automation of healthcare work is successful, there is another challenge for IT-enabled improvements (i.e., the high level of demand for medical services) (Berg 1998). Research on healthcare processes, especially on geriatric care, have shown that healthcare organizations and geriatric care units, unlike typical business units, tend to face a high level of demand and do not have full control over their market demand. This is especially salient for the particular site we are studying as the country is facing a rapidly ageing population whose demand for geriatric healthcare services is quickly outstripping its supply (Lundsgaard 2005; Penny 2007). Thus available geriatric facilities and providers are often operating at or near maximum levels (i.e., physicians are putting in long hours at work). As such any possible gains in efficiency are less likely to be derived from productivity gains that come from medical staff working harder under existing stressful conditions.

Allocative efficiency: Telemedicine through business process redesign and clinical task integration could enable a healthcare organization to gain timely and accurate information about its patients' conditions and its workload, and allow the organization to better organize and disseminate the information to the relevant healthcare personnel, thereby improving decisions on resource allocations (Mithas et al. 2011; Setia et al. 2013; Singh et al. 2011).[4] In other words, the implementation of new business processes around the telemedicine system could help healthcare managers *choose* the input mix that achieves a particular output level at minimum cost (i.e., increase allocative efficiency; in other words, healthcare workers are able to "work smarter" by assigning the right resources to tasks).

For example, a recent IS study found that IT use resulted in smoothing out a stochastic work schedule and raising productivity when users could reassign their work tasks to appropriate resources (Aral et al. 2012). In the healthcare context, researchers have shown that IT led to more effective process redesign such as grouping similar patients and elective procedures together when clinical scheduling systems are integrated with operation room scheduling systems (Devaraj and Kohli 2000; Devaraj et al. 2013).

Research on the impact of telemedicine has shown that the integration of telemedicine services with clinical task allocation led to higher allocative efficiency (Hui et al. 2001; Paré et al. 2006; Singh et al. 2011). Specifically, nursing homes or remote sites with a telemedicine system would be able to provide patient information prior to appointments. This integration of patient data across remote sites with the central specialist clinic enables more effective scheduling and coordination of clinicians' work with the patients' needs. Thus, the type of clinicians would be matched with the appropriate patient conditions. In addition, patients with similar ailments but located in different nursing homes could be scheduled together with the same (appropriate) clinician using telemedicine. Conversely, this would have been challenging when clinicians were making physical visits to the remote sites or when patients had to visit the specialist clinic as patient information would only be presented when they or the physician arrive at the site.

This type of impact on allocative efficiency enabled through the deployment of telemedicine also is evident in other studies. In a 12-month pilot study in a Hong Kong geriatric department that implemented telemedicine consultations for its nursing home outreach program, Hui et al. (2001) found that geriatricians were able to improve their follow-up and urgent referrals caseload when they integrated their new telemedicine process with the remote nursing processes of the nursing homes. They reported that the nursing staff redesigned their own work process to deal with the increased coordination required as well as acquire technical skills to operate remote equipment to aid with the geriatrician's work.

[4]This is similar to supply chain management research, which has shown how the effects of embedded interorganizational IT systems enable suppliers to gain more visibility of demand patterns of their products among their distributors through point-of-sale data or product return data and thereby make decisions on resource and product allocations (Cachon and Fisher 2000; Rai et al. 2006; Subramani 2004).

These healthcare studies, together with current ideas in IT value research (Kohli and Kettinger 2004; Mithas et al. 2011; Setia et al. 2013), show how telemedicine may lead to improved reconfiguration and integration of processes and information. Specifically, with greater visibility of workload and patient conditions in remote sites, healthcare organizations could reconfigure their processes in such a way as to reduce the degree of uncertainty in telemedicine-enabled healthcare processes and thus better allocate the appropriate resources to serve its patients (Kohli and Grover 2008; Mithas et al. 2011; Nevo and Wade 2010; Setia et al. 2013).

Based on these arguments, we propose that telemedicine has a positive impact on productivity and cost efficiency through process redesign and integration and dissemination of information across different clinical units. Due the nature of healthcare work and the work context, we propose that the impacts of telemedicine would improve allocative efficiency of its processes as it would allow for better allocation of resources to tasks through better visibility of workload and patient conditions. Thus, we hypothesize

> *H1: The use of telemedicine will improve the allocative efficiency of healthcare processes in the specialist clinic by the reallocation of tasks and resources within the clinic.*

Telemedicine and its Impact on Organizational Outcomes

While the above section details how telemedicine through business process redesign and integration of processes and information may improve allocative efficiency, it is unclear how the improvements in allocative efficiency may affect organizational effectiveness and outcomes. IT value research informs us that while initial impacts of IT would directly affect the organizational capabilities and processes where the IT is embedded, these initial impacts could potentially transform such capabilities and lead to positive organizational performances (Devaraj and Kohli 2002; Kohli and Grover 2008; Soh and Markus 1995). IS research on the impacts of IT on healthcare outcomes have looked at how IT investments could lead to health-related outcomes. For example, Devaraj and Kohli (2000, 2003) studied the impact of IT on patient revenues, mortality rates, and patient satisfaction. Menon et al. (2009) analyzed the impact of IT on days of patient care and labor productivity, while research on the impacts of telemedicine trials have looked at the impact of telemedicine on clinical benefits, patient management, and clinical care outcomes (Hailey et al. 2002). Yet the specific process by which such outcomes were related to IT have not been clearly spelled out.

Recent research has begun to explore this process in a more specific way. In a healthcare IT study, Devaraj et al. (2013) found that IT investment in hospitals was associated with improving the speed and even-ness of patient flow, and more importantly, these first order impacts led to improvements in patient revenues and quality of patient care. This implies that, for telemedicine, the system and its new processes could potentially have indirect impacts on overall geriatric care outcomes by transforming its immediate organizational processes as evidenced by allocative efficiency changes.

In order to clarify the process by which telemedicine through its impact on allocative efficiency may affect organizational process outcomes, we build on Devaraj et al.'s work by adopting the TSEF perspective used in their study. TSEF was proposed by quality pioneer W. Edwards Deming (1986), who argued that the more swift and even the flow of materials (or information) through a process, the more productive that process will be (Schmenner 2004; Schmenner and Swink 1998). Underpinning this theory are five basic laws: the law of variability, the law of bottlenecks, the law of scientific methods, the law of quality, and the law of factory focus. While these laws are broadly applicable to hospital settings as discussed by Devaraj et al., our focus on a specific class of HIT and on a specific clinical process resonated more with the first two laws of TSEF (i.e., the law of variability, which states that the process variability affects its productivity, and the law of bottlenecks, which suggests that the slowest stage of a process determines the speed and quality of the entire process).

With regard to TSEF's law of variability, we argue that the changes in allocative efficiency of the clinical process have a significant impact on reducing the variability of resource utilization and thus lead to improved even-ness of patient flow. Prior to telemedicine, geriatric patients presenting at the specialist clinic varied significantly in their conditions even though they are required to make an appointment. In these cases, patients only informed the clinic about their complaints and were then referred to the consultants on duty. However, their exact conditions were not clear until they arrived at the clinic for their consultation. With the implementation of telemedicine for the nursing homes, KGD required the nursing homes to provide information of patient conditions as part of the new telemedicine process. With the nursing home patient information, KGD's operational and clinical team could prescreen the patients and decide which cases were directed to the telemedicine pathway and the appropriate clinician to run the session and which cases were referred to the traditional clinical pathway (via specialist clinic), thereby improving allocative efficiency of clinician resources across its traditional and telemedicine pathways.

Further, patients from *different* nursing homes suffering from similar ailments can be scheduled together to the appropriate clinician, a scheduling arrangement that was not possible with prior nursing home site consultations. By streamlining the flow of nursing home patients via this new process, we would expect the cases seen at the specialist clinic to be relatively more standardized and less variable than before. Since the geriatric cases seen at the specialist clinic are more standardized, one plausible outcome would be the reduction of wait-time uncertainty at the specialist clinic (Kohli and Grover 2008).

Thus, we hypothesize

> *H2a: The positive impact of telemedicine on allocative efficiency of the processes of the specialist clinic will, over time, be associated with reduced uncertainty in wait-time at the clinic.*

With regard to the law of bottlenecks, the telemedicine system and its attending clinical pathway helped to deal with the main bottleneck (i.e., the rigid assignment of doctors to patients). Prior to telemedicine implementation, whenever nursing home patients complained of any health problems, they would have been referred to either the specialist clinic or the emergency department pathway (Interview notes, KGD's operations manager). In the specialist clinic, most patients were assigned to consultants by default (even though senior consultants might have been available) as they were usually scheduled to be on duty at the specialist clinic. Couple this policy with the high variability of case mix at the clinic and consultants would have needed more time to deal with a complex case as compared to a typical case.

However, with the telemedicine pathway available to the nursing homes, KGD is now able to better manage this bottleneck. The telemedicine pathway is not constrained by the hours a clinic is open, nor by physical examination rooms. Further, KGD also is able to access a larger pool of physicians—registrars and senior consultants—to run the telemedicine sessions across geographically dispersed nursing homes. Leveraging this ability to access a larger pool of physicians using the telemedicine system as well as having a clearer understanding of the condition of the nursing home patients, KGD's operational team is thus able to assign a more appropriate clinical resource (i.e., physician) to the patient type. Telemedicine introduces alternative clinical pathways by opening up more resource options and thereby relieving the traditional rigid assignment of patients to emergency room or specialist clinic. As a result of this improved allocative efficiency, patients are directed to the clinical pathway that is most appropriate to provide them with more effective treatment and thus improve the quality of care. This is in line with the argument by Devaraj et al. suggesting that improvements in process flow can lead to improved quality of patient care.

One clear evidence of this improved quality of care within the geriatric process is in the hospitalization rates of nursing home patients. Prior to telemedicine, nursing home patients who required quick medical attention were often sent to Karehealth's emergency department as specialist clinics were only available on an appointment basis. As a result, nursing home patients had to endure the trip to the clinic or emergency department, wait for their turn, and in most cases be admitted to inpatient care, which may not have been required in the first place (Interview notes, KGD's operations manager). With the telemedicine pathway and improved allocative efficiency, the team of senior consultants, registrars, and consultants could provide nursing home patients with timely diagnosis and treatment and improved quality of care. Consequently, an important quality outcome from the improved allocative efficiency of the KGD process is the reduction in the number of emergency department admissions of nursing home patients.

Thus, we hypothesize,

> *H2b: The positive impact of telemedicine on allocative efficiency of the processes of the geriatric clinic will, over time, be associated with reduced hospitalization rates of nursing home patients.*

Furthermore, as theorized and shown by both theoretical and empirical studies of IS value, such second-order outcomes of IT systems are usually latent and not immediate (Hitt et al. 2002; Kohli and Grover 2008; Menon et al. 2009). One reason for the latency effects of IT impacts is that organizations need time to learn and assimilate the technology (Hitt et al. 2002). Another reason is that outcome measures and the locus of IT use are usually influenced by organizational capabilities of changing the processes across KGD and the nursing homes. Thus, there is usually a degree of time lapse before the impacts of IT—telemedicine—are observed in the outcome measures as such capabilities also require time to be developed (Devaraj and Kohli 2002; Myers 2003). Thus, the indirect impacts of telemedicine on reduction of nursing home patient admissions to Karehealth and reduced uncertainty of wait-time would exhibit lagged effects.

Empirical Methods

In this section we outline the methodology that we applied to measure the change in allocative efficiency resulting from resource allocations and the resultant impact on performance outcomes as hypothesized above for KGD's specialist clinic after the implementation and use of the telemedicine system.

Although this study focuses on the impacts of telemedicine on allocative efficiency, we also modeled the impact of technical efficiency in order to have a complete picture of the underlying service production process given the possible interaction between both technical and allocative efficiency as shown in equation (1). We next describe the data that was used before describing in greater detail our empirical model.

Input, Output and Price Data

To quantify the cost benefits of any possible change in resource allocation with the new telemedicine-enabled process, we collected operational price levels and input quantities data from KGD's specialist clinic from October 1, 2010 (three months prior to the implementation of telemedicine, or pre-telemedicine) to August 31, 2011 (duration of eight months after implementation of telemedicine, or post-telemedicine). In the pre-telemedicine phase, we collected daily data of the total number of patients consulted within the specialist clinic, the type of physician (organizational rank) performing the consultation, the duration of each consultation, and the type of patient consulted. In the post-telemedicine phase, in addition to the typical clinic consultations, we added daily data of the telemedicine consultation (i.e., number of consultations, type of physician, duration, type of patient). Through our data collection, we were able to map all the *variable* internal resources (and costs) required to service the entire daily patient load for the clinic.

In KGD, geriatric patients who require more attention are classified into four specialized groups based on their ailment (delirium, falls, incontinence, and frailty). All other geriatric patients who require general consultation are listed under general care within the clinic. Clinical research has shown that these four ailment groups were associated with substantial morbidity and poor health outcomes (Inouye et al. 2007). Due to patient confidentiality reasons, we did not identify the ailment for each patient; instead, we collected the proportion of patients classified under the more severe ailments vis-à-vis patients classified under general care. We normalized our output (number of patients consulted) by the proportion of patients suffering from more severe ailments.[5]

We conducted field interviews with the physicians, operations managers, and executives working in KGD and attended various telemedicine workgroup meetings to understand the existing and telemedicine-based operating procedures and processes. We also collected archival data that included documentation of existing and planned processes, meeting minutes, and project presentations. The interviews provided in-depth information concerning the context of the inputs, outputs, and price data we collected, which assisted us in shaping our econometric specification and qualitatively verifying our statistical findings. We used the archival data to triangulate with our interview data and contextualized the results and insights derived from our economic modeling of the production process.

To quantify the costs involved in the consultation process, we collected the hourly wage levels of the different types of physicians involved in the consultation process. The product of the hourly wage level and duration of the consultation provided the key variable cost of the geriatric process.

Organizational Outcomes, Patient Satisfaction Data, and Other Controls

As discussed earlier, through telemedicine, the hospital hopes to achieve better process management so that nursing home patients can have timely access to healthcare services via telemedicine. This process improvement should reduce the number of nursing home patient emergency room visits and, in turn, lower the number of nursing home patient hospitalizations. Hence, one evident performance measure that we captured is the number of nursing home patients who were admitted to the hospital via emergency room pre- and post-telemedicine. Another tangible performance outcome the hospital hoped to achieve via better process management was the reduction in uncertainty in patient wait time at the specialist clinic. To measure this performance outcome, we obtained survey data from patients who have consulted at the specialist clinic (details in the next paragraph). The survey asks the patients to report the wait time they experienced for their consultation session.

Prior literature has suggested that customer value (Hitt and Brynjolfsson 1996) and customer satisfaction (Mithas et al. 2005) might be affected by the introduction of IT interventions. As such, considering only the tangible inputs (e.g., physicians' time) and outputs (number of patients consulted) of the production process might not provide the complete

[5]The amount of physician effort required for patients with more severe ailment varies from one patient to another. According to the physicians, a more severe ailment case takes, on average, twice the amount of effort than for a minor ailment case. Thus, we adjusted the output with a factor of 2 for more severe cases. As a robustness check, we also estimated all our models twice: the first model ***did not include*** any adjustment while the second model had an adjustment factor of 1.5. We found qualitatively similar findings for all models.

picture of the value of telemedicine. Hence, in our estimation, we attempted to control for any variation in the patients' satisfaction as well as the patient's overall experience during the consultation process. As satisfaction is subjective and cannot be *quantified* as an input or output (Hitt and Brynjolfsson 1996), we represented it as covariates in our specification. To achieve this, we collected data from the same hospital survey. Karehealth has an ongoing hospital quality survey on random patients across all departments as part of their operational performance indicator. This survey includes both in-person consultation patients as well as telemedicine patients. The quality survey measured all service touchpoints that a patient encounters in the specialist clinic (e.g., nursing staff, registration, physician care, etc.) and patients were asked numerous questions pertaining to their experience at the specialist clinic. The survey was open to all patients and was conducted after each patient consultation.

We collected the survey data of specialist clinic patients during the same period of our observation data on a monthly basis for the clinic. While patients are asked a variety of questions (on a five-point scale), we focused on only two main categories: the overall satisfaction with the physician during the consultation (physician care) and the overall satisfaction with the nurses during the consultation (auxiliary care). The overall satisfaction with the consultation is computed as the average of four measures: (1) the patient's satisfaction with the physician's treatment, (2) the physician's ability to provide information, (3) the skill of the physician, and (4) the coordination of the care provided in the clinic. The Cronbach alpha for these four measures is 0.87. The overall satisfaction with the nurses is computed as the average of four measures: (1) the level of service provided by nurses, (2) the nurses' ability to provide information, (3) level of care provided by nurses, and (4) the knowledge of the nurses. The Cronbach alpha for these four measures is 0.97. We combined the individual measures into two categories as individual measures within each category were highly correlated and would result in multicollinearity issues if each measure was employed separately in our estimation model shown in the next section.

Finally, we also controlled for the nurses' time (in hours) that was required to prepare for all the consultation sessions and other overhead variables. This variable measures the amount of time the nurses spent in preparing the consultation room, paperwork, and workgroup meetings on a daily basis, relating to both the in-person and telemedicine consultation sessions. The amount of time spent was aggregated on a daily basis and we were not able to attribute these resources to any particular consultation, hence this variable was only used as a control variable for the production function estimation. Table 1 provides the descriptive statistics of the data used in this study.

Research Model and Estimation

To provide empirical support for our hypotheses, we first specified the underlying healthcare production process. We defined the daily consultation process in the clinic as the production function and specified it in equation (2):

$$\ln y = \beta_0 + \sum_n \beta_n \ln x_n + v \qquad \forall n = 1,\ldots,N \qquad (2)$$

where y is the total number of patients consulted in the geriatric clinic for any particular day. On a daily basis, the *direct variable* inputs required for the outpatient consultation session is the physician's time, denoted by x. As described earlier, each consultation process requires a physician with varying levels of experience, and n represents the occupational grade of the physician (i.e., senior consultant, consultant, or registrar[6]). In this production function, we omitted other inputs that are fixed (invariant) on a daily basis; for example, counter staff who are assigned to the clinic do not change in the short run for all production level instances and are not directly attributable to any particular consultation session (i.e., counter staff do not get reassigned out of the clinic on days of low patient load). Invariant variables will violate full-rank assumption of any regression model. We also omitted variables that did not directly contribute to the consultation process (e.g., overhead), although we considered these variables as state condition controls instead (details in next section). β is the output elasticity and it represents the efficacy of the physician, whereby a higher β means that the physician is able to complete more consultation tasks per unit time. Finally, we assume decreasing returns to scale of the production and v represents the error term.[7]

In any production process, there is always a degree of technical inefficiency whereby the inputs are not operating at the maximum level due to operational slack. For example, a physician may take a longer duration to consult a patient in order to reduce job fatigue. In an interview with a physician in KGD, she commented that some geriatric physicians take longer than others in the specialist clinic consultation even though there are recommended guidelines for the duration of outpatient consultation. She attributed this to the personality

[6]The grading of physician is strongly correlated with the level of expertise of the physician and the wage level of the physicians. Physicians move up the grades through formal examinations conducted in university hospitals as well as by the medical council. The number of years of practice experience within the relevant field is also taken into consideration.

[7]The Durbin-Watson tests statistics were $d = 1.82$ (pre-telemed) and $d = 1.80$ (post-telemed). The test statistics, d, and 4-d were higher than the upper critical values, suggesting that positive and negative autocorrelation of error terms were not present ($\alpha = 0.05$).

Table 1. Descriptive Statistics

	Pre-Telemedicine		Post-Telemedicine	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Number of consultation hours per day (Senior Consultant)	3.76	3.57	4.26	3.92
Number of consultation hours per day (Consultant)	0.77	1.53	1.13	1.76
Number of consultation hours per day (Registrar)	0.61	0.82	0.66	0.92
Number of patients per day	14.72	12.65	16.83	14.76
Number of telemedicine sessions (session days)	–	–	2.96	0.77
Number of telemedicine sessions (all days)	–	–	0.23	0.82
Number of hospital admission (nursing home patients)	0.10	0.30	0.04	0.21
Wait time at geriatric clinic (minutes)	29.76	29.20	24.34	21.61
Number of nursing home consultations (in other hospitals)	0.29	0.93	0.13	0.41
Patient Satisfaction (physician care)	4.56	0.03	4.52	0.15
Physicians' overall treatment	4.67	0.04	4.58	0.17
Physicians' ability to share information	4.56	0.03	4.60	0.17
Skill of Physicians	4.60	0.05	4.58	0.15
Coordination of care provided	4.40	0.11	4.31	0.20
Patient Satisfaction (auxiliary care)	4.49	0.21	4.23	0.26
Nurses' overall service	4.49	0.20	4.28	0.27
Nurses' ability to share information	4.49	0.13	4.21	0.27
Level of care provided by nurses	4.56	0.24	4.21	0.25
Knowledge of nurses	4.40	0.26	4.19	0.28

Note: The data sample spans across 335 workdays from October 2010 to August 2011. In general, telemedicine sessions are prescheduled and do not occur on all days. The clinic, however, allows for *ad hoc* telemedicine sessions that can occur on any workday of the week. Physicians' wage statistics are not shown for confidentiality reasons.

of the physician as some physicians are more personable than others and are inclined to spend more time interacting with the patient. Hence, for a same quantum of input resources, technical inefficiency results in lower output and equation (2) can be rewritten into

$$\ln y = \beta_0 + \sum_n \beta_n \ln x_n + v - u \qquad \forall n = 1,\ldots,N; u \geq 0 \qquad (3)$$

where u represents the output-oriented technical inefficiency in the production. u is strictly nonnegative as it measures the reduction of output due to operational slack.

Patient Satisfaction and Other Covariates

As in prior production models (Kumbhakar and Lovell 2000; Menon et al. 2000), our model specification only considered direct, variable inputs of the production process. However, there are intangible factors that could influence the production process indirectly. For example, the service quality of the staff might influence the experience of the outcome. Such factors are intangible, not readily quantifiable, and are classified as state conditions (Olley and Pakes 1996). We extended our specification as shown in equation (3) to include other intangible covariates such as the patients' satisfaction with the physicians (physician care) and the patients' satisfaction with the nurses (auxiliary care), which might influence the estimation process. In addition, we also used the number of overhead hours required by nurses to prepare the consultation sessions, paperwork, and workgroup meetings, relating to both the in-person and telemedicine consultations.

Although these covariates are not *directly* involved in the production of the output, they could impact the estimation of the production function by either influencing the mean or variance of the technical inefficiency, u (Coelli 1995). For example, for the same level of patient output per day, to achieve higher patient satisfaction, physicians might need to put in more effort, hence reducing technical inefficiency, u. Given that patient satisfaction impacts the mean of technical inefficiency, difference in patient satisfaction across different time periods may result in changes to the variance of the technical inefficiency.

To account for the influence of patients' satisfaction on the mean of technical inefficiency, u, we allowed the mean to be modeled as a linear function of the set of patient satisfaction covariates as shown in equation (4) (Coelli 1995):

$$E(u) = k \bullet \alpha \qquad (4)$$

where $E(u)$ is the expectation of the technical inefficiency, u; k is a vector of covariates that influences the mean (i.e., covariates such as patient satisfaction–physician care, patient satisfaction–auxiliary care, and nurse time). α represents estimated parameters. Likewise, if these covariates influence the variance of the technical inefficiency, we can account for this heteroscedasticity by specifying the variance of the technical inefficiency, σ_u^2 as

$$\sigma_u^2 = e^{k \bullet \delta} \qquad (5)$$

where δ represents the estimated parameters of this relationship. This specification is in line with that proposed in Kumbhakar and Lovell (2000).

To measure any changes in allocative efficiency, we first specified the cost function as

$$c = \sum_n w_n x_n \qquad \forall n = 1, \ldots, N \qquad (6)$$

where w_n represents the price level of input x_n (i.e., per hour wage level of the physician). To minimize cost, c, of producing a particular level of patients consulted (output), the first-order condition for the cost minimization problem can be expressed as the system of equations represented by equation (3) with (N-1) first-order conditions (Kumbhakar and Lovell 2000):

$$\ln\left(\frac{x_1}{x_n}\right) = \ln\left(\frac{\beta_1 w_n}{\beta_n w_1}\right) \qquad \forall n = 2, \ldots, N \qquad (7)$$

As shown in Kumbhakar and Lovell, the input allocative efficiency can be represented by η_n as shown in equation (8):

$$\eta_n = \ln\left(\frac{\beta_1 w_n}{\beta_n w_1}\right) - \ln\left(\frac{x_1}{x_n}\right) \qquad \forall n = 2, \ldots, N \qquad (8)$$

where η_n represents input allocative efficiency for the input pair x_1 and x_n. η_n can be positive, zero, or negative, which suggests that the input x_n is over, appropriately, or underutilized (from a cost efficiency perspective) relative to input x_1. For example, if input allocative efficiency for the input pair of consultant and registrar was overutilized, it meant that for the same level of patient consultation output for the day, cost efficiency for the tasks could be improved by relocating more tasks from the registrars to the consultants.

Following Kumbhakar and Lovell, we adopted stochastic frontier analysis (SFA) to solve for the empirical model. SFA is a well-established technique to measure the level of technical inefficiencies in a production process. The SFA estimator charts out the maximum level of output y that can be produced with the inputs x, after considering stochasticity in the process (denoted by v) as well as the possibility of individual inputs not producing to the maximum due to operational slack.

We performed a conditional mean, SFA, using equations (3), (4), and (7). We used a maximum likelihood estimator (MLE) to solve for equation (3) simultaneously with N-1 conditions as shown in equation (7) as constraints, with u following a truncated normal distribution that is predicted by equation (4). To reduce notational clutter, the estimation of this equation is labeled as Model 1 in our "Results" section.

The estimators of this estimation were then substituted into equation (8) to obtain the input allocative efficiency scores, η_n, for all input pairs (consultant–registrar pair; senior consultant–consultant pair, and senior consultant–registrar pair). These scores allowed us to assess for any pair of physician inputs, if one type of physician is over (or under) utilized with respect to the other type of physician from an input allocative efficiency perspective. This procedure estimated the technical and allocative efficiency after partialing out the impacts of quality from the means of the inefficiency term. To test if the use of telemedicine was associated with changes in allocative efficiency in physicians' consultation, we split the sample into three panels,[8] one with the data before the telemedicine implementation (prior to January 2011), another with data from the first four months of implementation (January 2011 to April 2011), and the last with data from the fifth to the eighth month after telemedicine implementation (May 2011 to August 2011). The results of this estimation were applied to test Hypothesis 1.

As a robustness check, we triangulated the results of Model 1 with an alternative estimator. To do so, we reestimated the model, but, in this instance, with the covariates of patient

[8]We also estimated the models by splitting the dataset into two panels (pre- and post-implementation of telemedicine). We found similar results, but felt that having three panels would help better estimate and illustrate any temporal latency effects of telemedicine use.

satisfaction and nurse time influencing the variance of the inefficiency term as specified in equation (5). We simultaneously estimated equations (3) and (7) with u following an exponential distribution and its variance as specified by equation (5). Here, we allowed the technical inefficiency to be heteroscedastic with the effects of different treatment covariates captured as variance in the technical inefficiency as described earlier. We also considered a different technical inefficiency distribution function (exponential distribution) to ensure consistency in our results under different distribution assumptions of technical inefficiency as proposed in prior literature (Banker and Slaughter 1997). Similarly, for brevity, we labeled this estimation as Model 2 in our results section.

To test hypotheses 2a and 2b, we used the allocative efficiency scores for all three resource pairs estimated in Model 1 as independent variables. As described earlier, allocative efficiency scores for each resource pair measure the level at which a resource is over- or underutilized compared to the other paired resource. In terms of allocative inefficiency levels, both positive and negative values represent levels of allocative *in*efficiency. Hence, to ensure that we have a monotonic scale for regression estimations, we took the negative, absolute values of the allocative efficiency scores.[9] A detailed explanation for this transformation is provided in Appendix A.

To test if changes in allocative efficiency impact the uncertainty of wait time or the admission rates of nursing home patients, we specified these two organizational outcomes as a function of allocative efficiency scores, η_n, and other control variables, k. We operationalized uncertainty of wait time as the standard deviation of wait times (*Std. dev. wait time*) for patients on a daily basis. For the admission rates of nursing home patients, we measured the daily number of nursing home geriatric patients admitted to the hospital via the emergency room consultation (*Hospital admission*). See equations (9) and (10).

$$Std.dev.waittime = f\left(\eta_n, k\right) \qquad \forall n = 1, \ldots N \qquad (9)$$

$$Hospital\ admission = f\left(\eta_n, k\right) \qquad \forall n = 1, \ldots N \qquad (10)$$

The control variables include the number of patients consulted in the outpatient clinic and via telemedicine for the day, the proportion of patients with severe ailments, and amount of time the nurses spent to prepare for the consultations. These control variables are essential to ensure that model captures the patient and resource levels for the clinic. Further, given that the number of nursing home patient admissions is one of the organizational outcomes we measured, we also captured other alternative medical care options the patients have as controls. These alternative medical care options include visiting a different hospital for medical attention. Hence, we also collected the number of nursing home patient consultations in other hospitals to ensure that any possible decrease in admission rates was not due to the fact that nursing home patients were avoiding KGD and going to a different hospital for treatment instead.

For equation (9), we formed an equation for *each pair* of allocative efficiency score and the three pairs of scores resulted in a system of three equations[10] that were likely to have correlated error terms as the observations were from the same hospital and exposed to similar exogenous factors. We estimated all three equations simultaneously using seemingly unrelated regression (SUR) given the covariance structure of the error terms. We estimated equation (10) in a similar way except with a different dependent variable, *Hospital admission*.

Results

Our first analysis involves the estimation of Model 1 and 2. Our stochastic frontier analyses are presented in Tables 2 (Model 1) and 3 (Model 2). We present two alternative models: Model 1 uses additional controls as covariates influencing the mean of the technical inefficiency and Model 2 uses additional controls as variables that influence the variance of the technical inefficiency as described in the previous section. The χ^2 tests of model fit of all estimations are significant, suggesting that the overall fit of the proposed model is significantly better than the null model. The coefficient estimates of the main independent variables measure the efficacy for each type of physician and the log likelihood figures reported are generally low, suggesting good model predictability. Both models present qualitatively identical findings, and for brevity, we discuss only the results of Model 1. All conclusions drawn from Model 1 are also applicable to Model 2.

[9]By taking only the absolute values of the allocative efficiency scores, we also arrived at *identical* statistical conclusions. The negative transformation was solely to improve interpretation of the coefficients.

[10]We chose to use each resource pair in a single equation (hence specifying a system of three equations), instead of including all three resource pairs in a single equation to prevent overlapping of the independent variables. Recall that each resource pair measures the relative allocative efficiency between two physician types and given that there are three physician types, each physician type appears twice for all three resource pairs: Senior Consultant–Consultant, Consultant–Registrar, and Senior Consultant–Registrar.

Table 2. Model 1: Conditional Mean Stochastic Frontier Analysis (Truncated Normal)

Dependent Variable: Log Total Sessions of Consultations (Daily)† **Independent Variables**	**Pre-Telemedicine**	**0–4 Months Post-Telemedicine**	**5–8 Months Post-Telemedicine**
	Coefficients (Std. Error)	**Coefficients (Std. Error)**	**Coefficients (Std. Error)**
Log Time (senior consultant)	0.3959*** (0.0093)	0.3822*** (0.0112)	0.3875*** (0.0117)
Log Time (consultant)	0.0764*** (0.0093)	0.0830*** (0.0105)	0.0733*** (0.0109)
Log Time (registrar)	0.0617*** (0.0101)	0.0682*** (0.0113)	0.0683*** (0.0108)
State Conditions (Mean Controls)#			
Patient Satisfaction (physician care)	1.2972*** (0.2128)	2.0777 ** (0.7425)	-0.4329 (0.3861)
Patient Satisfaction (auxiliary care)	0.1874*** (0.0379)	0.6664 ** (0.2558)	0.8522 ** (0.3613)
Nurse time	0.0006 (0.3200)	-0.0003 (0.0008)	0.0001 (0.0008)
Constant	3.1275*** (0.0574)	3.2562 (3.5637)	3.3304*** (22.945)
Log likelihood	-1.430	-11.939	-24.95
χ^2 test of model fit	4424.42***	4068.57***	3570.09***

Notes: ****p*-value < 0.001; ***p*-value < 0.01. †Patient sessions normalized for severity of the ailments. #The variables below estimate the mean of the technical inefficiency error term as shown in equation (4).

Table 3. Model 2: Heteroscedastic Stochastic Frontier Analysis (Exponential)

Dependent Variable: Log Total Sessions of Consultations (Daily)† **Independent Variables**	**Pre-Telemedicine**	**0–4 Months Post-Telemedicine**	**5–8 Months Post-Telemedicine**
	Coefficients (Std. Error)	**Coefficients (Std. Error)**	**Coefficients (Std. Error)**
Log Time (senior consultant)	0.3999*** (0.0098)	0.3824*** (0.0116)	0.3884*** (0.0113)
Log Time (consultant)	0.0715*** (0.0098)	0.0801*** (0.0108)	0.0791*** (0.0113)
Log Time (registrar)	0.0567*** (0.0107)	0.0697*** (0.0116)	0.0680*** (0.0105)
Constant	3.0414*** (0.0591)	3.1256*** (0.0643)	3.1812*** (0.0616)
State Conditions (Variance Controls)#			
Patient Satisfaction (physician care)	-46.02 (62.75)	56.85 (44.47)	-33.75 (29.32)
Patient Satisfaction (auxiliary care)	17.66 (7.310)	17.43 (13.43)	33.44 (27.18)
Nurse time	0.001 (0.012)	-0.005 (0.019)	0.011 (0.013)
Constant	124.53 (260.73)	-335.14 (257.17)	6.78*** (18.98)
Log likelihood	-4.66	-14.13	-21.63
χ^2 test of model fit	3951.68***	4141.95***	3986.79***

Notes: ****p*- value < 0.001; ***p*-value < 0.01. †Patient sessions normalized for severity of the ailments. #The control variables below estimate the variance of the technical inefficiency error term as shown in equation (5).

From Tables 2 and 3, we observe that all inputs (time for all physician types) have a significant and positive impact on the total output produced. Similar to our earlier baseline estimation, our SFA estimation suggested that, after controlling for patients' satisfaction and variable overheads, in the months prior to telemedicine, more experienced physicians were able to consult patients at a faster rate (coefficients of senior consultants, consultants, and registrars are in descending order: 0.3959 to 0.0764 to 0.0617; Table 2 second column). This is in line with observation data, where, all else constant, a more experienced physician is able to arrive at a diagnosis faster than a less experienced one, thereby consuming less input resources (i.e., physician's time) (Schmidt and Boshuizen 1993). This time difference is significantly greater for the senior consultants compared to the other physicians. We observe similar patterns in terms of time difference across post telemedicine (see Tables 2 and 3).

Although we included patients' satisfaction variables as controls in both estimations, we observed that the coefficients are generally only significant in Model 1 and not Model 2. Model 1 specifies the mean of technical inefficiency as a function of the control variables and Model 2 specifies the variance of technical inefficiency as a function of the control variables. From the results, it appears that patients' satisfaction in general is significantly associated with an increase in the mean technical inefficiency. This finding is intuitive and corroborates our discussion with one of the employees of KGD: when physicians spend more time on each patient to establish rapport, elicit information, and communicate with them, patient satisfaction improves. However, the increase in the amount of time spent on the consultation will decrease the technical efficiency from a resource-cost perspective.

While we are able to establish that a senior consultant is able to cover more consultation tasks within a shorter time, it does not directly suggest that one should utilize more senior physicians to perform the tasks from a cost efficiency perspective; after all, wages of senior consultants are higher (higher inputs prices). To quantify the right mix of input resources to the outpatient consultation task, we computed the allocative efficiencies (η_n) for each physician-type pair. The allocative efficiency scores for each pair of inputs were computed by substituting the SFA estimates from Tables 2 and 3 into equation (8). We computed two sets of allocative efficiency scores by substituting the estimates from Model 1 and Model 2 into equation (8). The allocative efficiency scores, η_n, for all input pairs in pre- and post-telemedicine conditions are shown in Tables 4 and 5. The η_n for each input pair measures the extent to which the base input resource type is over- or underutilized compared to the paired input after considering the cost (wage) as well as the input's ability to generate output (i.e., efficacy in consulting patients).

In Table 4, we observe that the allocative efficiency score for the senior consultant–consultant pair decreases over time. The decline of allocative efficiency scores is only significant after five months of telemedicine use where it drops from 1.837 to 0.255 (p-value < 0.001). As described earlier, positive allocative efficiency scores represent overutilization of the base input resource. Prior to the use of telemedicine, consultants were overutilized (from a cost efficiency perspective) compared to senior consultants. After telemedicine was implemented for about five months, KGD experienced cost efficiency savings due to the reallocation of tasks from the consultants to the senior consultants (as seen by the decline of η_n toward zero).[11] Notably, during the first four months of telemedicine use, although we observe a shift toward more optimal allocative efficiency, the shift is not statistically significant (η_n drops from 1.837 to 1.369). Our result might sound counterintuitive in that reallocation of consultation tasks from a less costly input (consultant) to a more costly input (senior consultant) results in greater cost efficiency. This is plausible, however, if we consider that the costlier input (senior consultant) is able to complete the task in a significantly shorter amount of time as shown by the coefficients in Tables 2 and 3, thereby consuming fewer resources and achieving greater cost efficiency. The reallocation of consultation to senior consultants corroborates with our interview data (see the quote below), which suggests that nursing home patients preferred to switch their specialist clinic appointments to telemedicine sessions conducted by the senior consultants.

> *The scheduled telemedicine consult acts as a SOC [specialist clinic] appointment where the [nursing home patients] can have specific ailments follow-up (sic) by the physicians....Patients requested this because of the ease and convenience of the sessions that remove the hassle of transportation and wait-time at the SOC* (KGD Ops Executive).

The second observation from our analysis is the reallocation of tasks from the consultants to the registrars. Unlike the earlier reallocation of tasks between senior consultants and consultants, where we observe increasing allocative efficiency gains over time, the allocative efficiency gains for this pair of resources was not sustainable. During the pre-telemedicine phase, the negative allocative efficiency score suggests that the base input resource (i.e., registrars) were underutilized compared to consultants prior to telemedicine use. During the first four months of telemedicine use, the score increased to -0.137, suggesting reallocation of tasks from consultants and registrars resulted in greater allocative efficiency. These gains, however, were short-lived and during the next four months of telemedicine use (fifth to eighth month), the relocation of tasks from consultants to registrars became allocatively inefficient when the registrars experienced diminishing returns to scale (η_n increased from -0.358 during pre-telemedicine to 1.705; p-value < 0.001).

[11] η_n of 0 represents optimal allocative efficiency.

Table 4. Conditional Mean SFA: Allocative Efficiencies, η_n					
Input Pairs	**A: η_n Pre-Telemedicine (S.E.)**	**B: η_n 0–4 Months Post-Telemedicine (S.E.)**	**C: η_n 5–8 Months Post-Telemedicine (S.E.)**	**A–B *t*-statistic**	**A–C *t*-statistic**
Senior Consultant–Consultant	1.837 (0.355)	1.369 (0.288)	0.255 (0.267)	1.04	3.63***
Consultant–Registrar	-0.358 (0.378)	-0.137 (0.375)	1.705 (0.355)	-0.41	-3.93***
Senior Consultant–Registrar	1.528 (0.315)	1.232 (0.270)	1.960 (0.277)	0.72	-1.02

Notes: ****p*-value < 0.001, ***p*-value < 0.01, **p*-value < 0.05.

Table 5. Heteroskedastic SFA: Allocative Efficiencies, η_n					
Input Pairs	**A: η_n Pre-Telemedicine (S.E.)**	**B: η_n 0 – 4 months Post-Telemedicine (S.E.)**	**C: η_n 5 – 8 months Post-Telemedicine (S.E.)**	**A – B *t*-statistic**	**A – C *t*-statistic**
Senior Consultant – Consultant	1.761 (0.355)	1.332 (0.288)	0.248 (0.268)	0.95	3.47***
Consultant – Registrar	-.3779 (0.378)	-0.079 (0.375)	1.786 (0.355)	-0.55	-4.12***
Senior Consultant – Registrar	1.433 (0.315)	1.253 (0.270)	2.034 (0.277)	0.43	-1.43

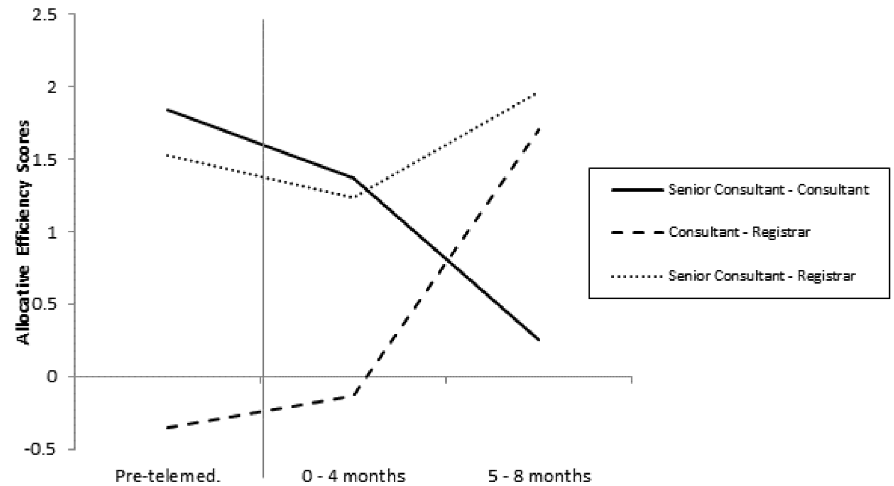
Notes: ****p*-value < 0.001, ***p*-value < 0.01, **p*-value < 0.05.

More importantly, this increase in the allocative efficiency scores also suggests that the registrars are now overutilized from a cost efficiency perspective as the result of the task reallocation. Registrars have lower wages and correspondingly lower performance efficacy compared to consultants as suggested by their lower β coefficients in Tables 2 and 3. The reassignment of (possibly complex) consultations from consultants to registrars results in more time being spent in consultation. The use of a less effective resource (although at a lower per unit cost) would thus lead KGD to experience a decline in cost efficiency due to increased use of the lower cost resource. The reallocation of consultation to registrars is in line with our interview findings (see the quote below), which revealed that the clinic had hired more registrars to handle the consultations after telemedicine.

> *The telemed sessions are workload over and above the physicians' current workload. As the telemed project becomes larger, other physicians were enrolled. We are planning to hire a full time registrar to attend to the ad hoc cases* (KGD Ops Manager).

For the final resource pair (senior consultant–registrar), we observed that the registrars were consistently overutilized compared to senior consultants in all three phases of telemedicine use (η_η 1.528 in pre-telemedicine, 1.232 after four months of use and 1.960 between five to eight months of use). Interestingly, the allocative efficiency scores did not change significantly during the first eight months of telemedicine use. This finding suggests that there is limited reallocation of tasks between the senior consultants and registrars. Such a finding corroborates the general medical practices as not all consultation tasks can be handled by physicians training to be specialists (registrars) (Crandall et al. 1984). Similarly, this also suggests that, although the use of IT allows the reallocation of resources to tasks to achieve higher cost efficiency, the extent of reallocation is limited by the inherent difference between the resource types (the skill set differences between senior consultants and registrars are significantly large). Highly effective (and possibly more costly) resources may not always be substitutable with less effective (and possibly less costly) resources due to challenges in completing the tasks. Likewise, it may not be cost effective to reallocate tasks from less effective resource to more effective resource.

In summary, our findings provide partial support for Hypothesis 1 in that only the allocative efficiency for the senior consultant–consultant pair improved over time. Figure 1 illustrates the changes in allocative efficiency scores for all three resource pairs.



Note: Allocative efficiency improves as scores tend toward zero. Allocative efficiency declines as scores deviate away from zero.

Figure 1. Changes in Allocative Efficiency

In our next set of analysis, we test H2a and H2b to examine if the positive changes in allocative efficiency resulted in reduction of patients' wait time uncertainty and hospital admissions via the emergency room. For the system of equations that estimate the wait time uncertainty (standard deviation), the SUR estimates show that the improvement in allocative efficiencies for the senior consultant–consultant resource pair is associated with a drop in standard deviation of the wait time (coeff. -0.776, p-value < 0.001) (see Table 6). This suggests that as allocative efficiency improves with the assignment of tasks between senior consultants and consultants, we will observe patients experiencing less variance in wait time. As discussed above, the decline in wait time uncertainty is in line with the TSEF's principle of improved even-ness of patient flow. With more patient information available, KGD's operational and clinical team could streamline the flow of nursing home patients, and thus have more standardized cases seen at KGD's specialist clinic than before. In addition, as more cases shift to senior consultants, their greater experience may also lead to greater consistency in consultation time and effort, which in turn reduces the standard deviation in wait time for patients.

To further examine if patients experienced an overall change in the uncertainty of waiting time, we plotted the distribution of waiting time experienced by patients using kernel density estimation (as seen in Figure 2). From the kernel density curves, it appears that after the use of telemedicine, the number of instances where patients waited for excessively long time periods (e.g., more than 50 minutes) decreased. Instances of excessive waiting time suggest the occurrence of contingencies in the consultation process given that patients' consultation appointments were generally scheduled. We use Levene's test to verify if the change in the variance of wait time is statistically significant. We reject the null hypothesis of equal variance (p-value < 0.01), with the standard deviation of wait time reduction from 29.20 minutes before the use of telemedicine to 21.61 minutes after the use of telemedicine.

Next, to test if improvements in allocative efficiency scores are associated with a decline in nursing home patient admissions we estimated the set of three equations as presented in equation (10) (see Table 7). The SUR estimation is similar to the preceding estimation, except that now the number of nursing home patients admitted to the hospital via the emergency room is the dependent variable. As hypothesized, we find that the improvement in allocative efficiency scores for the senior consultant–consultant pair is associated with a decline in the admission of nursing home patients to Karehealth. The provision of telemedicine to nursing home patients either as a scheduled visit or as an *ad hoc* consultation provided an alternative clinical pathway for these patients. As discussed above, following from the TSEF principles, the increase in number of senior consultants available to the nursing home patients ensured that these patients were accurately and efficiently diagnosed, thereby reducing the instances where they were sent to Karehealth's emergency room and later hospitalized.

Table 6. Impact of AE on Uncertainty in Patient Wait Time (SUR Estimates)

Dependent Variable = Std. dev. of patient wait time **Independent Variables**	**Coefficients (Std. Error)**	**Coefficients (Std. Error)**	**Coefficients (Std. Error)**
Senior Consultant – Consultant	-0.776 (0.229)***		
Consultant – Registrar		-0.377 (0.252)	
Senior Consultant – Registrar			-0.289 (0.239)
Number of nursing home consultations (in other hospitals)	-1.204 (0.564) *	-1.097 (0.558) *	-1.294 (0.581) *
Number of patients (outpatient and telemed.)	0.036 (0.035)	0.099 (0.035) **	0.097 (0.039) *
Proportion of severe patients cases	7.254 (3.020) *	6.450 (2.934) *	6.480 (2.941) *
Nurse time (hours)	0.005 (0.0141)	-0.005 (0.016)	-0.005 (0.016)
Telemedicine	-0.171 (1.490)	0.682 (1.427)	0.341 (1.495)
Constant	-8.016 (3.225) *	-7.496 (3.191) **	-7.024 (3.075) **

Notes: ****p*-value < 0.001; ***p*-value < 0.01; **p*-value < 0.05.

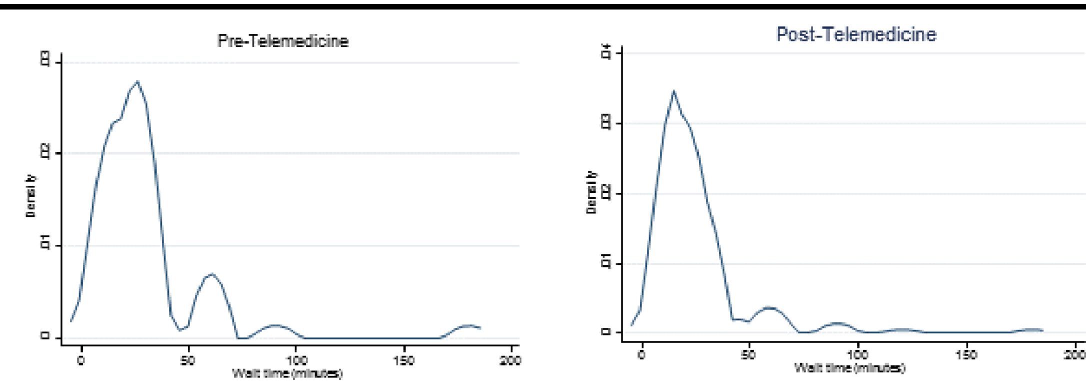


Figure 2. Distribution of Wait Time Pre and Post Telemedicine

Table 7. Impact of AE on Patient Admission (SUR Estimates)

Dependent Variable = Nursing home patient hospital admission via emergency room **Independent Variables**	**Coefficients (Std. Error)**	**Coefficients (Std. Error)**	**Coefficients (Std. Error)**
Senior Consultant–Consultant	-0.011 (0.004)***		
Consultant–Registrar		0.006 (0.005)	
Senior Consultant–Registrar			0.005 (0.004)
Number of nursing home consultations (in other hospitals)	0.018 (0.023)	0.017 (0.023)	0.019 (0.023)
Number of patients (outpatient and telemed)	-0.001 (0.001)	-0.002 (0.0008) *	-0.002 (0.001) *
Proportion of severe patients cases	-0.040 (0.091)	-0.043 (0.090)	-0.038 (0.090)
Nurse time (hours)	-0.001 (0.0002)*	-0.0004 (0.0002)*	-0.0003 (0.0002)*
Constant	0.151 (0.127)	0.156 (0.125)	0.144 (0.126)

Notes: ****p*-value < 0.001; ***p*-value < 0.01; **p*-value < 0.05.

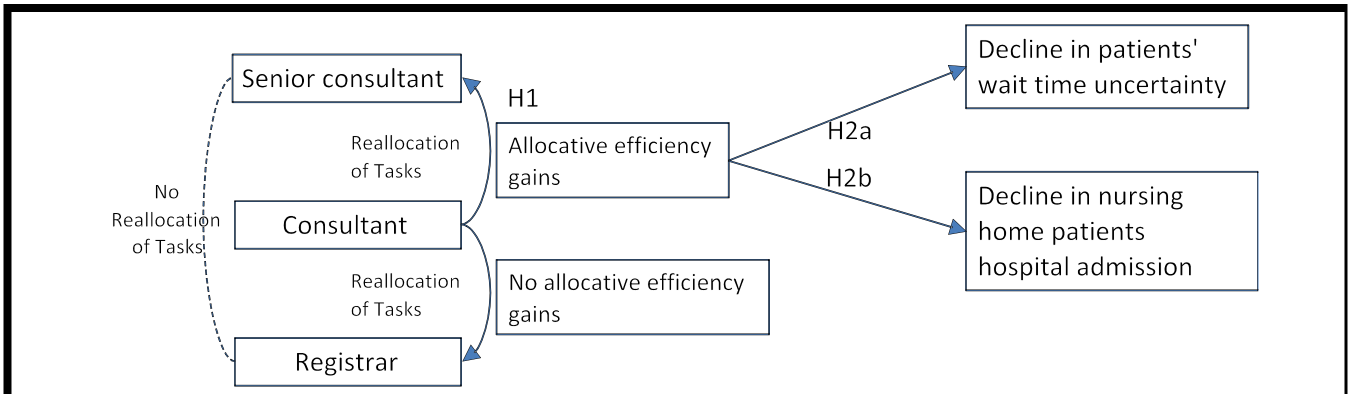


Figure 3. Resource Reallocation and its Impacts Through Telemedicine

In this estimation, we observe that one of the control variables—number of patients visiting the outpatient clinics (both in person and via telemedicine)—is negatively associated with hospital admission rates. This finding is intuitive as patients have more access to the physicians, thereby reducing the need to go the emergency room to seek medical attention.

Figure 3 summarizes the key findings of our study. Broadly, we found that the use of telemedicine was associated with shifts in resource allocation to organizational tasks. This is in line with our proposed Hypothesis 1. This shift was brought about by both planned and emergent changes to KGD's workflows and business processes as a result of the use of telemedicine. The planned changes were, on the one hand, supported by integration and dissemination of information across different clinical units that made visible the patients' condition in the nursing homes to the KGD operational and clinical team. On the other hand, the planned changes took place when the embedding of telemedicine brought about an alternative clinical pathway for geriatric consultations.

> *Given the changes, we saw the need for systematic workflows to handle them. We need [to have] more structure and probably more resources and a more robust method. The Ops [operations] team and the clinician team will work together on this* (KGD Ops Meeting Minutes).

In addition to our hypothesis, our field notes also revealed that these changes occurred partly due to unexpected events. Specifically, with the new clinical pathway available to them, more nursing home patients requested to replace specialist clinic visits with their scheduled telemedicine sessions. The use of telemedicine to replace specialist clinic visits thus also led to a resource shift as discussed above. Notably, the reallocation did not occur among resource types that were inherently different (i.e., between senior consultants and registrars), as the level of expertise required for more complex tasks could not be readily reallocated to junior physicians.

To sum up, among all the changes in allocative efficiencies, only the reallocation between senior consultants and consultants resulted in overall allocative efficiency gains. In examining the impacts of the changes in allocative efficiency, we found that this particular relocation of tasks was associated with a decline in patients' wait time uncertainty as well as a reduction in hospital admission via the emergency room.

Discussion

The goal of this study is to analyze the impact of telemedicine use on patient, physician, and healthcare process outputs in a geriatric department. Using granular longitudinal data on telemedicine usage, our study showed that telemedicine improved the allocative efficiency for one set of resources in the clinical process and that this change reduced the wait-time uncertainty at the specialist clinic and improved quality of care for nursing home patients. In this way, our study contributes to a small but growing stream of IS research that provides an enhanced and holistic understanding of HIT value (Devaraj and Kohli 2002; Devaraj et al. 2013; Menon and Lee 2000). Whereas many have focused on broad hospital IT investments, our study looks at HIT value at the *process* level and within a *specific* functional specialty. Given the unique characteristics of healthcare work and clinical processes, we drew on the concept of allocative efficiency and the TSEF perspective to provide a clear understanding of the process by which HIT may affect relevant healthcare outcomes (i.e., even-ness of patient flow and quality of care). Our study has several important implications for research and practice.

Theoretical Contributions

Theoretically, our study sheds some light on the current debate around the efficacy of HIT in delivering real results. First, we argue that the choice by past studies to use cross-sectional data as well as a broad notion of HIT may have introduced potential confounding contextual factors that could have masked the HIT impacts (Agarwal et al. 2010). The longitudinal approach used in our study is focused on a specific type of HIT (telemedicine) that helps to deal with these confounds. Second, and more importantly, we chose to focus on changes in clinical process allocative efficiency gains as a way to demonstrate tangible benefits of telemedicine. As we discussed earlier, allocative efficiency rather than technical efficiency is more appropriate in healthcare settings given the unique characteristics of healthcare work (e.g., high level of demand, specialized skills, and coordination). Finally, we clearly explicated and traced the mechanisms and processes that link the use of telemedicine to healthcare organizational outcomes (Agarwal et al. 2010; Fichman et al. 2011). Building on the work of Devaraj et al. (2013), we applied the TSEF perspective to show how the improved allocative efficiency achieved through the new telemedicine clinical pathway reduced variance of patient wait time in a specialist clinic and provided better care to nursing home patients.

Together, the findings of our study explain why HIT-enabled productivity in a healthcare setting is hard to detect and is equivocal. Since HIT impact on productivity is a multistep process and highly process-specific, it is only apparent when an organization is successful in facilitating changes to the flow of information and organizational resources and existing clinical processes. In KGD's telemedicine case, the process change was centered on the planned and emergent reconfiguration of the scheduling and consultation process for telemedicine patients. If those process changes had not occurred, the impacts of telemedicine would have been muted.

In sum, the allocative efficiency approach adds another perspective of IT value that reduces the risk of underestimating the value of IT in the healthcare context. Not only is this important for HIT impact research, it is also in line with recent calls by IS scholars to broaden our repertoire to capture other positive impacts of IT as well as provide a more precise theorizing of IT impacts (Kohli and Grover 2008).

In terms of research methodology contributions, our study highlights the importance of studying IT impacts at the process level and using a field study design to paint a more complete picture of the phenomenon. This granular approach is appropriate as it is more aligned with the goal of building a process-level explanation of how HIT and work practice changes complement each other (Aral et al. 2012), especially given the idiosyncrasies within the healthcare context and among diverse HITs (Agarwal et al. 2010; Fichman et al. 2011).

Another methodological contribution to IT value research is the use of unobtrusive, objective data (e.g., telemedicine sessions) captured as part of ongoing work processes to analyze IT impacts (Pentland et al. 2009). Using such work process data helps to surface HIT impacts as they reduce measurement errors and bias in studying changes to processes and resource allocation. Moreover, our study shows the importance of integrating qualitative and empirical modeling data so as to establish the robustness and validity of our results. Specifically, we informed our empirical model with field interview data, organizational archival data (e.g., physician wages), observational data (e.g., consultation duration), and survey data (e.g., patient satisfaction data) to test our empirical model and verify our results. The use of multiple data sources also highlighted the importance of a broader approach in studying the phenomenon of healthcare IT.

Boundary Conditions of HIT Impacts

Our study reveals two constraints to HIT's impact on allocative efficiency and organizational outcomes: the type of resources and the overall cost efficiency. With regard to the first constraint, our findings show that resource allocations did not occur across all resource pairs (i.e., it did not occur between senior consultants–registrars). This highlights an interesting boundary condition: the indirect impacts of a HIT on eventual organizational outcomes depends in part on the type of resources and in part on the specific processes and tasks involved. As discussed briefly above, one possibility was that the difference in capabilities between a senior consultant and a registrar might be significant due to the consultation process so that there was limited reallocation of tasks as part of the process changes. Another possibility is the cost of the resources, where KGD decided that it was not cost effective to reallocate tasks from the less costly to the more costly resource for relatively less complex tasks, even though they may be more efficient.

With regard to the constraint of cost efficiency, our analysis of the latency effects found that the continued shift of tasks from consultant to registrar resource actually resulted in cost *inefficiency*. This suggests that we have to balance between resource price levels and resource efficacy when using HIT (or IT in general) to reallocate tasks and resources. As organizations typically seek to contain costs with the use of IT, they tend to use IT to reallocate tasks to lower priced resources. For example, research on outsourcing and off-shoring has shown that the use of interorganizational IT systems facilitates the outsourcing of processes to lower cost venues (Levina and Ross 2003). Although this general strategy of substituting higher priced resources for lower priced resources may seem logical, our findings show that this may not always be effective. Instead, the overall impact of HIT and IT on cost efficiency has to take into account the ability of resources to generate tangible outputs. In certain cases, as in our findings, "excessive" reallocating of tasks to lower-priced resources may actually result in cost inefficiency; in turn, this inefficiency in the reallocation does not positively affect organizational outcomes. In other words, our empirical findings reveal a concave relationship—an inverted U—between the impact of HIT on reallocation of resources and organizational outcomes. A situation in which there is over-allocation of tasks to either high-cost or low-cost resources will result in cost inefficiency whereby positive organizational outcomes may not be realized. In our setting, it was possible that the increased shift of patients from consultants to registrars meant that patients with borderline severity were still referred to the specialist clinic or the emergency room, as the registrars might not have the necessary expertise to treat those cases directly via telemedicine. This finding sheds additional light to why HIT efficiency impact is hard to measure as HIT impacts on resource allocation efficiency are subject to such nuanced issues that require ongoing fine-tuning.

Implications for Practice

From a practical perspective, our study shows that organizations should adopt a holistic approach when implementing HIT to generate strategic capabilities and business value (Aarts et al. 2004). This involves examining the underlying work tasks, understanding the affordance of information technology, and reallocating the appropriate resource to the right set of work processes. For example, the earlier discussion of resource constraints highlights the fact that firms have to be aware that different inputs may have different applicability to specific processes and IT, and that these nuanced differences in turn may affect how much value the organization may gain from those new combinations of resources and IT.

With regard to telemedicine use, our study shows that healthcare organizations need to think of telemedicine not only as a remote location treatment tool or as a time/cost-saving tool but also as part of strategic process redesign that may bring about upstream and downstream benefits. Our study shows that the redesigned telemedicine clinical pathway allowed better allocation of care that probably provided greater convenience and better care to nursing home patients. The reduced nursing home admission rate may also be safer for geriatric patients as studies have shown that geriatric patients have a higher probability of acquiring diseases during hospital stays (Jepsen et al. 2013). Therefore, healthcare practitioners must broaden their view of telemedicine to recognize that it is about strategic changes; that is, (1) what tasks to allocate to whom, (2) what processes to change, and (3) the extent of these changes. These changes could then lead to improved quality outcomes across the care continuum—from hospitals to nursing homes and other step-down care facilities.

At the same time, our findings also point to the fact that healthcare organizations need to take into account *both cost and efficacy* of the resources in how they reallocate tasks and redesign IT-enabled processes to achieve optimal reallocation. In extant research, many process redesign efforts have over-emphasized the issue of cost and lost sight of the overall picture. Given that HIT impacts are complex, one general guideline is that managers of telemedicine systems should continually seek feedback on the process changes that have been implemented and be ready to intervene when diminishing returns occur or when negative downstream impacts emerge. The challenge however is to identify the intermediate benefits such as improved allocation of patients to physicians, and how they translate to favorable outcomes for the organizations.

Limitations

Our study is not without limitations. For example, for the measurement of technical inefficiency, the metric is always limited by the size and scope of the study sample. Ideally, a larger sample with multiple hospital sites would provide greater confidence and possibly more insights to the results. Nevertheless, the number of observations we obtained from the 11-months-long data collection is sufficient to arrive at statistically robust conclusions.

In our model specification, we did not consider transportation costs as a possible cost for the production process. It is unfortunate that in this study we do not have a record of transportation costs incurred by the nursing home patients as these costs tend to be *ad hoc* and were not captured by the hospital. Further, there is no single standardized mode of transport by which nursing home patients arrive at the hospital. Future research of telemedicine impacts on nursing home care should consider transportation cost as part of its data collection.

Conclusions

Our study attempts to reduce the current confusion and equivocality of HIT impact findings by studying how the use of telemedicine impacted the geriatric care process that led to beneficial organizational outcomes. Using a longitudinal field study of a telemedicine project, we explored how telemedicine and process improved allocative efficiency for some resources-task pairs, which in turn brought about patient benefits in the form of lower uncertainty in specialist clinic wait time and lower hospitalization admissions through better matching of patients with clinical pathways. Our findings surfaced several important issues and insights into how telemedicine improved healthcare outcomes for geriatric patients.

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Appendix

Transformation of Input Allocative Efficiency Score

The input allocative efficiency scores, η_n represents the extent to which the referent input, n, is over- or underutilized compared to the paired input, 1. A score of zero suggests input allocative efficiency being achieved. Positive and negative scores suggest input allocative inefficiencies with positive (negative) scores suggesting the referent input resource is overutilized (underutilized) compared to the paired input resource (see Figure A1).

In terms of inefficiency levels, extremely positive and negative values will represent high levels of allocative inefficiency. In order to ensure that we have an ordinal scale for the functional estimations, we compute a transformed allocative efficiency, s, score as follows:

$$s = -|\eta_n|$$

Under this new transformation, s essentially measures the magnitude of allocative efficiency without considering the directionality of allocative inefficiency (i.e., allocative inefficiency as a result of over- and underutilization are all regarded as allocative inefficiency) (see Figure A2).

With this transformation the new variable, s will decrease in tandem with allocative efficiency. As variable s approaches 0, allocative efficiency is achieved and as it deviates from 0 (i.e. becoming more negative), higher levels of allocative inefficiencies will be observed.

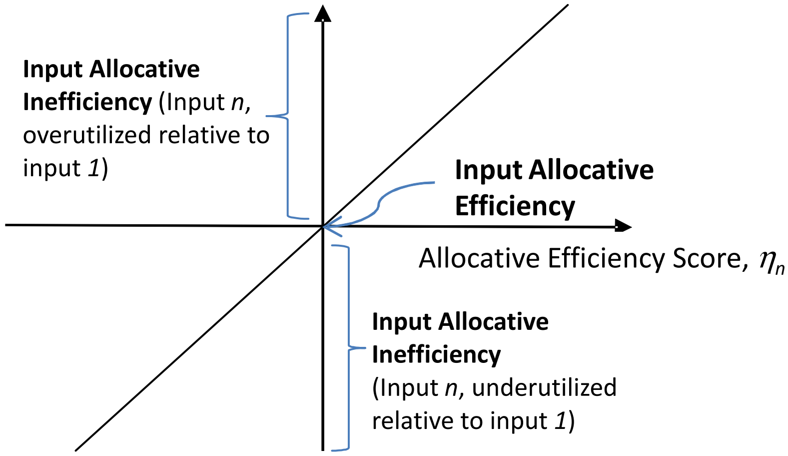

Figure A1. Allocative Inefficiency Scores

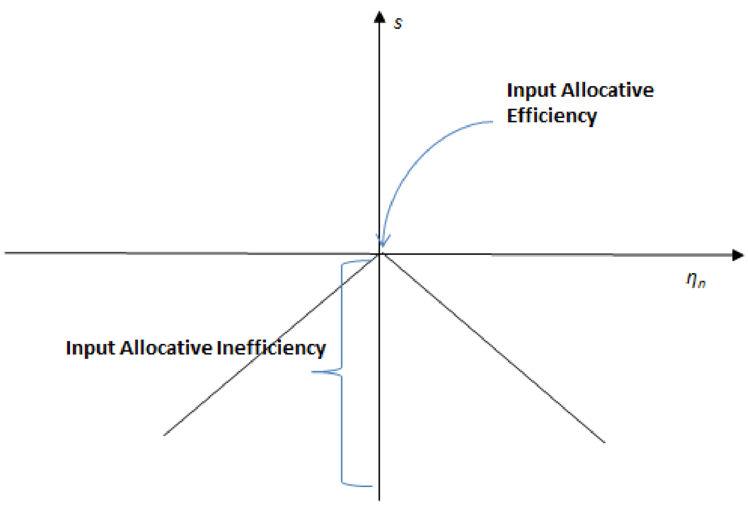

Figure A2: Transformed Allocative Inefficiency Scores, *s*