Access to quality healthcare is a precious benefit to possess. Being able to provide health insurance benefits that allow for that access, however, can be a prohibitively expensive proposition for employers and employees alike. As small businesses, especially, continue to be squeezed by high health insurance costs, they become more likely to drop this benefit, leaving employees without sponsored access to healthcare.

This issue’s interview subject, James I. Rodriguez, FACHE, puts forward the concept of multi-share health plans as a vehicle for addressing this problem. He explains multi-share health plans and their potential for encouraging small businesses to offer employee health insurance coverage. In addition, he describes how accountable care organizations can best position themselves to recruit primary care physicians, and he shares his thoughts on the power of financial incentives in the Affordable Care Act to motivate people to obtain healthcare coverage.

In this issue’s Patient-Centered Care column, Barbara Cliff, RN, PhD, FACHE, reinforces the centrality of leadership in initiating and maintaining patient-centered cultures. Our Efficiencies columnists, Vin Capasso and Michelle Johnson, note that the distractions and interruptions experienced by nurses during the administration of patient medications is a clear threat to patient safety as it increases the risk of medication errors. They describe a successful process improvement program aimed at eliminating interruptions during medication administration.

Dong Yeong Shin and colleagues examine the relationship between hospital payer mix and rates of electronic health record (EHR) adoption. This study shows how the meaningful use program influences hospital EHR adoption and offers a gauge for hospitals to assess their own EHR adoption progress.

Deborah Dahl, FACHE, and colleagues explore the determinants of intensive care unit (ICU) daily variable costs and how these costs change across an ICU stay. Their results indicate that severity of illness is an important antecedent of daily resource consumption and length of stay, irrespective of whether a patient presents at the ICU with high or low acuity. The growing proportion of longer-stay, low-acuity patients who deteriorate during an ICU stay is not widely recognized. This study highlights an important opportunity for lowering costs and improving patient outcomes.

Health information data sets combining clinical and administrative data are viewed as a way to improve quality reporting processes, quality measures and rankings, and health data systems. Michael Pine, MD, and colleagues describe a Minnesota pilot project linking hospital clinical information to administrative data, the challenges faced during implementation, and lessons for hospitals conducting similar data enrichment projects.

Pauline Vaillancourt Rosenau, PhD; Lincy S. Lal, PharmD, PhD; and Christiaan Lako, PhD, explore the increasingly popular pay-for-performance (P4P) programs in healthcare. The authors identify barriers to effective program implementation, summarize research-based P4P best practices, connect P4P program components to a priori budgetary considerations, and recommend a robust approach to P4P design.

Stephen J. O’Connor, PhD, FACHE

Editor
James I. Rodriguez, FACHE, is president and CEO of TexHealth Central Texas in Austin. Prior to this role, Mr. Rodriguez held various leadership positions, including executive director of the University of Texas Medical Branch Galveston’s three-share health benefits program and physician-hospital organization (PHO) administrator with Cincinnati Children’s Hospital. In addition, he has held leadership positions with provider-owned HMOs, PPOs, and a Medicare Advantage plan.

Mr. Rodriguez holds a bachelor’s degree in marketing from Wright State University and is a Fellow of ACHE. He is a founding member of the National Multi-Share Coalition, a contributing member of the TexHealth Coalition, and a governing board member of the National Forum for Latino Healthcare Executives.

Dr. O’Connor: You have had a long and successful career. What events in your career have been pivotal to your success?

Mr. Rodriguez: I graduated from college in the mid-1970s and started a local carpet-cleaning business. That experience imbued me with an entrepreneurial spirit that has served me well. I have always been on the cutting edge of things. When I got married, my wife said, “Jim, dress rehearsal is over, you have to get a real job!” Because there were not many opportunities available in 1977, I took a job as an administrative assistant in a community mental health clinic, working in accounting doing billing and collections and keeping books, which was not my area of training; my business degree was in marketing. But it exposed me to the financial side of the business. Eventually, I started doing some consulting with other community mental health centers and preparing them for their audits with public accounting firms. In due course, I got my license as a public accountant. (In Ohio, you can be licensed without being a CPA; that is, you can be a public accountant.) That experience was good as it was a counterbalance to my marketing training. In 1985, I was on the cutting edge helping to start a Medicaid HMO in Ohio. I always wanted to be in healthcare, so it was a good transition because it took me to the payer side, which was important for my career development. Over the years, I was either managing health centers, in leadership positions with payer organizations, or consulting.

Later, I was in a small boutique consulting group that was on the edge of the PHO movement in the 1990s when hospitals were buying physician practices. That was when I knew that healthcare was for me, as it exposed me to the things necessary for private practice operations as we were buying physician practices. We built big PHO entities. Those are a few of the key work experiences that allowed me to become a better-rounded leader. Today, folks tend to go unidirectional. That is to say, if they
are in accounting, they stay in accounting; they usually don’t get experience in the marketing area, and so on. To be a well-rounded individual in a leadership position, one needs to broaden one’s experiences by working on both sides of the fence.

**Dr. O’Connor:** What are multi-share health plans? How do they work? What are the benefits and challenges associated with such plans?

**Mr. Rodriguez:** A multi-share plan is like a health benefits program. The Texas Legislature paved the way for such plans to become legal entities. While we are not an actual insurance company, we function very much like a PPO insurer. Basically, we offer limited health benefits programs to small businesses. For example, caps on the number of annual physician visits an enrollee can make are fairly common in today’s market, but back in 2007, when we first started these plans, such limits were less common. These plans bring down the cost because of the limits. Essentially, a multi-share plan collects the premium from three different channels. One channel is the employer. The second channel is the employee, who must make a contribution. The third is an outside organization. This third channel could provide grant funding from state or local government or other outside sources. Even health systems and hospitals have contributed the third share in some of these programs. The point is that multi-share plans reduce premiums so that healthcare coverage is affordable for low-wage workers and small businesses. We are trying to target those segments in Texas that historically have been unable to afford a health benefits program, and we do it in a way that leverages employee, employer, and community contributions. With this model, everyone has “skin in the game.” I also think there are significant opportunities for a three-share plan to support the mission of an ACO. I’m still exploring what that model may look like. For example, some of the populations in the ACO are those who sometimes find low-paying jobs and consequently float in and out of the ACO. But what if the ACO can enroll those small businesses into the ACO system through a three-share plan? There would be not only continuity of care for those members but also the leveraging of employer and employee contributions to the care system.

The multi-share plan is not an entitlement program but a “boot strap” program that allows people to access the health insurance world that they have been shut out of previously. Once they have access to healthcare and start using services, they feel better, they become healthier, and their quality of life improves. They soon recognize the value of having a health care program and the access it provides. For example, we received a grant allowing us to reduce the employees’ contribution to the plan all the way down to $9.50 per month. We saw substantial growth in enrollment as a result. Then the grant went away. It was supposed to be a five-year grant, but it became a one-year grant due to budget cuts. The good part was that the grant allowed people who had enrolled to remain on the program for one full year. When the year ended, those folks had to go from paying $9.50 per month to paying $84.50 per month—which was a huge increase. However, about 75 percent of the people who were no longer on the grant continued with the program because they saw the value of being enrolled.
in a health benefits plan. That is really what a multi-share plan is all about. It’s a way to get people into the health insurance world and give them the opportunity to be as healthy as they can be if they take advantage of it. We offer one free physical per year, which is a benefit included in the Affordable Care Act (ACA), but we included it early on. We have people who actually leave our program and move into the commercial health insurance market. We think that is great. As business improves for the employers and they start making more money, they are in a position to purchase a regular commercial health insurance program, and that’s one of our ultimate aims.

Dr. O’Connor: Do you see the multi-share health plan as a universal and viable solution to the problems facing small businesses in providing health insurance coverage for employees?

Mr. Rodriguez: Yes, I believe both sides of the political spectrum see the value of a multi-share plan. For example, if you look at Congressman Paul Ryan’s proposal for Medicare, he is talking about premium support. We call it premium assistance. Basically, it is a subsidy—a word that people shy away from because it sounds like an entitlement. But Republicans are talking about using it for Medicare, and Democrats have proposed it for other healthcare programs. It is a viable method and can be a partial answer—not necessarily the full answer, but at least a partial answer to the issues that we face with healthcare access. The key, I think, is that you get as many people into these programs as possible so they can experience what it means to have healthcare coverage. We have encountered so many people who have not had health-care coverage for 5, 10, even 20 years, and who have not seen a doctor for eight or more years. It is mind-boggling to see what people do when they are without health-care coverage. Yes, I see the multi-share plans as a viable solution, especially for small businesses. It is like a first step. If you own a small business and you’ve got employees who are low wage, you know that a doctor visit is going to cost them at least $100. In addition, many of these small businesses cannot afford to pay people for sick leave. If an employee takes off from work to see a physician, he or she will probably not be paid for that time. So there is a real disincentive to see a physician. But if you have a program where the copay for a physician visit is $20 or $30, it is still a lot less than paying $100 or more. Even though the time off from work is unpaid, at least they will be able to get themselves well. Most uninsured employees wait until they can’t stand their health problem anymore. Then they run to the emergency department because they know they have to be treated there.

Dr. O’Connor: Can you offer some examples of how multi-share health plans address health disparities in a population?

Mr. Rodriguez: Because multi-share health plans offer a lower-wage employee the opportunity to have coverage, and thus access to healthcare that he or she may never have had before, the ultimate outcome is improved for minority populations. We have people who have had chronic diabetes for most of their adult life. Their blood sugars bounce up and down and they often cannot understand how to get it under control.
But when you have a nurse giving you a call once a week to help guide you in keeping your diabetes under control, it helps. There is that personal accountability. They know that the nurse is going to call, so they do things they’re supposed to do; they begin to understand more and feel better, and it has an impact. So yes, I see multi-share plans as an important way of addressing disparities in a lot of minority populations.

Dr. O’Connor: You have experience turning around underperforming PHO provider networks. What are the keys to strengthening relationships in physician network partnerships?

Mr. Rodriguez: When I was working with an HMO that contracted with PHOs for the delivery of services, what I found was a lack of communication. I believe that the key to strong relationships between two entities such as these is communication. When I visited a PHO and sat down with the CEO, I said, “Look, we are no different than you are. We are trying to establish a good product. Tell me what your problems are and how we can help.” Most of the time I got responses like, “I can’t believe you’re saying this. We never had anyone from your organization ask us what we need and how you can help us.” Taking the tack of viewing the PHO as the customer of the insurance company, and not the other way around, is important. The PHO is there to help you provide a service to your end customers. If you take the attitude that the PHO, too, is a customer, it makes a positive difference.

I also established what I called a purposeful partnership. I would bring in speakers and have events that just the PHOs were invited to. We would alternate facilities and locations so each PHO could host the event and take credit for it. It led to good relationships all the way around. The key is being able to look at the PHO as a customer and ask what we can do to help.

Dr. O’Connor: Shortages of primary care physicians are expected to become more acute as baby boomers age and as accountable care organizations (ACOs) become commonplace. Such shortages can be a barrier to the creation and functioning of ACOs. What can ACOs do to best position themselves to recruit primary care physicians?

Mr. Rodriguez: It is a tough issue, especially when we know there is a shortage of primary care physicians. It really boils down to a build-or-buy decision: You either build the primary care function yourself or go out and buy it. The attitude among physicians is changing. It used to be that most physicians were rugged individualists, but younger physicians don’t want that kind of life anymore. They want quality of life and more time with their families and kids. What kind of quality of life can an ACO offer to its physicians? It is not just pay; it is also quality of life. The mistake we made in the 1990s was that we were offering higher salaries. We were saying to physicians who were making $80,000 a year, “Come work with us, sell us your practice, and we will pay you $160,000 a year.” Well, that was unsustainable. There was not enough business to pay the physician that much. What we found was that hospital systems don’t really know how to operate physician practices; physicians do. You have to give some freedom to the physicians who are in the ACO to be able to run
the practice themselves. Obviously, you have to hold it accountable, and you can do that through pay and other methods, but the point is the doctors have to feel like they are still in control. So those are the two key areas to consider: physicians’ quality of life and their ability to run the practice the way they think it is best run.

**Dr. O’Connor:** Any thoughts about the ACA and its financial incentives for motivating people to obtain health insurance?

**Mr. Rodriguez:** I have been looking at the 2014 penalties in healthcare reform, and the structure has been bothering me. The individual mandate of the ACA requires people to pay a penalty if they choose not to obtain health insurance. My communication coordinator and I have been looking at this and are determining the level of penalty an individual would have to pay in 2014, 2015, and 2016. We are finding, for example, that a person who makes $30,000 a year would be required to pay a $200 penalty in 2014. This penalty would be paid through his or her federal taxes. If I’m 28 years old, just starting my career and making $30,000 a year, how do I deal with this mandated health insurance issue? Should I try to get a high-deductible, high-copay insurance policy that costs $150 a month? Or should I just wait until the end of the year when I file my income taxes, check off that I don’t have health insurance, and pay the $200 penalty out of my refund? Let’s say my tax refund is $600, but the $200 penalty is deducted, reducing my refund to $400. On an annual basis, the choice is between paying $1,800 ($150 × 12) or $200 out of my refund. I don’t think the incentive is strong enough to get younger people to buy health insurance. The ACA is intended to promote universal coverage and spread the financial risk of health reform. I don’t think we will see the young people jumping on board and purchasing their own insurance coverage to avoid the penalty.

The penalty does not impose enough financial pain. Moreover, we have many people who don’t want to participate due to cost, even though their health status is not good and they could truly benefit from the coverage. We need them to participate and spread the risk. How do we motivate them to come into the system? The only way to solve this is to make the penalty more severe. If you’re going to pay a $200 penalty at the end of the year instead of $150 per month for health insurance coverage, maybe those numbers should be made closer to each other. I am not seeing anyone address this issue.

**Dr. O’Connor:** What topics and issues would you like to see addressed by authors in the Journal of Healthcare Management?

**Mr. Rodriguez:** I would like to see authors address more on the insurance side of healthcare. We are on the advent of ACOs, and I still don’t see very much that addresses being totally responsible for a population’s health. When you start getting capitation to manage the healthcare for a specific population you are in essence an insurer. I would like to see authors address ACOs and how those entities will take responsibility (risk) for their population’s healthcare needs. How do they do that within a set, capitated fee, which in essence makes them an insurer?
Throughout the year, we have been discussing the value of patient-centered care. The columns have focused on important aspects of this topic, such as the evolution of patient-centered care, patient satisfaction, community engagement, and technology. At the heart of all these components, however, is healthcare leadership.

**HEALTHCARE LEADERSHIP REVISITED**

Strong leadership is critically important to organizations, regardless of the setting. Researchers have defined leadership in many different ways, but it is often associated with risk taking, dynamic, creative, change, and vision (Hughes, Ginnett, and Curphy 1999). Applying many of these same concepts, the Healthcare Leadership Alliance and American College of Healthcare Executives (2011) define healthcare leadership as “the ability to inspire individual and organizational excellence, create a shared vision and successfully manage change to attain the organization’s strategic ends and successful performance.” Leaders determine, communicate, and guide the vision of any organization, and thus leadership engagement in any culture change initiative toward patient-centered care is crucial (Frampton et al. 2008).

**HEALTHCARE LEADERSHIP AND PATIENT-CENTERED CARE**

Changing the paradigm of care to a patient-centered model represents one such organizational culture change and requires the involvement of senior executives. Implementing a patient-centered model of care has profound implications for the way care is planned, delivered, and evaluated. Although most leaders in healthcare organizations today embrace the basic tenets of a patient-centered philosophy, it wasn’t always that way. Prior to 2001, healthcare leaders frequently identified barriers to the widespread adoption of patient-centered practices resulting from (1) a general resistance to change, (2) the perception that implementation would cost too much time and resources, and (3) a lack of clarity on how to initiate and maintain a culture change of this magnitude (Frampton and Charmel 2009).

The dynamics surrounding patient-centered care changed significantly when the Institute of Medicine (2001) identified patient-centeredness as one of six aims of improvement for the US healthcare system. Even today, however, leaders often find that moving toward a patient-centered model requires an unanticipated level of commitment and significant adjustments in organizational structures (Ponte et al. 2003).

A study commissioned by The Picker Institute in 2007 explored what steps would be necessary to achieve more rapid and widespread implementation of
patient-centered care in both inpatient and ambulatory healthcare settings. Its findings indicated that the single most important factor contributing to patient-centered care is “the commitment and engagement of senior leadership . . . the organizational transformation required to actually achieve the sustained delivery of patient-centered care will not happen without top leadership support and participation” (Shaller 2007).

The Institute for Healthcare Improvement embarked on a study in 2011 to identify key factors in achieving an exceptional patient and family experience of inpatient hospital care. It, too, found that a primary driver was leadership, and the study’s authors reinforced the idea that “effective leaders focus the organization’s culture on the needs of patients and families (i.e., providing care that is patient-centered, rather than provider-centered), tap into innovative ideas, and have the persistence and skills to create a patient and family-centered care culture. Leaders from executives to front-line managers share a commitment to this goal, and understand that it is led by senior leaders and is part of the organization’s core strategy” (Balik et al. 2011).

Leaders must clearly articulate a hospital’s commitment to meet the unique needs of its patients to establish an organizational culture that values patient- and family-centered care (Joint Commission 2010). Furthermore, they must demonstrate that commitment “by communicating openly, soliciting and responding to input from staff, patients, families and others, and ensuring staff members have the resources and flexibility they need to provide patient-centered care” (Frampton et al. 2008). In their own behaviors and values, leaders set the tone for the successful implementation of patient-centered care.

CASE IN POINT AT WINDBER MEDICAL CENTER

Windber Medical Center (WMC), a 54-bed hospital in western Pennsylvania, is a Planetree-Designated Patient-Centered Hospital. We are the only Planetree hospital in Pennsylvania and, at the time of this writing, one of only 13 hospitals in the country to have achieved Planetree Designation status. Former executive staff were responsible for the introduction of Planetree to WMC, and current executive staff continued the designation process and provided the ongoing leadership required to achieve and sustain it. Overall, the hospital leadership embraces Planetree by supporting and nurturing extraordinary patient- and family-centered care. As with a tapestry, we weave Planetree concepts into everything we do.

Do not underestimate the importance of leadership in the implementation and ongoing development, enhancement, and sustainment of patient-centered care. You may find it to be the most rewarding function of your leadership role.

REFERENCES


For more information about the concepts in this column, please contact Dr. Cliff at bcliff@windbercare.org.
Improving the Medicine Administration Process by Reducing Interruptions

Vin Capasso, LSS MBB, manager, Covidien Customer Excellence, Mansfield, Massachusetts, and Michelle Johnson, MBB, Lean sensei, director, Operational Excellence–Northeast, Covidien Customer Excellence

One of the most stressful tasks nursing staffs undertake is administering patient medications. No matter the type of system used—whether highly automated, with sophisticated computer software and bar-code scanners; largely paper based; or some hybrid of the two—administering medications is a complicated process. Nursing staff are under constant pressure to fulfill their medicine administration duties while attending to their other responsibilities. A relatively new variable is the increased involvement of patients and their family members in the patient’s care management. In this spirit of heightened awareness, they ask numerous questions and seek clarifications about the medications, which, while a positive development in the overall care process, further affects the time needed to administer medications. Considering these and many other complicating factors, the medicine administration process lends itself well to a process improvement project.

OVERVIEW OF THE MEDICINE ADMINISTRATION PROCESS

Medicine administration can be broken out into five high-level process steps:

1. Prescribing
2. Documenting, transcribing, and verifying
3. Dispensing
4. Administering
5. Monitoring

As shown in Exhibit 1, steps 2, 3, and 4 are those in which nursing staff are most involved. To demonstrate the complexity of this series of steps, Exhibit 1 lists some typical problems or defects that occur in the execution of those steps.

Mary Beth Strauss, director, Magnet and special projects, Winchester (Mass.) Hospital, contributed to this column. She may be reached at mstrauss@winhosp.org.
Exhibit 1
Overview of the Medicine Administration Process

Substantial Nursing Involvement

1. Verify—Confirm medication order accuracy.
2. Remove medication and verify again—Remove the medicine from the medicine room and check again for accuracy.
3. Prepare medication—Split pills, load syringe, or complete any other necessary preparation to administer it.
4. Verify against electronic health record (EHR)—Verify that the EHR is accurate and up to date.
5. **Deliver**—Verify the patient’s identity and administer the medication to the patient.

6. **Document**—Update the EHR to reflect that the dose was given and the patient was educated properly about the medication, adding any notes about the administration activity as appropriate.

Using our Lean Six Sigma tools, the VSA team completed an in-depth analysis of the hospital’s medicine administration process and discovered several opportunities for improvement. To address five of these issues, the hospital created five Six Sigma Green Belt teams each assigned to resolve an issue. Here we present the work of one of those teams, the NO Interruption Team.

**Eliminating Interruptions During Medicine Administration**

Nursing staff were constantly interrupted during the medication administration process, causing a high level of inefficiency (nursing was not meeting its goal of delivering all medication within 60 minutes of prescribed time) and creating a significant risk that distracted nurses would make mistakes in administering medicines. Led by Mary Beth Strauss, director of Magnet and special programs, and Carla Destramp, manager of quality/process improvement programs, the NO Interruption Team was charged with fixing this vexing and dangerous problem. To do so, the team adopted the DMAIC (define, measure, analyze, improve, control) methodology. Following is an overview of the team’s work in terms of its DMAIC approach.

**Define**

The NO Interruption Team crafted a project charter, which outlined the process problems and future objectives as well as project scope and metrics to be tracked. Project charters are essential to completing process improvement initiatives, as they establish a clear and focused approach to the project. The NO Interruption Team charter set the reduction of interruptions during the morning medicine pass (“med-pass”), when the majority of medications are delivered, as its focus. The med-pass activity was defined as a nurse delivering medicine to all of his or her patients during a particular time period, in this case the morning. Each nurse was assigned three to five patients and delivered 10 to 30 medicines during each med-pass.

To further define the issue of interruptions during the morning medication administration routine, the team determined the collective “voice of the customer” (VOC; see the Efficiencies column in the July/August 2012 issue of the *Journal of Healthcare Management* for details on how to gather these data) through interviews and surveys. In this project, the customers were the nursing staff. In collecting the VOC, the NO Interruptions Team found that nurses were very vocal about their concerns with the current process. The team arranged the VOC comments in an affinity diagram, a tool used to organize comments and thoughts into categories (visit the Affinity Diagram page of the ASQ website, http://asq.org/learn-about-quality/idea-creation-tools/overview/affinity.html, for more information about this tool). The
team next constructed a critical-to-quality characteristics (CTQC) tree (Exhibit 2) from the information collected from process stakeholders, along with research data on preventing medication administration interruptions (see, for example, http://www.mindtools.com/pages/article/ctq-trees.htm). The CTQC tree helped the team understand where it should focus its efforts to meet the larger customer requirement: preventing interruptions at peak med-pass time.

**Measure**
For the “measure” portion of DMAIC, the team created a process map detailing the nurses’ current activities during med-pass. As part of the mapping process, it also collected baseline metric data against which to compare future progress and compiled the following information:

- During morning med-pass, nurses were interrupted 93 percent of the time.
- The nurses passing meds encountered an average of four interruptions on every med-pass.

**EXHIBIT 2**
**Critical-to-Quality Characteristic Tree**

<table>
<thead>
<tr>
<th>Need</th>
<th>Driver How will you do it?</th>
<th>Critical-to-Quality Characteristics What does that mean?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevent interruptions at peak med time</td>
<td>Establish time-out “rules” and support</td>
<td>No interruptions time: 8:30 a.m.–9:30 a.m.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No interruptions unless emergency (phone calls, pages, patient inquiries, clinician inquiries)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Define and assign specific roles: RN, CA, AA, and lead nurse</td>
</tr>
<tr>
<td></td>
<td>Buy-in from clinical staff</td>
<td>Get them involved in process</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Display baseline interruption data</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Physician/interdepartmental education</td>
</tr>
<tr>
<td></td>
<td>Education/training</td>
<td>Script for AAs and CAs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Define the handoff to LCN (consider assignment issues)</td>
</tr>
<tr>
<td></td>
<td>Create awareness during time-out</td>
<td>Patient and family brochure/posters</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Signage about process/explain time-out</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Signage explaining it is time-out</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A way to identify a nurse involved in med admin process</td>
</tr>
</tbody>
</table>
The length of time taken up by interruptions ranged from 1 to 25 minutes; the average time per interruption was 6 minutes.

With these data, the team could update its charter to reflect its project goals, as follows:

- Reduce the number of morning med-passes in which interruptions are encountered to 25 percent.
- Reduce the average number of interruptions per med-pass to one.
- Reduce the average time per interruption to one minute.

Many team members thought these improvement goals would be tough to achieve given the ingrained cultural acceptance of current practices. However, the team leadership’s research indicated that the goals were achievable, and the NO Interruptions Team adopted them then moved on to the “analyze” and “improve” phases of DMAIC.

Analyze, Improve
Using the CTQCAs as a guide, the team analyzed the current med-pass process, outlined its key problems, and proposed potential solutions to those problems. A partial sample of the solution matrix created as part of the analysis is shown in Exhibit 3; it included training for staff regarding how to address physician, patient/family, and other types of clinical interruptions and how to develop signage to reinforce the message about medication pass safety.

One improvement the team recognized was the need to develop a visual tool that alerts all staff and clinical personnel in the area that a nurse is engaged in a med-pass. After several trials, the NO Interruptions Team unveiled the sign shown on the right-hand side of Exhibit 4.

### Exhibit 3
Portion of the NO Interruptions Team’s Problem-Solving Matrix

<table>
<thead>
<tr>
<th>Problem</th>
<th>Ref #</th>
<th>Potential Solution</th>
<th>Who</th>
<th>Due Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interruptions from family</td>
<td>1</td>
<td>Script for AA and CA</td>
<td>CD</td>
<td>3/2/2012</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Signage to alert families and inform</td>
<td>CD</td>
<td>3/10/2012</td>
</tr>
<tr>
<td>Interruptions from MD</td>
<td>3</td>
<td>Script for AA and CA</td>
<td>MB</td>
<td>3/10/2012</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Conversation with MDs</td>
<td>MB</td>
<td>3/10/2012</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Visual alert so MDs know that nurse is engaged in med-pass</td>
<td>CD</td>
<td>3/2/2012</td>
</tr>
<tr>
<td>Lack of standard work</td>
<td>6</td>
<td>Create visual system for nursing</td>
<td>same as #5</td>
<td>3/10/2012</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Document standard work</td>
<td>Team</td>
<td>3/12/2012</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Train nursing and other clinical staff</td>
<td>Team</td>
<td>3/16/2012</td>
</tr>
</tbody>
</table>

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Now, when a nurse begins a med-pass, he or she attaches the sign in a prominent place on the mobile med-pass cart (shown on the left-hand side of Exhibit 4). Because the nurses do not always pass meds to each patient consecutively in one dedicated block of time, the time between med-pass activities affords opportunities for questions from colleagues without unintended disruption to the patient med-pass process. Physicians on the floor learned not to interrupt nurses engaged in passing meds (sign up) with nonemergency questions. Most of the time, physicians found, they could get their questions answered by consulting with other nurses who were not conducting a med-pass (sign down) or the lead clinical nurse.

**Control**
The new process is universally viewed as a success by stakeholders. The clinicians appreciate that a safe and understandable process is now in place to ensure the accurate and timely administration of medications. Patients and families overwhelmingly supported the process once they realized it was developed to improve patient safety and indeed did so.

To ensure the viability and sustainability of the new process, the NO Interruptions Team created a control plan and a rollout procedure for other units at the hospital. A control plan is a tool used to ensure sustainment of an improved process; it outlines critical sustainment activities and metrics that the process owners must address once the project team has disbanded. All nursing units are expected to be following the process by the end of 2012.
After 30 days from the start of the med-pass improvement initiative, the team had made excellent progress toward its goals:

- The number of interruptions per med-pass dropped from four to one on average.
- The percentage of med-passes interrupted dropped from 93 percent to 50 percent.
- The time per interruption dropped from an average of 6 minutes to 0.3 minutes, saving the nursing staff an estimated 15,000 hours of time per year, the equivalent of gaining seven staff members.

**CONCLUSION**

Hospitals that engage staff in the improvement effort can greatly increase efficiency and patient safety. But perhaps the most satisfying results involve the satisfaction the staff derived from the project described in this article. Following are some comments that illustrate the extent of the project’s success.

**RN Perspective**

"Less interruptions makes passing meds more efficient."
"I think if it makes it safer for the patient, it is well worth it."
"People don’t bother me constantly."

**Physician Perspective**

"I didn’t like it at first, but now it is working well, I am able to get my questions answered without interrupting the RN on a med-pass."

For more information about the concepts in this article, contact Mr. Capasso at vincent.capasso@covidien.com.
Managing Pay for Performance: Aligning Social Science Research with Budget Predictability

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EXECUTIVE SUMMARY

Managers and policymakers are seeking practical guidelines for assessing the outcomes of emerging pay-for-performance (P4P) programs. Evaluations of P4P programs published to date are mixed—some are confusing—and methodological problems with them are common.

This article first identifies and summarizes obstacles to implementing effective P4P programs. Second, it describes results from social science research going back several decades to support evidence-based P4P best practices. Among the findings from this research, the zero-sum and “earn it back” P4P incentive systems have important drawbacks and may be counterproductive, neither reducing health system costs nor improving quality. The research suggests that punishing participants for low performance may further reduce individuals’ performance, especially when involvement is required. We suggest that optimal P4P systems are those that reward all participants for performance improvements. Third, the article links P4P design to budgetary considerations. P4P program designs that provide incentives while improving quality and reducing costs are critical if budget neutrality is a priority for the organization and its resources are limited. In these types of P4P designs, cost calculations are straightforward: The greater the participation, the higher the savings. The article concludes by recommending an evidence-based P4P approach for practitioners that can be implemented without large upfront investment. More research on this topic is also advised.
INTRODUCTION

The variety of pay-for-performance (P4P) programs is vast, and practitioners need guidance in determining which types are most successful and where to begin implementing one (Young 2007). According to the Agency for Healthcare Research and Quality (2006), P4P payment systems are designed to “offer financial incentives to physicians and other health care providers to meet defined quality, efficiency, or other targets.” The collective goal of the P4P approaches is to reduce health system costs while improving quality.

P4P incentive systems are having an enormous impact on healthcare delivery in the United States (Epstein 2007). P4P is among the most important developments in the US healthcare sector since managed care and capitation (Kellis and Rumberger 2010). It aims to change the behavior of physicians, patients, and those working in hospitals through a system of rewards and punishments. A P4P reward or bonus for physicians might take the form of a salary add-on to the general fee-for-service. A reward for hospitals might be payments beyond those received through the diagnosis-related group–based scheme. A punishment under the P4P system might mean reduced compensation or some other penalty.

The purpose of this article is to assess and prioritize P4P programs for practitioners. First, we summarize the main obstacles to achieving a successful P4P program. Second, we employ theoretical principles and research findings from behavioral science and business to demonstrate how to improve P4P results. Third, we show the link between P4P systems and budget predictability. Finally, we recommend to practitioners a viable P4P design that includes evidence-based best practices and does not require a large initial investment.

ISSUES SURROUNDING PAY-FOR-PERFORMANCE IMPLEMENTATION

Results Are Mixed

Taken together, the results of P4P programs in the United States can be characterized at best as mixed and at worst as inconclusive (Peterson et al. 2006; Wodchis, Ross, and Detsky 2007). Some studies outline clear evidence of P4P effectiveness (Abelson 2007; CMS 2008). Others indicate that P4P innovations fail or the results are inconclusive (Glickman et al. 2007; Pearson et al. 2008; Damberg et al. 2009). In short, “pay-for-performance may not, necessarily, have the dramatic and or even predictable effects touted by its enthusiasts” (Mullen, Frank, and Rosenthal 2010). Mixed results have also been reported in other countries (Campbell et al. 2007, 2009; McDonald and Roland 2009).

Methodological Problems Abound

Several reasons explain why results from P4P experiments vary widely, and some of these are related to methodological problems. The samples involved are often very small. Participation in these programs is seldom based on random samples of practitioners or hospitals—it usually involves voluntary participation, leading to selection bias. Changes in performance measured under these P4P programs sometimes coincided with structural changes or operational
reorganization such that any observed change may not be attributable to P4P alone (Golden 2006; Pink et al. 2006). Positive results were sometimes attributable to “secular trends,” whereby researchers mistakenly concluded that P4P improves quality or cost when, in fact, most organizations operating in the healthcare sector were improving, even those in which P4P was not present.

According to some policy experts, P4P is observed to have failed, in part, because incentives are not large enough to change behavior. For example, P4P in the United States has not proved as effective as in Britain, where rewards are far greater—in some cases up to 50 percent of a physician’s salary (Davis 2008; Doran, Fullwood, and Gravelle 2006)—than those in US P4P programs, which are seldom more than 5 percent of a physician’s salary (Advisory Board Company and Foundation 2008). But even in Britain, generous rewards have been found insufficient to improve quality in some cases (Serumaga et al. 2011).

Obstacles Emerge

Common obstacles to the successful use of P4P programs have been identified and are related to both performance and process variables (McDonald and Roland 2009; Hoff et al. 2011). All reimbursement systems encourage manipulation of one sort or another, and P4P is no exception (Galvin et al. 2005; Hamblin 2008; Hayward and Kent 2008). The Journal of the American Medical Association has even published a guide explaining how providers can “game” a P4P system (Hayward and Kent 2008). Other troubling aspects include the fact that under P4P incentive systems providers tend to treat a presenting patient even if the diagnosis is unclear or uncertain (Jauhar 2008) and that when P4P incentives are in place, continuity of care may be reduced (Campbell et al. 2007, 2009). Furthermore, P4P increases the difficulty in treating patients with multiple medical problems (Young et al. 2010). These issues arise primarily because P4P focuses a provider’s attention on the reward, and this diversion may result in oversights in addressing the totality of a patient’s healthcare needs (Campbell et al. 2009).

P4P has been found to increase health disparities among populations in several ways. Most importantly, research suggests that physicians in these programs avoid sicker patients because they perceive those patients as likely to lower their quality scores. Because many members of minority groups have poor health, they tend to fall into the category of patients to be avoided by P4P-participating physicians (Blustein et al. 2011; Casalino et al. 2007b). In addition, many physicians view P4P as intrusive, controlling, and punitive rather than as educational (Giraud-Roufast and Chabot 2008). Among those physicians who do support it, many have little concrete experience with P4P programs (Casalino et al. 2007a).

Another problem for P4P programs involves how to bring them to an end if they are not needed anymore or if funding is no longer available. One classic sociological study found that when workers are being observed, they respond in socially desirable ways; the phenomenon is known as the Hawthorne effect (Mayo 1933). Indeed, tests of the Hawthorne effect in the health
sector find that intensive follow-up of participants in a clinical trial results in better outcomes than does minimal follow-up (McCarney et al. 2007). This finding suggests that caution should be exercised in the decision to allow P4P programs to lapse. One study reports that when providers ceased to be rewarded for their new behavior, they reverted to the old behavior (Lester et al. 2010). Another study found that P4P programs that initially demonstrated improved performance tended to taper off in the fourth and fifth years (Werner et al. 2011).

APPLYING BEHAVIORAL AND SOCIAL SCIENCE TO PAY FOR PERFORMANCE

Research results from behavioral science regarding individual behavior and system-level characteristics are not always explicitly incorporated into P4P systems (Mehrotra, Sorbero, and Damberg 2010). Too often P4P design is grounded in intuition and untested assumptions (Meltzer 2009). Here we present social science and behavioral science findings and point to their practical implications for P4P design. (See Exhibit 1.) Of course, such applications are no guarantee of success, no matter how logical and rational, because they have yet to be tested.

Social science research suggests that incentives should be both linked to a specific time frame and proximate to the desired behavior. The opportune moment to reward an individual for a specific behavior is immediately after that behavior is elicited (O’Daly and Fantino 2003). Furthermore, “People place more weight on the present than the future—they’re more attracted by immediate than delayed benefits” (Volpp et al. 2011). Therefore, if the time span between the receipt of the reward or penalty and the financial effects on the individual or organization are large, as is usually the case with P4P programs, the impact is reduced (Volpp et al. 2011).

P4P programs should target for reward those individuals or entities whose behavior you wish to change, such as a group, an individual physician, a hospital, or a patient. However, P4P programs typically are not structured to do so. For example, they reward a physician if his or her patients reduce tobacco use, lower cholesterol levels, comply with orders to take medication, or lose weight. In these cases the incentive is “distant” rather than proximate to the behavioral change. Rewarding those who successfully change their lifestyle and medication compliance is more in agreement with behavioral research (Volpp et al. 2009; Wharam and Sulmasy 2009). In fact, because even small financial incentives change patient behavior, rewarding the patients rather than the physicians may be effective (Oliver and Brown 2011).

The most successful incentive structures match an individual’s values and goals. Equally important to success is that P4P programs be aligned with an individual’s personality (Hamblin 2008). A provider that is motivated by self-interest might be open to P4P formats that are less than altruistic in their approach. Research suggests that in the general population about 50 percent of the population is altruistic, one-third is self-interested, and the rest exhibit a mix of these characteristics (Camerer

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## EXHIBIT 1
Findings from Behavioral Science and Business Relevant to Pay for Performance

<table>
<thead>
<tr>
<th>Question</th>
<th>Finding</th>
<th>Application</th>
<th>Relevance for P4P</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>When to reward?</td>
<td>Reward should be time-linked to desired behavior</td>
<td>Reward is immediate</td>
<td>Internet reporting of performance with immediate update and accessibility</td>
<td>O’ Daly and Fantino (2003); Volpp et al. (2011)</td>
</tr>
<tr>
<td>How to structure rewards?</td>
<td>Carrot works better than stick for many</td>
<td>Provide incentives for the positive rather than disincentives for the negative</td>
<td>Reward best practice</td>
<td>Workie (1974)</td>
</tr>
<tr>
<td>Can the stakes be too high?</td>
<td>High levels increase stress, fatigue, errors, aggression, and obstructive behavior</td>
<td>Moderate the interindividual and interinstitutional competition</td>
<td>Demands should be realistic and attainable</td>
<td>Leape (1994); McCaul, Glade, and Joppa (1992); Blake and Mouton (1986); Pepitone (1980); Hare et al. (1994)</td>
</tr>
<tr>
<td>Should personality and incentive structure be aligned?</td>
<td>1. Cooperative leadership style outperforms competitive leader</td>
<td>1. Train for cooperative leadership</td>
<td>Flexible design and open leadership approach adapted to the organizational and individual situation as much as possible</td>
<td>Hamblin (2008); Johnson and Johnson (1983); Tjosvold and Andrews (1983); Gordon et al. (2000); Camerer and Fehr (2006); Rosenau (2006); Robbins and Judge (2007)</td>
</tr>
<tr>
<td></td>
<td>2. Cooperative production is more production</td>
<td>2. Assess organization culture and modal personality style</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. The links between personality, competition, and social outcomes vary for individual</td>
<td>3. Consider individual motivation to be open-ended, with high variation within populations</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Do values and goals matter?</td>
<td>The most effective incentive structures are matched to an individual’s values and goals</td>
<td>Measure values and goals before implementing new policies</td>
<td>Avoid mismatch of individual/organization values and goals to reward structures</td>
<td>Johnson and Johnson (1989); Qin, Johnson, and Johnson (1995); Cosier and Dalton (1988); Steinmetz (1983)</td>
</tr>
</tbody>
</table>
and Fehr 2006; Rosenau 2006). Some personality types respond to one form of reward to a greater degree than to others. For example, in the health sector some physicians are likely to respond to P4P programs that are linked to the ethic of providing healthcare to the whole population rather than to personal financial incentives (Christianson, Leatherman, and Sutherland 2008).

Social science research points to the possibility that nonfinancial P4P rewards are often overlooked, though they may be highly effective for many individuals. For those attracted to their field because of the intrinsic value they derive from it, nonmonetary rewards could be optimal because such rewards fit their values (Strack and Deutsch 2004; Randolph 2005). In line with this expectation, a recent study found that a number of doctors left a hospital after a P4P program was implemented whose incentives were financially based (Golden and Sloan 2008). P4P is also said to crowd out individual initiative and discourage efforts to improve quality in situations where monetary gain is seen as substituting for professional and personal pride in performance. In some cases, emphasizing monetary P4P incentive systems may even be counterproductive (Ryan and Deci 2000). Increased pay has been reported to reduce physicians’ commitment to their hospital (Dukerich, Golden, and Shortell 2002; Wynia 2009), though this effect is not always observed (Young et al. 2010). In short, once a minimum level of extrinsic reward (financial) is reached, intrinsic rewards (values) may become the primary motivation factor (Pfeffer et al. 1998).

Other examples of effective non-monetary incentives or motivators involve public recognition, participation, praise, and an understanding that they (individuals or institutions) are “doing good” (Robbins and Judge 2007). The opportunity for more challenging work is an additional nonfinancial motivator (Dukerich, Golden, and Shortell 2002; Golden 2006). Motivation may differ from individual to individual (Steinmetz 1983). However, applying different P4P formats to various individuals in an organization may be difficult to implement in the real world.

For decades social scientists have studied how best to motivate the individual in the workplace. Several theories of motivation from different disciplines are relevant to P4P design, among them the field theory (Lewin 1943), goal theory (Locke and Latham 1990), expectancy theory (Vroom 1964), and hierarchy of needs theory (Maslow 1943). Not all are evidence based. Some have been modified to improve their ability to structure motivation, and these are the most useful for P4P design. Alderfer’s (1969) work on Maslow’s hierarchy of needs theory is an example. In the end, P4P design implicitly asks the question, “Are incentives best structured as rewards or as punishments, or both?” Almost forgotten are the studies indicating that, on balance, a positive reward is as effective as or more effective than a negative incentive (Workie 1974). Positive motivation, including increased workplace opportunities, is more effective than instilling fear or making threats (Steinmetz 1983). Experiments in the field of education confirm this.
Managing Pay for Performance

findings (Johnson and Johnson 1983). Another study that can be applied to P4P programs reports that for many individuals, workplace practices that require interindividual cooperation are associated with higher productivity than those employing competition between individuals in the organization (Cosier and Dalton 1988; Lam et al. 2011).

P4P designs should incorporate findings from research on the effects of various forms of competition, on transparency, and on innovation. Competition internal to an organization is detrimental to attaining organizational goals, and it reduces individual and group performance (Rosenau 2003, Chapter 3). An absence of P4P contractual transparency can increase competition internal to a program, which indirectly reduces productivity (Thompson et al. 2002). Restrictive P4P confidentiality contracts may reduce collaboration and efficacy. Finally, some evidence suggests that excessive competition in P4P programs could discourage innovation (Jauhar 2008).

Social science research predicts that zero-sum P4P designs that reward some individuals or groups at the expense of others have the potential to disrupt organizational performance and reduce overall individual and organizational achievement. Those forms of P4P involving zero-sum competition take money from participants who do not meet P4P reward criteria and give it to those who do meet the criteria (Exhibit 2). This type of competition polarizes an organization and divides the individuals who work there into winners and losers (Kelly 2010). Those at the low-performing end of the continuum may become discouraged, reduce their effort, and even give up trying to reach the level of performance required to merit a reward (Himmelberg, Hubbard, and Palia 1999; Vaughan 1999). If social science research is accurate, these P4P designs are likely to increase stress, fatigue, aggression, and obstructive behavior (Hare et al. 1994; Stanne, Johnson, and Johnson 1999). In addition, they may reduce the self-esteem of some workers (Meyer 1975), lower safety performance, and reduce workplace morale (FitzRoy, Acs, and Gerlowski 1998).

Does this form of P4P lead to competition that subsequently reduces performance for those receiving a penalty? Research indicates that this problem may not arise in P4P programs where participation is voluntary (Chen et al. 2010). Conversely, decades of behavioral research across many sectors suggests the opposite is likely to be true where participation is not voluntary.

A similar form of P4P reduces the base compensation for all individuals, or base reimbursement for the organization, with an explicit “earn it back” strategy. Only those who meet the P4P standard will receive the same pay as before the program was initiated. The effects discussed earlier resulting from zero-sum P4P may apply to this P4P design as well.

P4P designs that take from the lowest performers to reward the highest performers and those that reduce the base and require that individuals earn back any compensation lost to the program have one important advantage over others that makes them extremely attractive to managers: They are budget neutral and thus permit budget predictability.
The amount needed to finance these forms of P4P can be anticipated in advance and entered into the organization’s annual budget with known fiscal consequences. This advantage holds for all forms of P4P in which the amount of the reward comes from the penalty payments assessed to those who do not perform up to expectations. Yet better methods are available to achieve the goal of budget neutrality without employing a zero-sum P4P that has substantial negative externalities.

**THE IDEAL P4P**

Social science research supports P4P program designs that set a standard for excellence and offer a reward for all who attain this level of performance. In such a design, all who meet the standard are rewarded, and none are punished for not meeting the standard. This P4P strategy reduces the level of stress and anxiety associated with zero-sum incentive systems. The downside is that it is difficult to budget for because one never knows in advance how many individuals will perform to the standard required to be rewarded. Resources are limited, and provider/player uptake, or involvement, is hard to predict. If uptake is great, huge budget overruns may result, raising a dilemma: How can a P4P program be structured to avoid the downside of zero-sum systems and yet result in limited budgetary consequences?

**Budgeting for Optimal P4P Systems**

Achieving budget neutrality or budget predictability is vital for P4P programs. Some of the largest and most well-known P4P programs in the United States are optimal in that they are budget neutral, but they may not be ideal because they have the externalities outlined earlier. For example, as indicated in Exhibit 2, zero-sum P4P strategies are employed by Medicare and the Veterans Health Administration. Typically these programs offer 10 percent bonuses to the top 10 percent of performers and impose a financial penalty of 10 percent reductions in pay to the bottom 10 percent of performers (Burton 2011). By definition these approaches are budget neutral.

Some P4P structures can be optimal in the larger sense in that existing social research supports them and they are also budget neutral. They create an alignment between provider behavior change and the organizations’ need for budget predictability or budget neutrality. These P4P programs place success and rewards within reach of all participants and at the same time achieve the desired performance criteria that result in a cost savings to the system as a whole. This relationship is outlined in Exhibit 3. The greater the uptake, the larger are the realized savings. In other words, the more “winners” that result from this type of P4P, the more savings accrue to the organization. “The more you buy, the more you save” may not be possible to fulfill in every situation, but where it is, this form of P4P is optimal.

A real-world example is that of a P4P program offered by Highmark, a Pennsylvania-based health insurance plan, that targeted physician prescribing behavior for improvement. Primary care physicians were rewarded a bonus of $3.00 to $9.00 for every fee-for-service patient for which they wrote a
**EXHIBIT 2**

**P4P Systems That Are Budget Neutral but Not Optimal**

- **Example:** Medicare’s experiments—top 10% receive a bonus while bottom 10% receive a financial penalty.
- Behavioral science research suggests that those at the bottom “give up.”

- Compensation reduction with an “earn it back” approach has not been demonstrated to improve organizational morale.
- Research suggests that timing of reward makes for broad discontent.
- “Time-link” principle is violated.

**EXHIBIT 3**

**Solutions to P4P Problems**

**Problem**

- Resources are specific and limited.
- We need to anticipate provider/player uptake.

**Solution**

- Implement P4P in situation where change results in lower cost and higher quality.
- Budget unpredictability is not an issue due to increased uptake leading to higher savings.
prescription for a generic rather than a brand name medication. While many such private P4P incentive systems are considered proprietary, Highmark has publicized and shared its program design, structure, and outcomes performance results. With 5,000 physicians participating, the prescribing of generics increased from 46 percent to 73 percent in four years. Savings to Highmark amounted to $87 million in 2010 alone (Diamond 2010).

Managers and their organizations must be able to anticipate how much a P4P program will cost. In general, obtaining an accurate assessment of return on investment for a P4P program is complicated and expensive—in many cases it cannot be calculated with precision in advance of the program’s implementation (Curtin et al. 2006). This consideration strengthens the appeal of the optimal P4P programs described in this article.

**CONCLUSION**

P4P is a blunt instrument whose implementation is made more complicated by the unexpected consequences outlined here. P4P has advantages as well as disadvantages, and they need to be consciously and fairly assessed by managers and policymakers. No P4P program can guarantee success, but if the accumulated evidence of behavioral research is applied to their design, optimal P4P systems should permit all participants to be rewarded for quality improvements that also reduce costs (Exhibit 4). From this research we have determined that if carefully chosen and structured appropriately, the cost of pay-for-performance programs can be recovered at the same time that unexpected and expensive externalities can be avoided. Further investigation and research should be a priority to determine if this approach is as effective as we expect in the real world of healthcare environments.

**EXHIBIT 4**

*Putting Knowledge into Practice*

- **All participants should be rewarded for quality improvements that also reduce costs.**
- **Focus only on programs where savings from cost reductions will compensate for the cost of the program.**
- **OPTIMAL P4P SYSTEMS**
  - All P4P incentive programs are not equal.
REFERENCES


The authors present a comprehensive evaluation of pay-for-performance (P4P) programs as they align with issues of effectiveness, social science interrelationships, and budgetary considerations. They provide timely lessons that can be leveraged within today’s healthcare transformation to accountable care. I propose that transformation can take place within a pay for outcomes (P4O) framework, which “would adjust payments on the basis of a hospital’s relative performance on outcomes rather than processes . . . with initial focus on those outcomes for which a quality failure results in an increase in payment” (Averill, Hughes, and Goldfield 2011). In this model, hospitals are not required to adopt specific care processes to achieve the P4O standards. Their success is predicated on improved quality and access for a defined population of patients and on cost containment as part of an organized team of multiple healthcare providers across the continuum of care (Averill, Hughes, and Goldfield 2011).

**Population Health, Analytics, and Outcomes**

Before discussing my view of a P4O approach to healthcare transformation, I describe the factors that allow P4O to function in this capacity.
The emerging population- or episode-based healthcare model appears to be the most efficient way to deliver near-flawless clinical outcomes, especially within a framework that links outcomes to bundled and other payment methodologies. The availability of near-real-time, customized information, powered by analytics based on information obtained via electronic records, advanced technologies, and telemedicine encounters, provides the foundation on which to build a model of care coordination supported by evolving evidence-based practice.

Furthermore, the advent of machine learning integrating “new” clinical information such as genomics; instant device information transfer; and biometrics with social, functional, and psychological metrics represents a new paradigm of comprehensive patient information from which specific outcome measures can be derived. Outcome measures, incentives, and evolving payment methodologies will be further enriched by this increased granularity of information delivered to the right person at the right time for the right intended outcome.

**A P4O APPROACH**

My "hypothesis" for designing and building a data-driven P4O infrastructure features the ability to consume information and analyze it across the continuum of care within both a real-time and a retrospective scenario generated by analytics and simulation or modeling. An essential element of the model is to first build a strong basic infrastructure to support current and future clinical, payment, and process protocols.

Once this infrastructure is implemented, the P4O framework takes advantage of the ability to virtually manage high-risk patients toward achieving enhanced outcomes. Critical success factors can be defined as follows:

- **Strategy**: Identify overall business, clinical, and financial outcomes goals and build the P4O continuum of care objectives and payment methodologies to support them.
- **Information/analytic integration for a P4O model**: Ensure that an accurate, enterprise master population–integrated database is accessible to IT systems using sophisticated analytics/machine learning for real-time point-of-care management, instant alerts, and reports and performance/payment outcomes management.

After reading the article by Rosenau and colleagues, you may start to consider how you will design provider models to deliver high-quality care, track that care, and pay for outcomes. Once the model is in place, you must decide how to leverage information and technology to enable clinicians, patients, processes, and technology to deliver the best possible outcomes.

**REFERENCE**

Harnessing the Power of Enhanced Data for Healthcare Quality Improvement: Lessons from a Minnesota Hospital Association Pilot Project

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EXECUTIVE SUMMARY
The imperative to achieve quality improvement and cost-containment goals is driving healthcare organizations to make better use of existing health information. One strategy, the construction of hybrid data sets combining clinical and administrative data, has strong potential to improve the cost-effectiveness of hospital quality reporting processes, improve the accuracy of quality measures and rankings, and strengthen data systems. Through a two-year contract with the Agency for Healthcare Research and Quality, the Minnesota Hospital Association launched a pilot project in 2007 to link hospital clinical information to administrative data. Despite some initial challenges, this project was successful. Results showed that the use of hybrid data allowed for more accurate comparisons of risk-adjusted mortality and risk-adjusted complications across Minnesota hospitals. These increases in accuracy represent an important step toward targeting quality improvement efforts in Minnesota and provide important lessons that are being leveraged through ongoing projects to construct additional enhanced data sets. We explore the implementation challenges experienced during the Minnesota Pilot Project and their implications for hospitals pursuing similar data-enhancement projects. We also highlight the key lessons learned from the pilot project’s success.

For more information about the concepts in this article, contact Mr. Schindler at jschindler@mnhospitals.org.
INTRODUCTION
Healthcare data are essential components of performance assessment strategies and are increasingly relied on for targeting quality improvement efforts. As the United States continues to build and standardize the country’s health information technology (IT) infrastructure, information-driven quality improvement and efficiency gains are expected to become easier to achieve (Blumenthal 2009). This vision for the future of healthcare data formed the platform from which the Agency for Healthcare Research and Quality (AHRQ) launched an initiative in 2007 to enhance hospital administrative data with clinical information to improve quality measurement. AHRQ awarded two-year contracts to three state data collecting organizations—the Florida Agency for Healthcare Administration, Virginia Health Information, and the Minnesota Hospital Association (MHA)—to conduct in-depth pilot projects to determine the feasibility of creating powerful data sets by adding clinical data to administrative databases. This effort complemented existing efforts in the Healthcare Cost and Utilization Project (HCUP), which collects all-payer, statewide hospital administrative data through a federal–state–industry partnership in 46 states (HCUP 2012).

The purpose of this article is to describe the experiences and insights from the Minnesota Pilot Project, including the business imperative that prompted MHA to participate. We also describe project goals, the process of engaging hospitals and maintaining stakeholder interest, the data collection strategy, organizational and data security challenges, legal issues encountered, and lessons learned.

THE MINNESOTA HOSPITAL ASSOCIATION PILOT PROJECT
The Minnesota hospital community has a long history of using healthcare data to assess and improve hospital performance. In the 1980s, select hospitals began reporting abstracts from medical records to a database maintained by MHA, a trade association representing 148 hospitals. This database was expanded in 1995 to incorporate inpatient and outpatient claims data from all acute care hospitals in the state. All but a few long-term care and federal hospitals voluntarily report their data. MHA also maintains Minnesota’s Health Care Cost Information System, a state-mandated database of hospital indicators that holds hospital-specific financial, utilization, staffing, and services data. As the sole source for hospital administrative (patient billing) data in the state, MHA supplies the administrative data needed to support policy, epidemiological, and public health goals. Since 2000, MHA has participated in the HCUP Partnership, a federal–state–industry family of AHRQ-sponsored databases that serves as a national information resource for encounter-level healthcare data.

Project Genesis and Goals
The AHRQ contract ran from October 2007 to September 2009, with hospitals submitting information on discharges from calendar year 2008. The project allowed MHA to leverage and enhance its ongoing work of collecting and
analyzing administrative data. In particular, MHA hoped to enhance existing administrative data for quality reporting and expand its future efficacy by linking it to other clinically rich data sets (Son-neborn, Schindler, and Pine 2009). The primary purpose of this pilot project was to assess the improvement in standard risk-adjustment models when claims data are enhanced with numerical laboratory data. This study evaluated predictive models for inpatient mortality using risk-adjustment methods developed previously by Pine and colleagues (2007) in patients hospitalized with acute myocardial infarction, congestive heart failure, cerebrovascular accident, gastrointestinal hemorrhage, and pneumonia and in patients undergoing coronary arterial bypass graft and percutaneous coronary intervention procedures. The risk-adjustment results were used to provide feedback to hospitals on their performance to target quality improvement efforts. In addition to these goals, MHA sought to achieve the following:

1. Demonstrate the feasibility of creating hybrid administrative–clinical databases from hospital data that are captured electronically to improve measurement of risk-adjusted hospital performance
2. Identify and document best practices for capturing, transmitting, integrating, validating, and using data from organizations with different information capabilities
3. Engage multiple stakeholders and peer-group organizations to share and disseminate information and stimulate and support efforts to create and utilize hybrid databases
4. Develop the foundation for enrichment of hybrid databases as improved health IT becomes more widely available

BUSINESS CASE FOR LINKING CLINICAL AND ADMINISTRATIVE DATA SETS

MHA launched its pilot project because it was convinced of the value of adding clinical data to the statewide effort to collect hospital administrative discharge records. Administrative data convey a limited amount of clinical information, such as diagnoses present during the current hospital stay and significant procedures performed (particularly those that carry surgical risk or require specialized training). The appeal of administrative data is that they are relatively low-cost sources of information, are readily available, are easy to use, and represent all patients and care rendered by a provider organization (Iezzoni 1997). Despite these advantages, administrative data lack many clinically important pieces of information, including laboratory data for the accurate measurement of illness severity (Iezzoni 1997) and, in many cases, present-on-admission (POA) indicators for diagnoses; the POA indicators can help to distinguish between conditions that are present at the time of admission and those that arise during the hospital stay (Pine et al. 2007). The inability to distinguish between preexisting conditions and complications may misclassify hospitals in quality rankings (Glance et al. 2006). As a consequence, providers are concerned that inadequate risk adjustment may improperly penalize those that treat the sickest patients (Pine et al. 2007).
2007). Enhancing administrative data with additional clinical information in hybrid data sets may benefit hospitals in three specific ways: by improving the cost-effectiveness of reporting processes, by improving the accuracy of quality measures and rankings, and by strengthening data systems (Jordan et al. 2007; Pine et al. 2007; Fry et al. 2007).

Linking clinical and administrative data sets holds much promise for simplifying and improving the cost-effectiveness of hospital quality reporting through systematic processes (Jordan et al. 2007). For example, this type of linked data set can reduce the need for labor-intensive manual data abstraction from medical charts (see Exhibit 1).

An enormous benefit that hybrid or enhanced databases offer over existing administrative databases is improved identification of patients who are at a higher risk of death than others by accounting for the complexity and severity of the patient’s conditions. This utility enables more accurate risk adjustment and better designation of hospital performance using information that is already routinely collected (Pine et al. 2007). The advent of the POA modifier, in conjunction with laboratory data in enhanced data sets, makes it feasible to include important predictors in risk-adjustment models (Pine et al. 2007).

Laboratory data establish objective clinical evidence of the patient’s condition and provide a clearer picture of the patient’s acuity level. Thus, hybrid data provide greater clarity on clinical acuity and comorbidities than can be captured by administrative data alone. Hybrid data sets are able to expand the breadth and depth of information available for risk adjustment.

This study found that incorporating laboratory data with administrative data substantially improved the discriminatory power of risk-adjustment models for all of the quality indicators studied. The average c-statistic for all of the models studied increased by 0.12 (from 0.69 to 0.81). The c-statistic is an indicator of the accuracy for predictive models (Steyerberg et al. 2001). This type of

**EXHIBIT 1**

<table>
<thead>
<tr>
<th>Traditional Process</th>
<th>Enhanced Data Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data cover a small sample of encounters meeting study requirements</td>
<td>Data cover all patient encounters meeting study requirements</td>
</tr>
<tr>
<td>Limited generalizability due to small sample size</td>
<td>Broad generalizability due to comprehensiveness of population information</td>
</tr>
<tr>
<td>Abstraction subject to human error, including potential for missed, poorly coded, or miskeyed information</td>
<td>Electronic processes producing accurate results that capitalize on information collected for other purposes</td>
</tr>
<tr>
<td>Costly, labor-intensive data processes for one specialized purpose</td>
<td>Automated, cost-effective data processes with broad applicability</td>
</tr>
</tbody>
</table>
model improvement is supported by a previous study (Pine et al. 2007). For example, in the laboratory model, an admission albumin less than or equal to 3.1 (g/dL) increased the odds of dying by 54 percent. Adding laboratory data increased the c-statistic of the AMI model from 0.72 to 0.82.

Finally, the growth of health information exchanges and adoption of electronic health records (EHRs) can provide the infrastructure support needed for viable hybrid data sets. The use of EHR

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### Exhibit 2
Comparison of Risk-Adjustment Models for Mortality in Patients Hospitalized with Acute Myocardial Infarction (AMI) Using Administrative Data Only and Enhanced Administrative-Laboratory Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Odds Ratio for Model Using Administrative Data Only</th>
<th>Odds Ratio for Model Using Enhanced Administrative-Lab Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age 55 to 64 years</td>
<td>1.75</td>
<td></td>
</tr>
<tr>
<td>Age 65 to 74 years</td>
<td>2.82</td>
<td>1.87</td>
</tr>
<tr>
<td>Age 75 to 84 years</td>
<td>5.42</td>
<td>3.75</td>
</tr>
<tr>
<td>Age greater than 84 years</td>
<td>6.50</td>
<td>5.49</td>
</tr>
<tr>
<td>Very high risk AMI</td>
<td>2.50</td>
<td></td>
</tr>
<tr>
<td>High risk AMI</td>
<td>2.04</td>
<td></td>
</tr>
<tr>
<td>High risk pulmonary</td>
<td>1.86</td>
<td>1.75</td>
</tr>
<tr>
<td>High risk metabolic</td>
<td>1.70</td>
<td></td>
</tr>
<tr>
<td>High risk renal</td>
<td>1.47</td>
<td></td>
</tr>
<tr>
<td>High risk cancer</td>
<td>2.21</td>
<td>2.70</td>
</tr>
<tr>
<td>Albumin ≤ 3.1 (g/dL)</td>
<td></td>
<td>1.54</td>
</tr>
<tr>
<td>Base excess ≤ –9.0 (mEq/L)</td>
<td></td>
<td>4.18</td>
</tr>
<tr>
<td>Creatinine ≥ 1.3 (mg/dL)</td>
<td></td>
<td>1.80</td>
</tr>
<tr>
<td>Glucose ≥ 170 (mg/dL)</td>
<td></td>
<td>2.39</td>
</tr>
<tr>
<td>Blood urea nitrogen (BUN) ≥ 45 (mg/dL)</td>
<td></td>
<td>1.71</td>
</tr>
<tr>
<td>Serum glutamic oxalocetic transaminase (SGOT) ≥ 185 (U/L)</td>
<td></td>
<td>2.45</td>
</tr>
<tr>
<td>Sodium ≥ 145 (mEq/L)</td>
<td></td>
<td>2.58</td>
</tr>
<tr>
<td>pH ≤ 7.30</td>
<td></td>
<td>2.83</td>
</tr>
<tr>
<td>pO2 ≤ 60 (mm Hg) or O2 saturation ≤ 85 (%)</td>
<td></td>
<td>3.11</td>
</tr>
<tr>
<td>pCO2 ≤ 34 (mm Hg)</td>
<td></td>
<td>2.99</td>
</tr>
</tbody>
</table>
data to support quality improvement activities offers the promise of accessing much larger samples of patient data at lower cost in the future. Although most hospitals are still several years from fully harnessing the use of EHR data, hospital administrators can add clinical data to administrative data using existing infrastructures to support use of enhanced information within hospitals.

**STAKEHOLDER ENGAGEMENT AND IMPLICATIONS FOR HOSPITAL MANAGEMENT**

**Initiating Stakeholder Involvement**

The first major task was to engage hospitals to participate in the pilot by presenting a strong business case—this was a key step toward initiating and ensuring stakeholder interest and participation. Hospitals face enormous internal and external demands on their data collection capacities, making recruitment for a new data project a potentially daunting process.

A project kickoff meeting was held after the contract was awarded. The primary goal of this meeting was one that any hospital launching a similar project will share: familiarizing stakeholders with the details of the project, including an introduction to the planned project framework and the data methods that would be utilized. All hospitals in Minnesota were invited to the kickoff meeting.

MHA had no direct financial incentives to offer participants. Instead, it relied on the strength and merits of the concept being tested. It also offered project-specific incentives, such as access to severity-adjusted AHRQ quality indicators (QIs) and some evaluation of the quality of POA indicators (Pine et al. 2009).

MHA also leveraged the trust it had maintained with hospitals on the basis of its long experience of collecting sensitive patient-level data. MHA maintained that the primary purpose of the pilot was to identify the optimal laboratory data combined with POA codes to refine current risk-adjustment methods. The benefit to participating hospitals was direct feedback on their performance and a tool to address any areas of quality that needed improvement. MHA affirmed that it had no plans to publish results of the hospitals’ performance; rather, results would be used for quality improvement purposes.

Although nearly 30 hospitals expressed interest in the project, 13 hospitals ultimately agreed to participate.

**ONGOING COMMUNICATION STRATEGIES**

When undertaking a project of this type, a multifaceted communication strategy is necessary to sustain participant engagement for its duration. Project information must be widely available and easily accessible to all participants. MHA developed a dedicated project web page (MHA 2007) that cataloged reference materials, including the presentations from the kickoff event that detailed the planned project framework and the data methods to be employed. Project leaders also created a summary graphic depicting the data and information flow in the project with a description of the pilot and its intended outcomes (Exhibit 3). For a single hospital or system, using existing intranet functions may be a convenient way to achieve similar results. Monthly conference calls with the project’s contractors...
and with colleagues in other states conducting similar pilots presented valuable opportunities to share ideas, challenges, and best practices that informed the Minnesota Pilot Project.

MHA disseminated information to nonparticipants through presentations to the Minnesota chapter of the American Academy of Professional Coders and the Medical Account Managers Association (hospital billing office managers). Hospitals may find that encouraging participants to share this work in similar ways helps to sustain their enthusiasm, solicits feedback to inform and improve the project, and increases visibility for the hospital and its data projects. These benefits may facilitate future partnerships on data initiatives with other hospitals and further strengthen the business case for participation.

**DATA COLLECTION**

Participating hospitals agreed to collect and submit to MHA a mix of administrative and laboratory data.

Administrative data elements collected in the Minnesota Pilot Project included:

- admission and discharge dates,
- admission source,
- discharge type,
- age,
- sex,
- ICD-9-CM diagnosis codes with POA modifiers, and
- ICD-9-CM procedure codes with data on procedures performed.

Selected elements of laboratory data—numerical chemistry, blood gas, and hematology test results—were then added to the administrative data to

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**EXHIBIT 3**

Summary Graphic of Project Data Information Flow and Intended Outcomes

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Adding Clinical Data to Administrative Data

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create hybrid data sets. The initial list of numerical data elements appears in Exhibit 4. The project’s technical sub-contractor chose these data elements on the basis of their availability and analytic value in determining severity of illness upon admission.

IMPLEMENTATION CHALLENGES AND IMPLICATIONS FOR HOSPITAL MANAGEMENT

MHA worked with hospitals to overcome both organizational impediments and legal issues surrounding the privacy and security of health information data. These hurdles illustrate common challenges that may be faced by any organization attempting a large-scale data-linking initiative.

Hospitals that initially expressed interest in the pilot project but ultimately did not join provided insights into the reasons hospitals might decline to participate in data-linking processes:

1. **Lack of available staff and resources.** Some smaller hospitals found that the pilot project was more complex than they had envisioned, and they simply did not have the staff and resources necessary to sustain participation. At larger hospitals, the primary challenge that MHA faced was that many hospital departments are compartmentalized and collaboration across departments posed a hurdle.

2. **Relevance of the AHRQ QIs.** Some smaller rural hospitals were concerned that their patient volume was too low for risk adjustment of the AHRQ QIs. They also conveyed

<table>
<thead>
<tr>
<th>EXHIBIT 4</th>
<th>Numerical Laboratory Data Elements Added to Administrative Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Chemistry</strong></td>
</tr>
<tr>
<td>Aspartate aminotransferase</td>
<td>Calcium</td>
</tr>
<tr>
<td>Albumin</td>
<td>C-reactive protein</td>
</tr>
<tr>
<td>Alkaline phosphatase</td>
<td>Creatine kinase</td>
</tr>
<tr>
<td>Amylase</td>
<td>Creatine kinase-MB</td>
</tr>
<tr>
<td>Bicarbonate</td>
<td>Creatinine</td>
</tr>
<tr>
<td>Bilirubin (total)</td>
<td>Glucose</td>
</tr>
<tr>
<td>B-type natriuretic peptide</td>
<td>Lactic acid</td>
</tr>
</tbody>
</table>

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lack of integration hampered the timely creation of hybrid data sets. MHA encouraged hospitals to automate the process, which is an important step that can be adopted by hospitals pursuing similar initiatives.

Internal communications within hospitals proved to be a large obstacle during the implementation phase. Despite the project communication strategies detailed earlier, the aims and importance of the project were not always adequately conveyed to all relevant hospital staff. Frontline hospital staff, like the IT or laboratory staff members responsible for writing code or interpreting laboratory values, were often further removed from the flow of project information than were kickoff-meeting participants. This distance is believed to have resulted in some deterioration of hospital participation over time. Project leaders feel that a more active communications strategy—one aimed at more frequently engaging project members at all levels—would have been more successful. The team discovered that pairing tools such as a project web page with active outreach is the most effective way to ensure that staff instrumental to the process receive the information they need.

Initially, MHA required the use of Health Level Seven (HL7) interoperability standards for the exchange and integration of electronic health information in transmitting the required information from individual hospitals to MHA. This standard is used by IT personnel at healthcare facilities to exchange files in a common format. However, during the course of the project, MHA began offering an alternative to HL7
for receiving information from hospitals because hospital programmers participating in the project indicated that adhering to the HL7 standard was creating an unnecessary administrative burden. Also, the process was costly and cumbersome because MHA did not have access to software tools to interpret and standardize the HL7 codes. As a result, MHA began accepting American Standard Code for Information Interchange (ASCII) text files, thereby easing the burden faced by participating hospitals. This midstream switch in transmission format, however, created additional problems for MHA in merging data submitted in ASCII format with data submitted by two hospital systems that were able to send data files in the HL7 format. Nonetheless, flexibility, particularly on technical matters, proved to be essential to sustaining efforts to build enhanced databases.

Data and Transmission Standards Issues

Legal issues surrounding the privacy and security of health information are particularly relevant for projects that seek to create clinically enhanced hybrid data sets. Patient consent to collect data for the pilot was covered under the general privacy release agreements obtained at hospitals for sharing information for operational purposes with MHA. Further data sharing for the Minnesota Pilot Project was aided by legal groundwork that had been laid for other MHA data-oriented initiatives. For example, MHA had already established business associate agreements between MHA and each member hospital to ensure Health Insurance Portability and Accountability Act compliance. However, even these existing agreements were not sufficient for the pilot project because they did not cover subcontractor access to the data. MHA developed an addendum to these agreements, giving MHA permission to share patient data with its subcontractors for linking and analysis. Hospitals working on data-linking projects independently may need to address legal issues surrounding data use if they grant subcontractors access to health information.

Technical challenges also arose during the project. Understanding the data standards used in the project—the HL7 standard for exchange mentioned earlier as well as the Logical Observation Identifiers Names and Codes (LOINC) standard, a common code set for identifying medical laboratory test names—was essential to the data collection process. MHA’s technical subcontractor was responsible for developing LOINC codes and LOINC code crosswalk maps for each participating hospital’s laboratory coding system. Through this process the internal, idiosyncratic codes used by individual hospitals to identify observations were translated to the universal identifiers of the LOINC code system. Many hospitals were initially unfamiliar with the LOINC standard, but those that followed through were ultimately successful in mapping their internal codes to the LOINC system. The team benefited from educational tools and resources provided by AHRQ that are available online (HCUP 2010).

MHA’s technical subcontractor also designed instructions for participating hospitals related to the HL7 standard. These instructions were intended to
guide hospitals in programming for laboratory data files so that they understood the specifications required by the project. Some delays were experienced in formulating the instructions as the details were defined and guidance from a national expert on HL7 was secured. Facilities whose internal IT staff members were unfamiliar with the use of HL7 benefited from being able to use a simplified (ASCII flat file) format that retained HL7 definitions but was limited to fields required to augment administrative claims data; this format allowed participating hospitals to enjoy the advantages of the HL7 definitions without overburdening their IT departments.

Additional technical issues arose in using MHA’s secure web portal to transmit and receive data files. MHA encountered difficulties in attempting to receive laboratory data files larger than 25 megabytes. The issue was ultimately resolved by MHA’s IT staff. However, a long-term program to collect laboratory data would be best served by requesting the data in shorter time increments.

LESSONS LEARNED
MHA learned several important lessons in implementing the Minnesota Pilot Project.

Linking administrative and clinical data offers great potential for generating more useful data sets to help hospitals transform patient care. Hospitals have large amounts of diverse data stored in various silos across their systems. Despite the wealth of available data, most analyses to date have focused on claims data, which lack clinical details. Enhancing the clinical power of data sets by linking laboratory data with claims data increases their analytic power at a lower cost than that of medical record review.

Project leaders lay the foundations for success during the project initiation phase. Securing stakeholder buy-in (in particular, the buy-in of the hospital IT staff who will bear significant responsibility for implementing the project) is essential. It is one of the first major challenges encountered during the initiation phase. Patterns of communication and engagement that begin during the project initiation phase may characterize the project for its duration, underscoring the importance of building a strong foundation at the outset. The Minnesota Pilot Project benefited at its inception from the existing trust between participating hospitals and MHA.

Formulation of a detailed communications plan helps to keep stakeholders engaged. A sound communications strategy might include identification of key contacts, a timeline, a kick-off event, ongoing meetings, periodic conference calls, and a dedicated project website or intranet site. The strategy must involve keeping all participants informed, and it must be designed to foster the exchange of ideas and feedback. Proactive efforts to keep participants enthusiastic and engaged, such as encouraging them to share results with colleagues at professional conferences, are important for sustaining interest.

Flexibility enables projects to clear inevitable implementation hurdles. The Minnesota Pilot Project personnel encountered difficulties in collecting data but were able to adapt their plans to meet the stakeholders’ needs. This flexibility prevented inconvenient
obstacles from becoming insurmountable. Similarly, flexibility in allowing time for negotiations with partner hospitals or contractors may be necessary. The need for flexibility must be balanced against certain baseline goals and procedures; for example, MHA found that the use of standardized data content (such as LOINC) was important to the success of its pilot despite the extra time its use consumed.

**Recommendations and Future Directions**

We have several recommendations for hospitals considering a similar project. Close communication between experienced IT and clinical staff is essential to ensure collaboration and achieve the project’s goal. Having a champion who will work with the staff to bridge the claims and clinical data is paramount to smooth implementation. Building off of existing hospital IT infrastructure allows the data to be collected more efficiently from different database silos and helps to minimize the duplication of efforts. Lastly, using software tools that are able to interpret HL7 codes reduces the burden of data standardization.

To continue building on these successful efforts to link clinical and administrative data, MHA is undertaking a new AHRQ grant-funded effort to compare the effectiveness of different treatment interventions for patients with acute decompensated heart failure. Toward this end, MHA is developing ways to routinely collect enhanced data by tapping existing hospital IT infrastructure and to more efficiently obtain laboratory, pharmacy, and claims information. These efforts will create a first-of-a-kind statewide inpatient database that will enable researchers to compare clinical performance and relate risk-adjusted outcomes to drug therapy without expensive medical records abstraction. This initiative will be guided by the lessons learned during the Minnesota Pilot Project.

Additional future directions for MHA include continuing to expand and build on the IT infrastructure at hospitals and use available software tools to obtain clinical data on an automated and real-time basis. This development will allow hospitals to have more actionable data with which to engage clinicians during the delivery of patient care and thereby mitigate risks. In the long term, MHA would like to establish a system to collect clinical data for risk adjustment of the AHRQ QIs and integrate these data with the Minnesota Community Measurement, a statewide quality reporting system. The possibilities of a statewide hybrid data initiative hold much promise for harnessing the power of enhanced databases for sustained quality improvement efforts.

**Conclusions**

MHA demonstrated the feasibility of linking administrative with clinical data through the Minnesota Pilot Project. Despite some initial challenges, the benefits of hybrid data have allowed more accurate comparisons of risk-adjusted mortality and risk-adjusted complications across Minnesota hospitals—an important first step toward targeting quality improvement efforts. Through its new, expanded effort to build on the pilot, MHA will leverage the lessons learned about engaging and
assisting hospitals, and it will continue to advance its broad goal of identifying best practices for constructing and utilizing hybrid data to set the stage for quality improvement.

ACKNOWLEDGMENTS

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REFERENCES


In recent years, interest in and availability of clinical quality data have risen exponentially and electronic health record systems have proliferated. This article touches on both as the authors describe a two-year pilot study, funded by the Agency for Healthcare Research and Quality and conducted by the Minnesota Hospital Association, to determine “the feasibility of creating powerful data sets by adding clinical data to administrative databases” as a way to increase the accuracy of measuring risk-adjusted mortality and complications. Several related findings were also included in the article, which I mention later.

When I began my healthcare leadership career more than 25 years ago, I worked in the “Quality department.” My job centered on conducting quality assurance audits, or episodic manual reviews of medical records to discover any egregious clinical or administrative errors. The work was time consuming and tedious; I was grateful that The Joint Commission required only one such audit per department per year. The concept of actually sharing the results of these audits beyond the hospital walls was not even contemplated at the time.

Audits have long been replaced by ongoing quality improvement efforts with widespread electronic reporting of the information. For many measures, this information is available on a variety of comparative websites accessible to the public. However, inconsistency remains among these websites. Two recent articles focused on the varied methods used to determine healthcare rankings and the often conflicting results (Begley 2012; O’Donnell 2012). Alternatively, the enhanced data collection methodology described in the research article suggests a more standardized approach that couples the administrative/claims data (i.e., admission and discharge dates, admission source, discharge type, age, sex, and ICD-9 codes) with discrete laboratory data. The Minnesota Hospital Association study found that this hybrid data set more accurately reflected risk-adjusted mortality and complications across the state’s hospitals than did the claims data alone. Perhaps this standardized approach to reporting could be considered by the comparative websites in the future.

In reading the article, I was particularly impressed with the authors’ description of the link between adding laboratory data to claims data and the increase of the odds ratio. For example, an admission albumin less than or equal to 3.1 in acute myocardial infarction patients “increased the odds of dying by 54 percent.” There seems to be an inherent benefit to using the modeling on a real-time basis, not just retrospectively, to potentially change the patient’s course of treatment. Steps could be taken in the future to add pharmaceutical and radiology/imaging information to the hybrid database to further refine the model.
Included in the article is a summary of lessons learned that could prove useful for organizations embarking on any project, particularly those that are IT related. Recommendations such as securing stakeholder buy-in, developing a comprehensive communication plan, and remaining flexible throughout the project are logical ideas to consider. Having been involved in the electronic health record implementation for five separate health systems (with multiple vendors), I can speak firsthand in particular to the importance of a multifaceted communication strategy to engage all the affected parties throughout the duration of the project.

The study depicted in the article reflects the kind of forward-thinking work being conducted by the Minnesota Hospital Association and other progressive state associations such as Wisconsin and Iowa. I applaud their efforts and look forward to reading the results of the next phase.

REFERENCES


The High Cost of Low-Acuity ICU Outliers

Deborah Dahl, FACHE, senior director, clinical innovation, Banner Health, Phoenix; Greg G. Wojtal, CPA, FACHE, chief financial officer—Arizona West, Banner Health; Michael J. Breslow, MD, vice president, research & development, Philips VISICU, Baltimore; Randy Holl, managing director, IdeoMetrics, New York City; Debra Huguez, senior director, decision support, Banner Health; David Stone, MD, professor, anesthesia and neurosurgery, University of Virginia School of Medicine, Charlottesville; and Gloria Korpi, consultant, Allscripts (TSI) Decision Support System/Sunrise Decision Support manager, Banner Health

EXE C U T I V E S U M M A R Y

Direct variable costs were determined on each hospital day for all patients with an intensive care unit (ICU) stay in four Phoenix-area hospital ICUs. Average daily direct variable cost in the four ICUs ranged from $1,436 to $1,759 and represented 69.4 percent and 45.7 percent of total hospital stay cost for medical and surgical patients, respectively. Daily ICU cost and length of stay (LOS) were higher in patients with higher ICU admission acuity of illness as measured by the APACHE risk prediction methodology; 16.2 percent of patients had an ICU stay in excess of six days, and these LOS outliers accounted for 56.7 percent of total ICU cost. While higher-acuity patients were more likely to be ICU LOS outliers, 11.1 percent of low-risk patients were outliers. The low-risk group included 69.4 percent of the ICU population and accounted for 47 percent of all LOS outliers. Low-risk LOS outliers accounted for 25.3 percent of ICU cost and incurred fivefold higher hospital stay costs and mortality rates. These data suggest that severity of illness is an important determinant of daily resource consumption and LOS, regardless of whether the patient arrives in the ICU with high acuity or develops complications that increase acuity. The finding that a substantial number of long-stay patients come into the ICU with low acuity and deteriorate after ICU admission is not widely recognized and represents an important opportunity to improve patient outcomes and lower costs. ICUs should consider adding low-risk LOS data to their quality and financial performance reports.

For more information about the concepts in this article, please contact Ms. Dahl at deb.dahl@bannerhealth.com.
INTRODUCTION
Intensive care units (ICUs) serve high-acuity patients with complex and life-threatening illnesses. The number of ICU beds in the United States has increased despite overall decreases in total hospital beds (Halpern, Pastores, and Greenstein 2004), likely reflecting higher inpatient acuity. ICU costs are three- to fourfold higher than care costs in general medical-surgical wards (Rapoport et al. 2003). ICU beds account for approximately 10–15 percent of inpatient beds, but ICU costs account for one-quarter to one-third of all inpatient costs (Kahn 2006). The higher cost of ICU care reflects both higher staffing ratios and greater consumption of materials and services (Dasta et al. 2005; Weber et al. 2003). Rapoport et al. (2003) reported that 85 percent of ICU costs are explained by ICU length of stay (LOS). The literature demonstrating the importance of acuity of illness on ICU admission as a predictor of ICU LOS is extensive (Zimmerman et al. 2006b; Vasilevskis et al. 2009; Knaus et al. 1993). However, little is known about factors that affect daily ICU costs. The present study examines ICU costs at four hospitals in a large urban health system. The goals of the study were to define the contributors to ICU daily variable cost, understand how costs change over the duration of the ICU stay, and evaluate the effect of illness acuity on daily cost.

METHODS
All patients discharged from four Banner Health, Phoenix, hospitals’ ICUs between July 1 and December 31, 2007, were eligible for inclusion in the study. Of the four ICUs, three were general medical-surgical units and one was a neurologic ICU. Detailed financial and clinical data were obtained on all patients; those for whom the hospitals had not gathered complete data were excluded from the analysis. For patients with more than one ICU stay during the same hospitalization, only data from the first stay were analyzed.

Financial data were obtained from the TSI cost accounting system. Direct variable costs were determined using actual incurred costs, and labor costs of direct care providers were treated as variable costs. Total care provider salaries for each cost center were allocated to specific services (e.g., ICU or general ward care per patient day, respiratory care per hour of service). Consumable supplies were classified as direct variable costs and assigned to individual patients on the day of use. Reusable equipment (e.g., ventilators, infusion pumps) costs were classified as direct fixed cost. Direct fixed and indirect costs were allocated to individual patients using consistent department-specific allocation formulas. Direct fixed and indirect costs were used to estimate average daily ICU and floor total costs for patients from each institution. However, only direct variable costs were included in subsequent analyses, as these reflect actual accrued costs and thus potential cost savings. Individual patient costs (e.g., labor, supplies, pharmacy, laboratory) for each hospital day were allocated to 21 cost categories. The presence of an ICU labor cost entry was used to identify ICU days. All costs incurred on an ICU day were included in ICU costs except for emergency department, operating room, and catheterization laboratory costs. A similar
approach was used to calculate general medical-surgical ward costs. Operating room (OR) costs were subtracted from daily costs, as these are unrelated to care received in the ICU or on the general ward. OR costs include those incorporated into the surgery/anesthesia cost center and supplies and medications used in the OR, which are accounted for in separate cost centers. The latter costs were estimated by subtracting average daily supply and pharmacy costs on non-OR ICU days from those incurred on OR ICU days. OR days were identified by OR cost center entries in excess of $500. OR cost center entries lower than $500 were assumed to represent costs incurred during an earlier surgery (delayed billing) or in anticipation of a surgery that did not occur (canceled case). ICU supply and pharmacy costs on OR days were assumed to be equal to average daily supply and pharmacy costs for non-OR ICU days.

Patients were classified into three different acuity groups on the basis of their predicted mortality on admission to the ICU. Low-risk patients had predicted hospital mortality <10 percent, medium-risk patients between 10 and 50 percent, and high-risk patients >50 percent. The APACHE III methodology (Cerner, Kansas City, Missouri) was used to calculate predicted mortality (Zimmerman et al. 2006a). The APACHE system uses in its algorithms ICU admission diagnosis, chronic health status, and illness severity in the first ICU day. Seventeen physiologic variables are used to calculate illness severity. The APACHE methodology shows both good discrimination and calibration and is used extensively in ICU outcomes assessment (Zimmerman et al. 2006a; Breslow and Badawi 2012; Keegan, Gajic, and Afessa 2011).

**ANALYSIS**

Three separate analyses were performed. The first analysis was an observational study of direct variable and total costs in the four facilities. ICU direct variable cost and the contribution of each ICU cost category were determined for each patient for each ICU day. Daily direct variable general ward costs were determined using the same methodology, as were daily ICU total cost calculations, which also include direct fixed costs and indirect costs. These costs were then averaged to calculate average daily costs for each facility. The contribution of ICU direct variable cost to total hospital stay direct variable cost was determined by calculating the average ICU and general ward stay cost and the average OR cost for patients having surgery. ICU and general ward stay costs were obtained by multiplying average daily ICU and general ward costs by average ICU and ward LOS. OR direct variable costs included OR cost center entries and OR supply and pharmacy costs, as calculated using the methodology described previously. For nonsurgical patients, the percentage of total hospital direct variable cost attributed to the ICU stay was determined by dividing total ICU costs by the sum of total ICU and floor costs. For surgical patients, total ICU direct variable costs were divided by the sum of ICU, floor, and OR direct variable costs.

The second analysis evaluated daily cost changes over the duration of an ICU stay to determine whether daily costs for early ICU days are greater than for later ICU days, a commonly held
assumption (Rapoport et al. 2003). For this analysis ICU daily direct variable cost for each patient was calculated by day in the ICU (e.g., ICU day 1, ICU day 2, ICU day 3, . . . , ICU day n). All first-day direct variable costs were then summed and divided by the number of patients with first-day cost data to compute average day 1 cost. Second and subsequent day average costs were calculated in the same manner.

The third analysis examined whether severity of illness affects average daily ICU direct variable cost and average total ICU and hospital stay direct variable cost. Average ICU daily direct variable cost was calculated separately for low-, medium-, and high-acuity patients. Average daily labor costs were used in this analysis, as no data capture actual time spent by individual providers for specific patients. Banner ICU nurses generally care for two patients, with the occasional high-acuity patient requiring a full-time nurse. Average ICU stay direct variable costs for low-, medium-, and high-acuity patients were determined by multiplying average ICU LOS for each group by the average ICU daily direct variable cost computed for that cohort. Average total hospital costs for each group were determined by adding average ICU and general ward care costs. We performed similar analyses on low-acuity patients with short and long ICU stays (short stay defined as six days or less), as we have reason to believe that patients only remain in the ICU for long stays if they have significant ongoing problems.

RESULTS
A total of 2,784 patients were discharged from the four ICUs during the study period. We obtained both financial and APACHE data for 2,056 of the eligible patients, and these patients constituted the study population. Key population demographic data were as follows:

- **Age:**
  - Mean age 58 ± 19 years
- **Gender:**
  - 53.5 percent male
  - 46.5 percent female
- **Race/ethnicity:**
  - 71.5 percent white
  - 16.1 percent Hispanic
  - 5.4 percent African American
  - 4.7 percent Native American
  - 1.7 percent unknown race/ethnicity
  - 0.6 percent Asian

The ICU mean admission APACHE score was 46 ± 21.5, with a hospital mortality of 7.68 percent. The top four ICU admission diagnoses were respiratory medical, other; diabetic ketoacidosis; coronary artery bypass graft; and cerebrovascular accident.

Average daily ICU direct variable cost was $1,597 across the four ICUs (range $1,436 to $1,759), and average daily general ward direct variable cost was $683 (range $632 to $721). ICU direct variable cost was approximately 50 percent of total average daily cost (average daily cost, including fixed and indirect costs, ranged from $2,833 to $3,627 across the four facilities). Labor (nursing and other staff) accounted for 56.2 percent of daily ICU direct variable cost. Pharmacy, lab/blood, and respiratory therapy costs were significant contributors, representing 15.9 percent, 7.3 percent, and 8.9 percent of
daily direct variable cost, respectively. Average ICU LOS was 4.06 days (sd 4.81 days), and average floor LOS, for patients with a floor stay, was 5.52 days (4.13 days for all patients). The average direct variable ICU stay cost was $6,488 per patient, and the average direct variable general ward stay cost was $2,833. Of the patient population studied, 488 (23.7 percent) underwent surgery during their hospitalization. Surgical costs averaged $5,099 per patient. ICU direct variable costs comprised 69.4 percent and 45.7 percent of total hospital direct variable cost for medical and surgical patients, respectively.

To evaluate changes in daily cost over the duration of the ICU stay, daily costs were examined as a function of ICU day. Exhibit 1a shows the number of study patients with ICU cost data as a function of ICU day. Large numbers of patients had cost data for the early ICU days (e.g., days 1–3), with fewer patients experiencing stays in excess of six days. Only 4.5 percent of patients had an ICU stay of more than 14 days. Daily cost data are shown in Exhibit 1b. Overall, costs changed little as a function of ICU day. In some ICUs we found a tendency for costs in later days to be higher than in earlier days. This trend is best explained by examining daily pharmacy and respiratory costs, which reflect actual resource utilization (Exhibits 2a and 2b). Both pharmacy and respiratory costs increased over the first four ICU days and remained elevated thereafter. Other component costs showed little appreciable change over time.

To assess whether acuity of illness on admission to the ICU affects ICU daily direct variable cost, patients were divided into three groups using APACHE-predicted mortality ranges of <10 percent, 10–50 percent, and >50 percent. Of the study population, 69.4 percent were in the low-acuity group (range 57.1–90.3 percent), 26.6 percent were in the moderate-acuity group, and 4 percent were in the high-acuity group (Exhibit 3a). The low-acuity patient average daily ICU cost was $1,471, the middle-acuity average was $1,604, and the high-acuity average was $1,936 (Exhibit 3b). Average ICU LOS was 3.36, 5.52, and 6.61 days for low-, medium-, and high-acuity patients, respectively. Longer LOS combined with higher daily costs resulted in higher total ICU stay costs and higher total hospital stay costs (ICU plus general ward) for the higher-acuity patients, with average total hospital stay direct variable costs of $7,740, $12,459, and $15,921, respectively, for the three groups (Exhibit 3c). The percentage of total hospital non-OR costs attributable to the ICU stay was lowest in the low-acuity group (65.7 percent), intermediate in the moderate-acuity group (73.9 percent), and highest in the high-acuity group (80.4 percent). Despite having significantly lower per patient costs, low-acuity patients accounted for 54.4 percent of total ICU costs, while medium- and high-acuity patients accounted for 37.8 percent and 7.9 percent of total ICU costs, respectively.

Because low-acuity patients accounted for more than two-thirds of the ICU patients and more than half of all ICU direct variable costs, we examined this group in greater detail. On average, 88.9 percent of low-risk patients had an ICU LOS less than or equal to six days, and 11.1 percent had stays
longer than six days (the range across the four ICUs was 5.4–19.2 percent). While the percentage of patients with long stays (> six days = LOS outliers) was lowest in the low-risk population (11.1 percent vs. 26.7 percent in the medium-risk and 34.1 percent in the high-risk populations), low-risk patients accounted for 47.7 percent of all LOS outliers (Exhibit 4). Average ICU daily direct variable cost for low-risk LOS outliers was higher than for low-risk patients whose ICU stay was short ($1,605 vs. $1,409). ICU stay costs were

EXHIBIT 1
Distribution of Costs

A. Number of patients with charge data, by date in the ICU

B. Average ICU direct variable cost, by day in the ICU
sevenfold higher for low-risk outliers ($21,142 vs. $3,095), while total hospital stay costs were 4.5-fold higher ($25,486 vs. $5,515). Low-risk LOS outliers accounted for 25.3 percent of all ICU costs. Moreover, these outliers also had fivefold higher severity-adjusted mortality (raw vs. predicted mortality).

**DISCUSSION**

This study examined ICU costs in four Phoenix-area hospitals. Daily ICU direct costs were $450.00 for the first ICU day and decreased to $350.00 for the 51st ICU day. The average ICU pharmacy direct variable cost was $300.00, and the average ICU respiratory direct variable cost was $250.00. 

**EXHIBIT 2**

**Resource Utilization**

A. Average ICU pharmacy direct variable cost, by ICU day

<table>
<thead>
<tr>
<th>ICU Day</th>
<th>Pharmacy Cost</th>
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<tbody>
<tr>
<td>1</td>
<td>$450.00</td>
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<td>2</td>
<td>$400.00</td>
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<td>3</td>
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<td>9</td>
<td>$50.00</td>
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<td>10</td>
<td>$0.00</td>
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B. Average ICU respiratory direct variable cost, by ICU day

<table>
<thead>
<tr>
<th>ICU Day</th>
<th>Respiratory Cost</th>
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<tbody>
<tr>
<td>1</td>
<td>$450.00</td>
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variable costs averaged $1,597, which was almost 2.5 times higher than daily floor cost. ICU costs were fairly consistent across all four facilities. Labor accounted for slightly more than half of total daily cost. Pharmacy and respiratory costs were the next largest contributors and varied depending on acuity of illness. ICU daily cost was similar for all ICU days, with a tendency to be lower in the first two ICU days, once OR-related costs were excluded from true ICU costs. Acuity of illness on ICU admission, as reflected in APACHE-predicted mortality, was a major determinant of average daily ICU cost and total ICU

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**EXHIBIT 3**

Impact of Acuity of Illness at ICU Admission on ICU Daily Direct Variable Cost

A. Percentage of patients in each acuity group

B. Average daily ICU cost by acuity group

C. Average case cost by acuity group
and hospital stay cost, reflecting both higher daily resource consumption and longer ICU and general ward stays in sicker patients. The majority of ICU patients have low predicted mortality on ICU admission. However, more than 10 percent of these lower-acuity patients ended up with ICU stays of longer than six days. An observed fivefold increase in mortality in this subset of low-acuity patients suggests prolonged stays may be due to complications. These low-risk outliers had higher ICU daily cost and dramatically higher ICU and hospital stay costs.

For patients requiring ICU admission, their ICU care accounts for the majority of total hospital direct variable cost. ICU costs were more than twice total floor costs. This primarily reflects the difference in daily cost in the different environments, as total ICU days were almost identical to total floor days (average LOS 4.06 and 4.13, respectively). ICU costs represented a smaller fraction of total hospital cost in surgical patients due to the added OR costs but still approached 50 percent of total cost. Labor accounts for the majority of ICU cost, reflecting the number of skilled providers required to care for these high-acuity patients (Kahn 2006). In the Banner Health system, the standard patient-to-nurse ratio in the ICU is predominantly 2:1, against 4–6:1 on the general wards. Pharmacy costs accounted for 16 percent of daily cost, reflecting the large number and high cost of medications ICU patients receive. Respiratory costs were almost threefold higher than floor respiratory costs. Both medication and respiratory average daily

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**EXHIBIT 4**

<table>
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<tr>
<th>ICU LOS Outliers</th>
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<tr>
<td>% of total LOS outliers per acuity category</td>
</tr>
<tr>
<td>Outliers as a % of the total ICU population</td>
</tr>
</tbody>
</table>

Low-acuity patients | Mid-acuity patients | High-acuity patients

Note: Although the percentage of patients with long stays was lowest in the low-acuity population, those patients accounted for almost half of all ICU LOS outliers.
costs increased markedly across the three acuity groups.

Prior studies of ICU cost have identified ICU LOS as a major determinant of overall cost (Rapoport et al. 2003; Kahn 2006), a finding confirmed in the present study.

The ICU scoring system literature has highlighted the strong relationship between severity of illness and ICU LOS (Zimmerman et al. 2006b; Vasilevskis 2009; Knaus et al. 1993), and it is not surprising that average ICU (and floor) LOS in mid- and high-acuity patients in our study was 64 percent and 97 percent higher, respectively, than LOS in the low-acuity patients. The present study also demonstrates that daily ICU cost varies with patient acuity. We used the APACHE methodology to segment patients into three acuity groups based on predicted hospital mortality. Patients with a 10–50 percent predicted mortality incurred 10 percent higher average daily costs than those with a predicted mortality less than 10 percent, while those with a greater than 50 percent mortality risk incurred 28 percent higher average daily costs. Although prior studies have demonstrated higher care costs in older patients and those with chronic health problems (Carson and Bach 2002), our study demonstrates that acuity of illness predicts not only duration of time in the hospital but also amount of resources consumed on any given day. So while age and chronic health status may contribute to severity of illness, it is actually severity of illness that determines both daily resource consumption and the time course of recovery.

The present study confirms prior observations that the majority of ICU patients have a fairly low mortality risk (Knaus et al. 1991). We found that fully two-thirds of patients had predicted hospital mortality less than 10 percent. Lower-risk patients also have a shorter predicted ICU LOS. LOS is the major determinant of ICU cost (Rapoport et al. 2003), and patients with a long ICU stay account for a disproportionate amount of total ICU cost (Martin et al. 2005). In the study population, 16 percent of patients had an ICU stay longer than six days’ duration. We define these patients as LOS outliers, and they accounted for 57 percent of total ICU cost. Illness severity at the time of ICU admission was a good predictor of the risk that a patient would become an LOS outlier, with mid- and high-acuity patients having 2.4- and 3.1-fold incidences, respectively. However, 11.1 percent of low-risk patients had an ICU stay greater than six days. That incidence, when combined with the predominance of this population, resulted in almost half of all LOS outliers coming from the low-risk group. Low-risk LOS outliers accounted for 25 percent of total ICU costs. The observed fivefold higher mortality of this subset of low-acuity patients, compared to short-stay low-acuity patients when adjusted for individual patient mortality risk (actual to predicted mortality ratios), suggests that the long stay of these patients may have been due to complications. These patients also had higher average daily pharmacy, respiratory, and total costs (116 percent, 130 percent, and 20 percent higher, respectively), indicating higher resource consumption than the lower-acuity patients who had a less eventful ICU stay.
Our data suggest that costs are lowest on ICU days 1 and 2 and rise to a steady plateau thereafter. This finding is at odds with the perception of many hospital financial analysts, who often look only at daily cost numbers without factoring out the contribution of OR costs. The majority of surgical ICU patients undergo surgery the same day they are admitted to ICU, and the inclusion of these costs artificially elevates ICU costs for that day. Our data indicate that direct variable OR costs average $5,100 per surgical patient and $1,200 when spread over all ICU patients. When these OR costs are eliminated from ICU costs, average ICU costs are actually somewhat lower on the first ICU day. We attribute the observation of lower costs in the first two ICU days to the routine practice of admitting lower-acuity patients to ICU for observation. Most of these patients do not receive mechanical ventilation, cardioresuscitative medications, or broad-spectrum antibiotics—therapies in widespread use for higher-acuity ICU patients. Once these low-acuity patients leave the ICU after a day or two of observation, the patients who remain are those who are sick and need ongoing, resource-intensive ICU care.

Limitations
Direct variable costs were determined using actual labor and supply costs. Direct variable labor costs included all salaries and benefits of direct care personnel in each service area. Total direct care labor costs were divided by the number of patient days or hours of service provided and then allocated to individual patients based on the services they received each day. We chose to focus the study on direct variable costs, as these reflect true costs of care and are potentially amenable to future cost savings. Total average daily cost information was provided to illustrate that direct variable costs represented approximately 50 percent of total cost. Direct fixed costs included salaries for personnel not engaged in direct patient care (e.g., ward clerk) and nonconsumable supplies and devices. As in all cost accounting systems, decisions are made regarding what constitutes variable versus fixed expenses, and different health systems may allocate costs somewhat differently to specific cost centers. Because the same methodology was used for all analyses in our study, it is very unlikely that cost allocation strategies used by Banner Health account for the observed differences among the groups we report on in this study.

We examined only the first ICU stay in patients who had more than one ICU stay during a single hospitalization. This factor likely resulted in a minor underestimation of total stay costs and the percentage of costs attributable to the ICU. Another limitation is in how labor costs were allocated to individual patients. The Banner Health cost accounting system assumes equal staffing for all patients. The study ICUs generally use a 2:1 staffing ratio. Very high-acuity patients are cared for by a single nurse. Even where one nurse cares for two patients, the staff routinely devote more time to sicker patients. As a result, the demonstrated impact of patient acuity on average daily, total ICU, and hospital cost almost certainly underestimates the true difference. For the
population could reduce mortality, LOS, and cost. Banner Health observed a nearly 50 percent reduction in low-risk LOS outliers after implementing a tele-ICU care program (percentage based on internal Banner Health data). This experience indicates that many of these long stays may be avoidable. We encourage hospital leaders to segment the ICU population by mortality risk and quantify the incidence of LOS outliers in the three different populations. Low-risk LOS outlier rate is an important statistic that should be incorporated into ICU quality and financial scorecards, as these data provide valuable performance information.

**Implications**

LOS outliers have a disproportionate effect on total ICU cost (Kaushal et al. 2007), and it is important for quality and financial analysts to review data for this subset of patients on a regular basis. Our data suggest this group is composed of two distinct populations: (1) those very sick on arrival to the ICU and (2) those with low mortality risk on admission who develop complications that extend their stay and increase their mortality. Prior studies have shown that high-acuity patients have long LOS (Zimmerman et al. 2006b); high costs are expected and may not be avoidable. In contrast, low-risk patients who develop complications that result in a long ICU stay represent an important target for quality improvement efforts. Avoiding complications in this population could reduce mortality, LOS, and cost. Banner Health observed a nearly 50 percent reduction in low-risk LOS outliers after implementing a tele-ICU care program (percentage based on internal Banner Health data). This experience indicates that many of these long stays may be avoidable. We encourage hospital leaders to segment the ICU population by mortality risk and quantify the incidence of LOS outliers in the three different populations. Low-risk LOS outlier rate is an important statistic that should be incorporated into ICU quality and financial scorecards, as these data provide valuable performance information.

**Conclusions**

High staffing ratios and the use of multiple complex therapies account for the high costs of ICU care. While illness severity affects resource use and therefore costs, the duration of the ICU stay is the most important determinant of overall ICU and hospital cost. Although high-acuity ICU patients have longer ICU stays, reflecting the disease burden on admission, a subset of lower-acuity ICU patients who develop complications represent an equally important group of long-stay, very costly patients. Costs attributed to high-acuity patients likely cannot be avoided. In contrast, preventing avoidable complications in low-risk patients can result in substantial savings. Stratifying patients by acuity can assist in predicting costs; however, identifying the etiologies underlying reasons for longer LOS in lower-acuity patients may provide greater opportunities for improvements in quality of care and financial performance.
REFERENCES


When reading this article, I thought how the findings in it were not immediately apparent. It is easy to understand a correlation between high acuity and total costs incurred by a patient’s stay. However, as in most cases, when data are dissected and viewed through multiple lenses without preconceived notions, gems can be found. Neither a hospital nor its staff can predetermine the acuity levels of its admitting patients. However, when a patient enters its walls, measures can be taken to ensure that high quality is delivered in a cost-effective way. Determining that higher costs can be associated with lower-acuity patients who experienced complications during their stay allows the clinical and administrative staff to take actionable steps toward lowering costs and raising quality.

I have been involved in many projects initiated to lower length of stay (LOS), including developing better sepsis protocols, enhancing the case management function, and improving the discharge process. Each initiative, as with the project to anticipate possible complications associated with low-acuity patients discussed in the article, can be acted and improved on by the hospital.

This knowledge might be introduced to a hospital by asking the following questions:

1. Do we currently capture the needed data (variable ICU costs by LOS day and patient acuity suitable for stratification) where and how it is stored?
2. How do we determine who has the ability and responsibility to affect these metrics?
3. What complications are causing the extended length of stay for lower-acuity patients?

After determining what data and metrics are available, lowering the cost and length of stay by reducing or eliminating complications associated with low-acuity patients can be accomplished through the As-Is, To-Be process improvement approach. The As-Is phase includes documenting current processes in the ICU specific to lower-acuity patients and determining benchmark data points. The To-Be phase consists of establishing process and policy changes, roles and responsibilities, and quality goals. After determining the new processes, a gap analysis is performed that allows mapping from As-Is to To-Be. Upon completion of the gap analysis, a test should be conducted with a small subset of low-acuity patients. The implementation should be created and executed with best practices learned from the test phase.

Through their analysis, the authors identify a group of patients who incur additional costs and hypothesize that the additional costs are the result of complications during what otherwise would be a short visit. What is exciting about this discovery, unlike costs associated with higher acuity, is that the hospital staff can improve the length of stay and cost per day metrics through process and quality improvement approaches.
Payer Mix and EHR Adoption in Hospitals

Dong Yeong Shin, doctoral student, Department of Health Services Administration, University of Alabama at Birmingham; Nir Menachemi, PhD, professor, health care organization and policy, University of Alabama at Birmingham; Mark Diana, PhD, assistant professor, School of Public Health, Tulane University, New Orleans; Abby Swanson Kazley, PhD, associate professor, Medical University of South Carolina, Charleston; and Eric W. Ford, PhD, distinguished professor of healthcare, Bryan School of Business, University of North Carolina at Greensboro

EXECUTIVE SUMMARY

Payers are known to influence the adoption of health information technology (HIT) among hospitals. However, previous studies examining the relationship between payer mix and HIT have not focused specifically on electronic health record systems (EHRs). Using data from the Nationwide Inpatient Sample and the American Hospital Association Annual Survey, we examine how Medicare, Medicaid, commercial insurance, and managed care caseloads are associated with EHR adoption in hospitals. Overall, we found a weak relationship between payer mix and EHR adoption. Medicare and, separately, Medicaid volumes were not associated with EHR adoption. Furthermore, commercial insurance volume was not associated with EHR adoption; however, a hospital located in the third quartile of managed care caseloads had a decreased likelihood of EHR adoption. We did not find empirical evidence to support the hypothesis that payer generosity and other indirect mechanisms influence EHR adoption in hospitals. The direct incentives embedded in the Health Information Technology for Economic and Clinical Health Act may have a positive influence on EHR adoption—especially for hospitals with high Medicare and/or Medicaid caseloads. However, it is still uncertain whether the available incentives will offset the barriers many hospitals face in achieving meaningful use of EHRs.

For more information about the concepts in this article, contact Dr. Menachemi at nmenachemi@uab.edu.
INTRODUCTION

Research has shown that payer mix, defined as the combination of third-party payers that makes up a hospital’s book of business, can influence hospitals’ strategic behaviors. Studies have found that higher percentages of Medicaid (Cleverley and Harvey 1992; McKay and Deily 2005) or Medicare patients (Rosko 2001) are negatively associated with financial performance. Furthermore, given that varying reimbursement rates are negotiated in the private insurance book of business, hospital revenue per admission has been demonstrated to predict operational efficiency (Dor and Farley 1996; McKay and Deily 2005) and clinical performance (Clement and Grazier 2001; Menachemi et al. 2007). Attempting to leverage the influence that the public insurance programs have on hospitals, the federal government, through the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, aims to increase the adoption and “meaningful use” of electronic health record systems (EHRs) by providing incentives and penalties to hospitals through the Medicare and Medicaid programs (CMS 2010).

The HITECH Act, part of federal stimulus legislation, allocated billions of dollars in incentive payments to providers to facilitate the adoption and use of EHR technology (Blumenthal and Tavenner 2010). The incentive payments, made to hospitals that adopt, implement, upgrade, or successfully demonstrate their meaningful use of certified EHRs, are available as of fiscal year 2011. Hospitals that do not achieve meaningful use by 2015 are potentially subject to Medicare and Medicaid payment penalties of up to 2 percent in later years (CMS 2010).

The relationship between hospitals’ EHR adoption rates and payer mix is not fully understood. However, several researchers have found that payer mix is correlated with health information technology (HIT) adoption. Based on 2004 data, Furukawa and colleagues (2008) found that the adoption of computerized physician order entry systems, but not EHR systems, was associated with an increased rate of Medicare patients as a percentage of all discharges. Similarly, McCullough (2008) found that the adoption of pharmacy information systems was positively related to Medicare caseload. The McCullough study also found that the adoption of laboratory information systems and radiology information systems was negatively associated with higher levels of Medicaid caseloads. Lastly, evidence from Florida hospitals suggests that an increase in privately insured patients is positively associated with the number of HIT applications adopted (Menachemi et al. 2007). While the Florida study did not examine EHR adoption per se, differences in public insurance (e.g., Medicare, Medicaid) as a percentage of a hospital’s discharges were not correlated with overall HIT adoption in that study. Therefore, the relationship between Medicare and Medicaid programs and EHR adoption rates is unclear.

The purpose of this article is to examine the relationship between acute care hospitals’ payer mix and their EHR adoption rates. The study uses national data and a series of statistical analyses including chi-square, logistic regression, and multinomial regression to explore...
these relationships. A better understanding of how payer mix and EHR adoption are related will allow hospital leaders and public policymakers to capitalize on the legislative intent of the HITECH Act, which utilizes the relationship between payer mix (e.g., Medicare and/or Medicaid payer mix) and HIT adoption to directly motivate hospitals to use EHR technology. Our findings will also benefit those trying to better understand the impact that the meaningful use program may have on hospitals’ EHR use. Moreover, our study will help hospital decision makers to better gauge their overall progress on EHR adoption relative to a national cohort of hospitals with similar payer mix combinations.

CONCEPTUAL FRAMEWORK

Payer mix may influence EHR adoption in two ways. The first is related to the concept of payer generosity; the second is related to certain reimbursement mechanisms inherent to some payers. Payer generosity refers to the relative payments a given insurance company provides for a given procedure or diagnosis. In general, certain payers are believed to reimburse less generously than others (Friedman et al. 2004). Specifically, government payers, such as Medicare and Medicaid, tend to provide lower reimbursement rates than do private payers, such as traditional indemnity insurance plans (Dobson, Davanzo, and Sen 2006). Given the negative relationship between the proportion of Medicare and Medicaid patients and hospital operating margin (e.g., Rosko 2001), the lower reimbursement rates of public insurance programs may not cover the entire cost of patient care (AHA 2010). This shortfall could lead to decreased operating margin in hospitals, thus leaving them with less financial flexibility to consider major capital investments. Researchers have noted that upfront capital requirements and high maintenance costs are the primary barriers to EHR adoption in acute care US hospitals (Jha et al. 2009). All other factors being equal, hospitals with higher proportions of Medicare and Medicaid patients are less likely to have the financial wherewithal to make the large capital investments necessary to buy an EHR system compared to facilities with higher percentages of private-pay patients. Thus, we would expect that a high amount of publicly insured patients is associated with a decreased likelihood of EHR adoption in hospitals.

Second, reimbursement mechanisms may play a role in EHR adoption. Under capitation arrangements and other prospective payment contracts, hospitals are financially motivated to improve efficiencies and lower costs in order to maximize profits. Under capitated reimbursement conditions, common among health maintenance organizations (HMOs), hospitals are paid a set amount for each enrolled person assigned regardless of the number or type of services provided to the person in a given time period (Mello, Stearns, and Norton 2002; Miller and Luft 2002). Many proponents of EHRs have claimed that EHRs will increase organizational efficiency while reducing duplication of effort (Brailer 2005). To the extent that EHR adoption is viewed as a strategy for improving efficiencies and lowering costs (Ali et al. 2005; Boger 2003;
Garrido et al. 2004), it may be pursued at higher rates by hospitals with a relatively higher number of HMO patients.

**METHODS**

We used a cross-sectional design with secondary data and with the acute care hospital as the unit of analysis. The analysis combines data from HCUP’s (Healthcare Cost and Utilization Project) Nationwide Inpatient Sample (NIS) for 2007, the 2008 American Hospital Association (AHA) Annual Survey database, and the 2007 Medicare Cost Reports. We drew hospital discharge data from the 2007 NIS, while the data indicating EHR adoption status and organizational characteristics of hospitals were drawn from the 2008 AHA database. In addition, because of the relatively small sample size we obtained from the NIS, we performed a parallel analysis using the limited payer mix variables, but with a much larger sample size, from the AHA Annual Survey. Doing so allows us to robustly examine the relationship between payer mix and EHR adoption.

The AHA database contains organizational information on US hospitals and on EHR systems use, which the AHA added to its annual assessment beginning in 2007 (Jha et al. 2009). The dependent variable is a categorical measure representing (a) fully implemented EHR, (b) partially implemented EHR, and (c) no EHR implemented in response to the following AHA survey question: “Does your hospital have an electronic health record?” Data measuring payer mix were extracted from the NIS database, which is the largest all-payer inpatient database in the United States and contains all discharge data from approximately a 20 percent stratified sample of community hospitals. The NIS database is frequently employed by health services researchers interested in hospital management and related issues (Boxer et al. 2003; LaPar et al. 2010; Russell et al. 2006).

To operationalize payer mix, we calculated the percentage of discharges for each hospital that were covered by each of the following primary payers: (1) Medicare, (2) Medicaid, (3) commercial indemnity insurance, (4) managed care organizations, and (5) all other payers. Of the 646 hospitals in the 2007 NIS data set that include AHA identifiers, 392 hospitals (60.7 percent) included all the information necessary to construct our main independent variables. We compared the excluded hospitals to our sample for validity purposes. Given the loss in sample size that occurred as a result of merging with the NIS data, we also examined the relationship between Medicare caseloads and Medicaid caseloads using the AHA Annual Survey data. The AHA sample is much larger than the NIS but is limited to information on only two payers’ caseloads (i.e., Medicare and Medicaid). By examining the relationships of interest with the NIS (comprehensive payer data limited to a small sample) and the AHA survey (limited payer data on a comprehensive sample size), we believe we were able to robustly examine the relationship between EHR adoption and payer mix.

**Variables**

To compute each payer mix variable in the NIS, we conducted a series of
aggregations and calculations. First, we aggregated from the patient level to the hospital level the total number of discharges paid in each category of primary payers in each hospital from the Inpatient Core Files. Next, we merged this aggregated data set with the Hospital Weights Files to compute the proportion of discharges paid for each payer type for each hospital (i.e., the total number of discharges paid by each payer divided by the total number of discharges in a hospital). Each payer mix variable in the data set was converted into quartiles to facilitate ease of interpretation. The result is four payer mix variables, one for each primary payer category (i.e., Medicare, Medicaid, commercial, and managed care). Lastly, hospitals were assigned a value from 1 to 4 depending on the quartile in which they resided for the distribution of each payer mix variable.

The AHA Annual Survey data include measures representing the percentage of each hospital’s discharges that are Medicare and, separately, Medicaid. These variables were each broken into quartiles to align them with the NIS data we prepared. Because various organizational factors are associated with HIT adoption (Furukawa et al. 2008; Hikmet et al. 2008; Wang et al. 2005), each analysis we performed included control variables for the following hospital characteristics: bed size (measured as the natural log of the number of staff beds), system affiliation (yes or no), teaching status, geographic location (urban or rural), and tax status (for-profit or not-for-profit). These variables were derived from the AHA data. In addition, we controlled for case mix (defined as the average severity of patients treated at a given hospital) using the case mix index from the Medicare Cost Reports.

Data Analyses
All variables were examined for their distribution, suitability for analysis, and the existence of any potential data anomalies based on descriptive statistics. Next, we conducted chi-square analyses and independent-samples t-tests or analysis of variance (as appropriate) to identify any organizational differences between included and excluded hospitals, and we explored the univariate relationships between full EHR adoption and each variable measuring payer mix. Finally, using the NIS data, we examined the relationship between Medicare, Medicaid, commercial insurance, and managed care mix and EHR adoption while controlling for hospital characteristics and “other” types of discharges in a logistic regression model. We used the AHA data to examine a similar model with the obvious exclusion of the payer mix variables that do not appear in this data set (i.e., commercial insurance and managed care). In both the NIS and AHA models, we present EHR adoption as a binary variable (full EHR and partial EHR versus no EHR). In addition, we present the results of the NIS analysis specified as a multinomial regression that takes advantage of the categorical nature of the EHR variable. The results we present include adjusted odds ratios (ORs) and 95 percent confidence intervals for the logistic models, and beta coefficients for the multinomial regression model. Multivariate results are flagged for significance at the $p < 0.05,$
or a partial EHR (55.9 percent vs. 42.2 percent; \( p < 0.001 \)). No differences were observed in EHR adoption quartiles by Medicaid, commercial insurance, or managed care caseload. Increased hospital size, urban location, not-for-profit tax status, and teaching hospital status were positively associated with EHR adoption in univariate analyses (see Exhibit 2).

In multivariate analysis of the NIS sample and, separately, the AHA sample, controlling for payer mix, geographic location, tax status, bed size, system affiliation, teaching status, and case mix, virtually none of the payer mix variables were related to EHR adoption (see Exhibit 3). The only exception was that hospitals in the third quartile for managed care discharges (NIS sample only) were significantly less likely than those in the bottom quartile to report having an EHR (OR = 0.18, \( p = 0.026 \)). In the AHA model, several control variables, including geographic location, tax status, bed size, and system affiliation, were significantly associated with EHR adoption (see Exhibit 3).

Lastly, in the multinomial regression that examines the EHR adoption variable with three categories using the NIS sample, most of the payer mix variables were still not related to EHR adoption (see Exhibit 4). The only exception was the third quartile of managed care discharges, where hospitals in this category were again less likely to have adopted an EHR system (no EHR vs. full EHR, beta = 2.289, \( p = 0.038 \)).

**Discussion**

While researchers have found that payer mix is associated with HIT adoption in
### Exhibit 1
Organizational Characteristics of Included and Excluded Hospital Samples

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean percent Medicare discharges (sd)</td>
<td>47.9 (16.6)</td>
<td>50.6 (17.5)</td>
<td>49.9 (18.4)</td>
<td>0.086</td>
</tr>
<tr>
<td>Mean percent Medicaid discharges (sd)</td>
<td>20.1 (15.7)</td>
<td>19.0 (15.4)</td>
<td>18.8 (15.7)</td>
<td>0.293</td>
</tr>
<tr>
<td>Mean percent managed care discharges (sd)</td>
<td>14.2 (12.2)</td>
<td>N/A</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Mean percent commercial insurance discharges (sd)</td>
<td>16.5 (15.4)</td>
<td>N/A</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Geographic location</th>
<th>Included</th>
<th>Excluded</th>
<th>AHA</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural</td>
<td>147 (37.6%)</td>
<td>128 (58.4%)</td>
<td>2021 (50.1%)</td>
<td>0.000</td>
</tr>
<tr>
<td>Urban</td>
<td>244 (62.4%)</td>
<td>91 (41.6%)</td>
<td>2015 (49.9%)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Tax status</th>
<th>Included</th>
<th>Excluded</th>
<th>AHA</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For-profit</td>
<td>56 (14.3%)</td>
<td>30 (13.6%)</td>
<td>706 (17.2%)</td>
<td>0.142</td>
</tr>
<tr>
<td>Not-for-profit</td>
<td>336 (85.7%)</td>
<td>190 (86.4%)</td>
<td>3389 (82.8%)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>System affiliation</th>
<th>Included</th>
<th>Excluded</th>
<th>AHA</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>222 (56.6%)</td>
<td>130 (59.1%)</td>
<td>2159 (52.7%)</td>
<td>0.072</td>
</tr>
<tr>
<td>No</td>
<td>170 (43.4%)</td>
<td>90 (40.9%)</td>
<td>1936 (47.3%)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Teaching hospital</th>
<th>Included</th>
<th>Excluded</th>
<th>AHA</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>33 (8.4%)</td>
<td>10 (4.5%)</td>
<td>233 (5.7%)</td>
<td>0.062</td>
</tr>
<tr>
<td>No</td>
<td>359 (91.6%)</td>
<td>210 (95.5%)</td>
<td>3862 (94.3%)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mean bed size (sd)</th>
<th>Included</th>
<th>Excluded</th>
<th>AHA</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>205.0 (211.9)</td>
<td>143.2 (150.6)</td>
<td>163.7 (182.1)</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unadjusted case mix index (sd)</th>
<th>Included</th>
<th>Excluded</th>
<th>AHA</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.40 (0.25)</td>
<td>1.35 (0.26)</td>
<td>1.37 (0.28)</td>
<td>0.129</td>
</tr>
</tbody>
</table>

*Note: Numbers may not add to 100% due to rounding. N/A is not applicable because information about commercial insurance and managed care discharges is not provided for excluded hospitals in the NIS 2007 data set or for all hospitals in the AHA 2007 data set.*
### EXHIBIT 2

Univariate Relationship Between Payer Mix and EHR Adoption in Hospitals Using the National Inpatient Sample ($n = 392$)

<table>
<thead>
<tr>
<th></th>
<th>Partial EHR Adoption (%)</th>
<th>Full EHR Adoption (%)</th>
<th>$p$-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Medicare discharges</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st quartile (&lt;33% of discharge)</td>
<td>55.9</td>
<td>19.1</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2nd quartile (34–42% of discharge)</td>
<td>57.7</td>
<td>15.4</td>
<td></td>
</tr>
<tr>
<td>3rd quartile (43–53% of discharge)</td>
<td>63.2</td>
<td>15.8</td>
<td></td>
</tr>
<tr>
<td>4th quartile (54+% of discharge)</td>
<td>42.2</td>
<td>3.1</td>
<td></td>
</tr>
<tr>
<td><strong>Medicaid discharges</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st quartile (&lt;8% of discharge)</td>
<td>44.4</td>
<td>11.1</td>
<td>0.115</td>
</tr>
<tr>
<td>2nd quartile (9–15% of discharge)</td>
<td>62.9</td>
<td>15.7</td>
<td></td>
</tr>
<tr>
<td>3rd quartile (16–21% of discharge)</td>
<td>58.3</td>
<td>9.7</td>
<td></td>
</tr>
<tr>
<td>4th quartile (22+% of discharge)</td>
<td>54.3</td>
<td>17.3</td>
<td></td>
</tr>
<tr>
<td><strong>Commercial insurance discharges</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st quartile (&lt;4% of discharge)</td>
<td>64.3</td>
<td>12.5</td>
<td>0.185</td>
</tr>
<tr>
<td>2nd quartile (5–12% of discharge)</td>
<td>43.6</td>
<td>14.1</td>
<td></td>
</tr>
<tr>
<td>3rd quartile (13–21% of discharge)</td>
<td>53.4</td>
<td>15.1</td>
<td></td>
</tr>
<tr>
<td>4th quartile (22+% of discharge)</td>
<td>62.0</td>
<td>12.7</td>
<td></td>
</tr>
<tr>
<td><strong>Managed care discharges</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st quartile (&lt;2% of discharge)</td>
<td>52.5</td>
<td>12.5</td>
<td>0.346</td>
</tr>
<tr>
<td>2nd quartile (3–14% of discharge)</td>
<td>50.8</td>
<td>13.8</td>
<td></td>
</tr>
<tr>
<td>3rd quartile (15–26% of discharge)</td>
<td>62.0</td>
<td>8.9</td>
<td></td>
</tr>
<tr>
<td>4th quartile (27+% of discharge)</td>
<td>54.1</td>
<td>21.3</td>
<td></td>
</tr>
<tr>
<td><strong>Bed size</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small (&lt;125 beds)</td>
<td>49.6</td>
<td>6.3</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Medium (126–399 beds)</td>
<td>61.4</td>
<td>14.9</td>
<td></td>
</tr>
<tr>
<td>Large (400+ beds)</td>
<td>55.6</td>
<td>31.1</td>
<td></td>
</tr>
<tr>
<td><strong>Geographic location</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>49.1</td>
<td>5.7</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Urban</td>
<td>58.9</td>
<td>18.3</td>
<td></td>
</tr>
<tr>
<td><strong>Tax status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For-profit</td>
<td>36.4</td>
<td>12.1</td>
<td>0.024</td>
</tr>
<tr>
<td>Not-for-profit</td>
<td>57.7</td>
<td>13.8</td>
<td></td>
</tr>
<tr>
<td><strong>System affiliation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>55.9</td>
<td>14.5</td>
<td>0.806</td>
</tr>
<tr>
<td>No</td>
<td>54.5</td>
<td>12.7</td>
<td></td>
</tr>
<tr>
<td><strong>Teaching hospital</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>58.6</td>
<td>34.5</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>No</td>
<td>54.9</td>
<td>11.3</td>
<td></td>
</tr>
</tbody>
</table>
### Exhibit 3
Multivariate Relationship Between Payer Mix and EHR Adoption in Hospitals

<table>
<thead>
<tr>
<th>Payer Mix: Independent Variables</th>
<th>EHR Adoption Results Using the NIS 2007 Data (n = 392)</th>
<th>Odds Ratio (95% CI) Results Using the AHA 2007 Data (n = 4,707)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Medicare caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (low volume)</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Quartile 2</td>
<td>0.84 (0.30–2.37)</td>
<td>1.04 (0.76–1.44)</td>
</tr>
<tr>
<td>Quartile 3</td>
<td>1.34 (0.36–4.98)</td>
<td>1.12 (0.80–1.56)</td>
</tr>
<tr>
<td>Quartile 4 (high volume)</td>
<td>0.19 (0.02–2.20)</td>
<td>1.01 (0.69–1.46)</td>
</tr>
<tr>
<td><strong>Medicaid caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (low volume)</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Quartile 2</td>
<td>1.00 (0.27–3.71)</td>
<td>1.34 (0.99–1.79)</td>
</tr>
<tr>
<td>Quartile 3</td>
<td>0.61 (0.14–2.64)</td>
<td>1.06 (0.76–1.48)</td>
</tr>
<tr>
<td>Quartile 4 (high volume)</td>
<td>1.39 (0.33–5.88)</td>
<td>0.82 (0.56–1.22)</td>
</tr>
<tr>
<td><strong>Commercial insurance caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (low volume)</td>
<td>1.00</td>
<td>N/A*</td>
</tr>
<tr>
<td>Quartile 2</td>
<td>1.68 (0.50–5.69)</td>
<td>1.34 (0.99–1.79)</td>
</tr>
<tr>
<td>Quartile 3</td>
<td>1.71 (0.44–6.70)</td>
<td>1.06 (0.76–1.48)</td>
</tr>
<tr>
<td>Quartile 4 (high volume)</td>
<td>1.13 (0.19–6.73)</td>
<td>0.82 (0.56–1.22)</td>
</tr>
<tr>
<td><strong>Managed care insurance caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (low volume)</td>
<td>1.00</td>
<td>N/A*</td>
</tr>
<tr>
<td>Quartile 2</td>
<td>0.32 (0.08–1.28)</td>
<td>1.34 (0.99–1.79)</td>
</tr>
<tr>
<td>Quartile 3</td>
<td>0.18 (0.04–0.82)*</td>
<td>1.06 (0.76–1.48)</td>
</tr>
<tr>
<td>Quartile 4 (high volume)</td>
<td>0.34 (0.06–2.04)</td>
<td>0.82 (0.56–1.22)</td>
</tr>
<tr>
<td><strong>Other payers caseloadb</strong></td>
<td>0.00 (0.00–2.32)</td>
<td>N/A*</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geographic location:</td>
<td>Urban</td>
<td>2.36 (0.61–9.14)</td>
</tr>
<tr>
<td>Tax status:</td>
<td>For-profit</td>
<td>1.33 (0.36–5.00)</td>
</tr>
<tr>
<td>System affiliation:</td>
<td>Yes</td>
<td>1.03 (0.45–2.37)</td>
</tr>
<tr>
<td>Teaching hospital:</td>
<td>Yes</td>
<td>1.30 (0.38–4.49)</td>
</tr>
<tr>
<td>Natural log of bed size</td>
<td></td>
<td>1.70 (0.82–3.55)</td>
</tr>
<tr>
<td>Unadjusted case mix index</td>
<td></td>
<td>1.71 (0.24–11.96)</td>
</tr>
</tbody>
</table>

Note: Logistic regression used to compute adjusted odds ratio controlling for variables listed in table. CI = confidence interval.

N/A = not applicable.

*aNot applicable because the AHA data set does not include information on private payers’ caseload.

*bMeasured continuously.

*p < 0.05, **p < 0.01, ***p < 0.001.
**EXHIBIT 4**
Relationship Between Payer Mix and EHR Adoption in Hospitals: Results of a Multinomial Regression Whereby “Full EHR Adoption” is the Reference Category

<table>
<thead>
<tr>
<th>Payer Mix: Independent Variables</th>
<th>EHR Adoption (coef.)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Medicare caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (&lt;33% of discharge)</td>
<td>−0.278</td>
<td>0.378</td>
</tr>
<tr>
<td>Quartile 2 (34–42% of discharge)</td>
<td>−0.613</td>
<td>−0.925</td>
</tr>
<tr>
<td>Quartile 3 (43–53% of discharge)</td>
<td>1.038</td>
<td>2.210</td>
</tr>
<tr>
<td>Quartile 4 (54+% of discharge)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Medicaid caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (&lt;8% of discharge)</td>
<td>0.319</td>
<td>−0.879</td>
</tr>
<tr>
<td>Quartile 2 (9–15% of discharge)</td>
<td>0.827</td>
<td>0.424</td>
</tr>
<tr>
<td>Quartile 3 (16–21% of discharge)</td>
<td>−0.575</td>
<td>−0.390</td>
</tr>
<tr>
<td>Quartile 4 (22+% of discharge)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Commercial insurance caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (&lt;4% of discharge)</td>
<td>−0.818</td>
<td>0.232</td>
</tr>
<tr>
<td>Quartile 2 (5–12% of discharge)</td>
<td>−0.715</td>
<td>0.160</td>
</tr>
<tr>
<td>Quartile 3 (13–21% of discharge)</td>
<td>−0.458</td>
<td>0.416</td>
</tr>
<tr>
<td>Quartile 4 (22+% of discharge)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Managed care insurance caseload</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 1 (&lt;2% of discharge)</td>
<td>0.834</td>
<td>2.036</td>
</tr>
<tr>
<td>Quartile 2 (3–14% of discharge)</td>
<td>1.440</td>
<td>2.289*</td>
</tr>
<tr>
<td>Quartile 3 (15–26% of discharge)</td>
<td>0.586</td>
<td>1.970</td>
</tr>
<tr>
<td>Quartile 4 (27+% of discharge)</td>
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<td>Natural log of bed size</td>
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<tr>
<td>Unadjusted case mix index</td>
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<td>0.268</td>
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*Measured continuously.

*p < 0.05, **p < 0.01, ***p < 0.001.
hospitals, less attention has been paid to the association of payer mix and hospital EHR adoption. Given the federal government’s provision of financial incentives to promote the adoption and meaningful use of EHR through the HITECH Act, we suggest that policymakers and hospital decision makers need a better understanding about the influence of payer mix on EHR adoption to fully realize the benefit of the legislation. In the absence of a previous analysis utilizing national data, we examine how the proportion of discharges paid by each payer is associated with EHR adoption by hospitals.

The findings in our current study suggest a weak relationship between payer mix and hospital EHR adoption. Even though we found that certain increases in Medicare caseloads were generally negatively associated with EHR adoption in univariate analysis, overall, these differences disappeared in our adjusted models. Furthermore, most of the other payer mix variables were not associated with our outcome measure in any systematic way. These findings are in conflict with the existing studies that have found a relationship between individual HIT applications and payer mix (Furukawa et al. 2008). One possible explanation for this result may be that the adoption of an EHR system is differentially influenced by payer mix relative to the adoption of other types of HIT applications. Full EHR adoption may be the final phase of HIT adoption in hospitals. Thus, it is possible that payer mix influences the adoption of infrastructure-related HIT applications such as pharmacy, laboratory, and radiology systems, but not complete EHR systems. If so, it is possible that the infrastructure-related HIT applications are less sensitive to resource availability. Perhaps the financial flexibility arising from serving patients from relatively generous payers may only apply to certain, not all, HIT decisions. This possibility would explain why we found a weak relationship between payer mix and hospital EHR adoption, whereas previous studies found a significant relationship between payer mix and the adoption of pharmacy and laboratory information systems (McCullough 2008) as well as other clinical, administrative, or strategic HIT applications (Furukawa et al. 2008; Menachemi et al. 2007).

We expected that hospitals with higher proportions of public payer caseloads would be less likely to have an EHR system. We found no evidence to support this hypothesis in either the model using the NIS data or the model using the AHA payer mix data. Overall, this lack of evidence suggests the possibility that indirect incentives generated by payer generosity (as discussed earlier) may not be a strong factor influencing EHR adoption in hospitals. Under the HITECH program’s direct incentives for EHR adoption, hospitals with comparably larger Medicare and Medicaid patient caseloads will be compensated proportionately higher for achieving meaningful use of EHRs. Thus, the HITECH Act has the potential, with some provisos, to assist in motivating hospitals that disproportionately serve Medicare and/or Medicaid patients to adopt an EHR and achieve meaningful use, thus fulfilling the intended objective of the legislation.
The first consideration for hospitals with high Medicare and/or Medicaid case mix is the level of HITECH program reward versus the total cost of ownership for an EHR. If the program’s payback exceeds the financial cost of the EHR, then adopting a system is a rational choice. However, the program is designed to offset the EHR’s purchase price and does not take into account the expenses associated with workflow redesign, temporary losses in productivity, and so forth (i.e., the total cost of ownership). Such analysis also may not consider potential quality gains associated with EHR use. Therefore, the decision to adopt an EHR is more complicated than merely to pursue the HITECH rewards. Considering discussions in a recent study that focused on ambulatory EHR adoption (Song et al. 2011), hospitals could benefit from considering the financial and nonfinancial benefits of EHRs when calculating the expected cost-benefit ratio of pursuing the incentive payments.

A second concern regarding hospitals with high Medicare and/or Medicaid caseloads relates to unintended consequences from the policymaker’s perspective. The EHR incentive program may induce already undercapitalized hospitals to adopt a more leveraged position and face an increased risk of failure as they strive to meet the goals. Even if facilities choose not to invest in an EHR, the penalty phase of the meaningful use program may further cut into already faltering budgets. If these facilities are safety-net hospitals, the program may have the unintended consequence of hastening the failure of some of the very hospitals it is intended to assist and the concomitant impact on the most vulnerable populations in the United States. Of particular concern is the possibility that small, rural facilities will be adversely affected.

Our study also found that hospitals in the third highest category (out of four) as measured on the basis of managed care insurance caseloads were less likely than those with the lowest managed care caseloads to adopt EHR. While this finding is inconsistent with our hypotheses, it does not represent a systematic relationship between managed care caseloads and EHR adoption in hospitals. Thus, more research is needed to further understand this finding. On the other hand, several of our control variables were associated with EHR adoption in ways consistent with expectations based on previous HIT research. For example, in our study, urban hospitals (Burke et al. 2002; Furukawa et al. 2008), non-profit hospitals (Menachemi et al. 2007), system-affiliated hospitals (Wang et al. 2005), and larger hospitals (Burke et al. 2002; Furukawa et al. 2008) were all more likely to have adopted EHRs.

The findings of this study offer practical implications for hospital decision makers and raise an important issue regarding national efforts imbedded in the HITECH Act. If payer generosity, or the indirect influence of payers, does not spur EHR adoption in hospitals, then the direct incentives in HITECH may represent the needed policy lever to influence EHR adoption. The important question becomes whether the direct incentives in the EHR adoption program will be motivation enough to overcome the resistance from some hospitals to begin the process.
of achieving meaningful use. Future research is needed to determine the full impact of the HITECH Act. Such research can utilize either the NIS or the AHA data to examine how Medicare and Medicaid caseloads are associated with EHR adoption after the HITECH Act has had more time to take hold. In the meantime, hospital decision makers should be aware that while the financial flexibility afforded by catering to more privately insured patients may enable the adoption of certain infrastructure HIT applications, such changes may not enable the adoption of EHRs.

The current study has several strengths. First, our topic is concerned with an important contemporary issue and makes use of a relatively large sample of hospitals potentially representative of US community hospitals. Furthermore, we make use of multiple data sources, which may help overcome common methods bias that negatively impacts the internal validity of studies using data extracted from a single source (Iezzoni 2003). Despite these strengths, our analysis is limited in some aspects. First, given the cross-sectional observational nature of our analyses, we are unable to infer any causal relationship between payer mix and hospital EHR adoption. Therefore, our findings should be interpreted as associations only. Second, our sample size was inevitably decreased in the process of merging data sets and operationalizing our dependent and independent variables. We tried to overcome this limitation by running parallel analyses using a larger sample from the AHA Annual Survey, which contains less detailed payer information. The results of both analyses were similar. Lastly, our work is limited by the possibility of data entry and coding errors that can occur in secondary databases.

REFERENCES


PayEr M Ix an D EH r aDoPtIon In H os PI tals

The authors make an important distinction between health information technology (HIT) and an electronic health record (EHR) in terms of considering the impact of payers on the adoption and use of EHRs. HIT includes numerous processes, from billing and demographic systems to laboratory results systems. EHRs, on the other hand, are mainly used to document patient visits and to combine those discrete data into useful and manageable data elements.

The requirements for reimbursement from most payers—especially the Centers for Medicare & Medicaid Services (CMS)—are constantly changing, and healthcare providers must be able to change rapidly to meet them. HIT systems make available accurate data to providers for obtaining reimbursement, reducing the risk of having to refund payments following audits. EHRs provide practices and organizations—especially those with a significant CMS patient mix—with a tool to help them avoid penalties for noncompliance of the Health Information Technology for Economic and Clinical Health (HITECH) Act once they are in effect.

The physician practice within the Department of Pediatrics at the University of Alabama at Birmingham, consisting of approximately 140 physicians in 16 subspecialty divisions, gained an important head start that many did not have in facing compliance challenges. In 1998, the Department of Pediatrics began its transition to electronic charting with guidance and financial support from the Children’s Hospital of Alabama. Our physician population, then, was already accustomed to using electronic documentation when the HITECH Act was passed.

Our patient mix is approximately 70 percent Medicaid, 25 percent Blue Cross, and 5 percent other. The high proportion of Medicaid patients positioned us to work closely with our state Medicaid agency and allowed us to capitalize on the incentives available. The theory that practices with high Medicaid caseloads will adopt EHRs more quickly than other practices proved true in our case. With such a high volume of Medicaid patients and an established EHR, we were able to meet the adoption, implementation, and upgrading (AIU) requirements for receiving the Medicaid incentives offered for implementation. The time frame in which we received payments from the year 1 AIU incentives was fortuitous considering the poor financial condition of the state’s Medicaid program and our reduced reimbursement. Our senior leaders have taken a firm stance in support of implementing technical and user requirements to earn further incentives and avoid impending penalties. While EHR adopters should understand that the demands on clinicians’ time may be as much a detriment to their implementation as the financial cost, we found that spreading the implementation costs over many years was the key to our success.
In general, however, Medicaid’s lower reimbursement rates put groups with high Medicaid volumes at a disadvantage when it comes to implementing EHRs, as suggested in this study. While CMS reimbursement may be lower than ever before, the agency’s influence on EHR adoption is undeniable, as most providers cannot afford to exclude CMS patients. Given the rising enrollment in CMS programs, most providers, both private and government sponsored, will be forced to conform to the provisions set forth in the HITECH Act, whether or not they choose to capitalize on the incentives available.

For the Department of Pediatrics, the incentives not only pushed our group to advance our EHR usage but also provided much needed support during challenging financial times.
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Jul/Aug 2012

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