The Creating Incentives and Continuity Leading to Efficiency Staffing Model: A Quality Improvement Initiative in Hospital Medicine

Shalini Chandra, MD, MS; Scott M. Wright, MD; and Eric E. Howell, MD

Abstract

Objective: To determine the effect of a hospitalist-developed, continuity-centered hospitalist staffing model on patient outcomes and resource use.

Methods: The Creating Incentives and Continuity Leading to Efficiency (CICLE) staffing model was conceived by a group of hospitalists who sought to improve continuity of inpatient care. Using a retrospective, observational, pre-post study design, we compared patient-level data for all discharges from our hospitalist service from 6 months after implementation of the CICLE staffing model (September 1, 2009, through February 28, 2010; n=1585) with data from those same months in the prior year (September 1, 2008, through February 28, 2009; n=1808). We used the number of unique hospitalists who documented an encounter during the admission as a measure of continuity of care. Length of stay and hospital charges per admission constituted the measures of resource use.

Results: The odds of having a single hospitalist for the entire hospitalization nearly doubled under the CICLE model (odds ratio, 1.87; 95% confidence interval, 1.60-2.2; $P<.001$). Mean length of stay decreased 7.5% (from 2.92 before to 2.70 days after initiation of the model; $P<.001$). Mean hospital charge per admission decreased 8.5% (from \$7224.33 before to \$6607.79 after initiation of the model; $P<.001$). Thirty-day readmission rates were not substantially affected by the CICLE model (15.0% before to 17.3% after initiation of the model; $P=.08$).

Conclusion: Improved continuity of care among hospitalists was associated with reductions in length of stay and lower health care costs. These benefits were realized without substantially affecting readmission rates. The staffing model can be achieved by reorganizing existing hospitalists and may not require the hiring of additional personnel. The CICLE staffing model is a viable option for hospitalist groups that are aiming to diminish resource use and improve quality of care.

© 2012 Mayo Foundation for Medical Education and Research ■ Mayo Clin Proc. 2012;87(4):364-371

From the Division of Hospital Medicine (S.C., E.E.H.), and Division of Internal Medicine (S.M.W.), Johns Hopkins Bayview Medical Center, Johns Hopkins University School of Medicine, Baltimore, MD.

Hospital medicine is the fastest growing medical specialty, with hospitalists numbering close to 30,000 and providing care in more than half of US hospitals.^{1,2} Several studies³⁻⁸ have linked hospitalists with improved efficiency and efficacy of inpatient care. A major drawback of hospital medicine is the breach in continuity of care. By definition, hospital medicine creates discontinuity between outpatient and inpatient settings. In-hospital continuity of care is further fractured by the shift-based and block-based scheduling models that are required to ensure the 24-hours-per-day, 7-days-per-week coverage—a mainstay of most hospitalist programs. Shift-based and block-based scheduling models result in increased “hand-offs” between hospitalists at change of service. As identified by the Joint Commission’s National Patient Safety Goals, handoffs are known to be vulnerable to communication failures and are associated with sentinel events,⁹ excess resource use, and prolonged length of stay (LOS).¹⁰⁻¹² Although the hospital medicine literature is rich with reports focusing on the inpatient-outpatient transitions¹³⁻²⁰ and the Society of Hospital Medicine (SHM) has been devel-

oping guidelines for best handoff procedures,²¹ to our knowledge no reports have been published about innovations that improve in-hospital continuity of care by hospitalists.

Our hospitalist group developed and implemented a quality improvement initiative that focuses on improving in-hospital physician continuity of care and reducing the number of handoffs among hospitalists. The objectives of this study were to test whether the Combining Incentives and Continuity Leading to Efficiency (CICLE) staffing model improved continuity of care and to assess the effect of the model on resource use. We hypothesized that the CICLE model would influence continuity of care positively and reduce resource use.

METHODS

Setting and Study Design

This study took place at Johns Hopkins Bayview Medical Center, a 335-bed, university-affiliated medical center in Baltimore, Maryland. The Hospitalist Division is a combined physician and nurse

practitioner/physician assistant (NPPA) academic division within Johns Hopkins University School of Medicine. The division admits approximately 6000 patients annually to the Collaborative Inpatient Medicine Service (CIMS), the 24-hours-per-day, 7-days-per-week hospitalist service that provides direct patient care without house officers. The CICLE intervention was implemented on August 8, 2009. We used a retrospective, observational, pre-post study design to compare patient-level clinical data from 6 months of the intervention period (September 1, 2009, through February 28, 2010) with data from those same months in the prior year (September 1, 2008, through February 28, 2009).

Study Population

Hospitalists. All CIMS physicians and NPPAs were included in both staffing models. Between the 2 study periods, the division increased from 31 hospitalists under the traditional model (22.9 full-time equivalent [FTE] physicians and 5.9 FTE NPPAs) to 35 hospitalists under the CICLE model (+11%; 24.9 FTE physicians and 7.7 FTE NPPAs). Three hospitalists left the CIMS and 7 new hospitalists joined the CIMS between the 2 study periods. NPPAs had a daily maximum. The mean number of years of experience as a hospitalist was similar for both periods (3.3 under the traditional model and 3.5 under the CICLE model; $P=.77$; Table 1).

Patients. All admitted patients discharged from the CIMS during the study periods were included in the analysis. We excluded patients who were considered to be outpatients, namely, those hospitalized under observation status. The patients were similar in sex, race, age, insurance status, and primary diagnosis (Table 1).

Intervention

Traditional Model. Before implementation of the CICLE model, the CIMS daytime clinical staffing model consisted of 1 Monday-to-Friday 5-day block and several 3-day, 2-day, and 1-day blocks haphazardly scheduled during weekdays and weekends. Given the academic mission of the division, multiple 5-day blocks could not be scheduled without compromising the scholarly activities of the faculty. Physicians and NPPAs had a daily maximum census of 12 and 10 patients, respectively. Hospitalists would be eligible for new patients any time their census was below the maximum. They admitted and/or received new patients every day to maintain their census cap. When a hospitalist completed his/her block of shifts and went off service, he/she would hand off

the care of the remaining patients by providing a verbal and electronic sign-out to the incoming hospitalist.

CICLE Model. The CICLE model was conceived by a group of our hospitalists who were dissatisfied with the traditional model because (1) they were admitting and/or caring for new patients every day, (2) they were receiving and handing over up to 12 patients when coming on or going off service, and (3) as salaried health care professionals there was a disincentive for discharging patients before the end of their block because they would receive the equivalent number of new patients the following day to maintain their census cap. CICLE's primary goal is to improve the continuity of care by attempting to pair each patient with a single attending physician for the duration of the hospitalization. A secondary objective is to provide physicians with an incentive to discharge patients at the appropriate time with high-quality discharge planning. Because the mean LOS on general medical wards is approximately 4 days, the 4-day CICLE sequence became the foundation of the CICLE staffing model.

Each day a new physician begins a 4-day CICLE sequence that is scheduled as a 40-hour cycle (8 hours, 12 hours, 10 hours, and 10 hours). On day 1, the physician cyclist exclusively admits patients. On day 2, the physician continues to care for the remaining day 1 patients and patients admitted overnight to attain a personal census of 10 to 12 patients. On days 3 and 4, the physician continues to care for the remaining day 2 patients and does not receive any new patients. At the end of the CICLE sequence, the physician transitions the remaining patients to the next physician cyclist or to the red team via a verbal and electronic sign-out.

Because CICLE was implemented without any supplementary funding or additional FTE resources, staffing allowed for only 60% penetrance of the CICLE sequence. The remaining 40% of CIMS patients were cared for by the red team. The red team consists of 2 NPPAs daily (except on weekends, when there is only one) and one supervising physician. The physician works a 4-day clinical block. Every 4 days a new 4-day block begins, regardless of weekday or weekend. The NPPAs work 1- to 3-day blocks. Each NPPA covers a maximum of 10 patients per day, and the physician supervising the NPPAs covers a maximum of 8 additional patients. Red team hospitalists are eligible for new patients any time their census falls below the maximum. Night shift staffing and scheduling remain unchanged under the CICLE model.

TABLE 1. Characteristics of Hospitalists and Patients^{a,b}

Characteristic	Traditional model, No. (%)	CICLE model, No. (%)
Total hospitalists	31	35
Physicians	24 (77)	26 (74)
Nurse practitioner or physician assistant	7 (23)	9 (26)
Sex		
Female	18 (58)	22 (63)
Race		
African American	3 (10)	6 (17)
Asian	8 (26)	8 (23)
White	19 (61)	20 (57)
Hispanic	1 (3)	1 (3)
Board-certified physicians	24 (100)	26 (100)
Years as hospitalist, mean (SD)	3.27 (3.34)	3.54 (3.52)
Ratio of total admissions to full-time equivalent	55	55
Total patients	1585	1808
Sex		
Female	863 (54)	981 (54)
Age, y		
18-50	428 (27)	508 (28)
51-64	375 (24)	502 (28)
65-80	421 (27)	407 (23)
≥81	361 (23)	391 (22)
Race		
African American	354 (22)	418 (23)
White	1193 (75)	1332 (74)
Insurance status		
Federally funded plan (Medicare or CHAMPUS)	842 (53)	868 (48)
Managed care plan	383 (24)	480 (27)
State-funded plan (Medicaid or medical assistance)	183 (12)	206 (11)
Commercial insurance plan	110 (7)	157 (9)
Self-pay	67 (4)	96 (5)
Most common diagnosis related groups (code)		
Chronic obstructive pulmonary disease (140)	146 (9)	132 (7)
Cellulitis (383)	101 (6)	100 (6)
Pneumonia (139)	85 (5)	100 (6)
Heart failure (194)	84 (5)	92 (5)
Kidney and/or urinary tract infection (463)	61 (4)	85 (5)

^aCICLE = Creating Incentives and Continuity Leading to Efficiency; CHAMPUS = Civilian Health and Medical Program of the Uniformed Services.

^bData are presented as No. (percentage) unless otherwise indicated. $P > .05$ for all entries.

Data Sources, Data Collection, and Outcomes

The case management department compiled the personally deidentified patient-level data that were used for all analyses. The measurement of continuity of care was based on one of The Joint Commission's definitions of handoff: "physician's (provider's) transfer of complete responsibility for a patient."²² The case management department queried the electronic medical

records to count the number of unique hospitalists who documented a history and physical examination or a progress note for each admission during the 2 study periods. Admissions were then categorized as having 1, 2, or more than 2 unique hospitalists for the entire hospitalization. Each increase in the number of unique hospitalists beyond one represented a "service-change handoff," as described previously.

The LOS, readmission rates, payer-denied days, and hospital charges measure various aspects of efficiency, resource use, and quality. Readmission rates were calculated for 7-, 15-, and 30-day readmissions as the number of elapsed days since discharge from the incident hospitalization. Admissions were categorized as having zero vs any payer-denied days of care. Case mix (CM) weight served as an effect modifier for LOS and hospital charges.

Each fiscal year, the state of Maryland determines a CM weight for each combination of diagnosis related group code and severity of illness (ranging from 1 to 4) based on its expected resource use. To reduce potential confounding from differences in the state's fiscal year CM assignments, the case management department provided us with the fiscal year 2010 CM weight and calculated the CM-adjusted LOS for each admission by dividing the actual LOS by the CM weight for every admission in the entire data set.

The case management department also generated patient-level data for hospital charges, categorized by cost center. Total hospital charges, inpatient medication charges, inpatient laboratory charges, and inpatient radiology charges were used as markers of health care costs from the patient and payer perspective. The state of Maryland regulates each hospital's inpatient charges based on the hospital's mean CM weight or CM index. In fiscal year 2008, the difference between the mean charge per admission and the respective cost per admission was approximately 4% in the state of Maryland.²³

Sample Size Calculation and Data Analyses

The CICLE model was implemented on August 8, 2009. To allow for 1 month of transition, we included patient-level data for all discharges from the CIMS service during the 6 months following approximately 30 days after implementation (September 1, 2009, through February 28, 2010) and from the same months from the previous fiscal year (September 1, 2008, through February 28, 2009). The sample size for the efficiency and resource use analysis was thus based on available data.

We conducted all data analyses using the statistical software Stata/IC 11.1 (StataCorp LP, College Station, TX). Simple descriptive measures were calculated for all outcome variables: mean and SD for continuous variables and proportions and percentages for categorical variables. For the continuity-of-care analysis, we first categorized each admission in 2 separate ways: as having (1) 1 vs more than 2, or (2) 1 or 2 vs 3 or more unique hospitalists for the entire hospitalization. We then used separate simple logistic regression models to assess and compare the odds of having (1) 1 vs more than 1 and (2) 1 or 2 vs 3 or more hospitalists per admission under the

CICLE model vs the traditional model. To assess the effect of CICLE on CM index, LOS, and hospital charges per admission, we constructed robust linear regression models using the Huber-White sandwich estimator of the variance, a method of robust linear regression, to account for the lack of independence (correlation) among observations in the data set and to adjust for outliers.²⁴⁻²⁶ To investigate the potential influence of CM as an effect modifier of LOS on hospital charges, we included an interaction term in the Huber-White robust regression model and compared CM-adjusted LOS charges between the traditional model and the CICLE model. To measure the effect of CICLE on readmission rates, we used simple logistic regression. To appraise the effect of CICLE on payer-denied days, we categorized each admission as having zero vs any payer-denied days and then performed simple logistic regression analysis.

RESULTS

The CIMS cared for approximately the same number of patients under the CICLE model as they did under the traditional model in the prior year (1585 and 1808, respectively) (Table 1). The total number of admissions per FTE was stable at 55 admissions per hospitalist during both study periods (Table 1).

Continuity of Care

The proportion of patients cared for by a single hospitalist for the entirety of their hospitalization increased 10.9% (from 17.3% under the traditional model to 28.2% under the CICLE model; $P < .001$; Table 2). The odds of having a single hospitalist for the entire hospitalization nearly doubled under the CICLE model (odds ratio, 1.87; 95% confidence interval, 1.589-2.213; $P < .001$; Table 2). Adjusting for LOS, the odds of having a single hospitalist for the entire hospitalization was also significantly higher under the CICLE model (odds ratio, 1.82; 95% confidence interval, 1.542-2.161, $P < .001$). For any given admission, each additional hospitalist was associated with an increase in LOS by 1.91 days ($P < .001$), accounting for 34.3% of the variance in LOS based on the r^2 of linear regression modeling.

LOS and Readmission Rates

The outlier-adjusted mean LOS decreased 7.5% (from 2.92 days before to 2.70 days after initiation of the model; $P < .001$; Table 2). The 7-day, 15-day, and 30-day readmission rates were all slightly lower under the traditional model compared with the CICLE model; however, these differences were not statistically significant ($P = .17$, $P = .06$, and $P = .08$, respectively; Table 2).

TABLE 2. Comparison of Data From the 2 Study Periods: The Traditional Staffing Model and the CICLE Staffing Model^{a-d}

Variable	Traditional model	CICLE model	Difference (%)	95% CI	P value
Volume	1585	1808	223 (12.3)		
Case mix index, mean (SD)	0.67 (0.01)	0.63 (0.01)	0.04 (6.0)	−0.046 to −0.018	<.001
Length of stay (days) mean (SD)	2.92 (0.05)	2.70 (0.05)	0.22 (7.5)	−0.349 to −0.090	.001
Hospital charge per admission (\$), mean (SD)	7224.33 (97.39)	6607.79 (91.19)	616.54 (8.5)	−878.12 to −354.95	<.001
Variable	Traditional model	CICLE model	Odds Ratio	95% CI	P value
Admissions with a single hospitalist involved in care, No. (%)	274 (17.3)	509 (28.2)	1.87	1.589-2.213	<.001
Admissions with 1 or 2 hospitalists involved in care, No. (%)	1004 (63.3)	1321 (73.1)	1.57	1.357-1.816	<.001
7-Day readmission rate, No. (%)	81 (5.1)	112 (6.2)	1.22	0.914-1.646	.17
15-Day readmission rate, No. (%)	150 (9.5)	207 (11.5)	1.24	0.991-1.544	.06
30-Day readmission rate, No. (%)	238 (15.0)	312 (17.3)	1.20	0.982-1.42	.08
Admissions with ≥1 payer-denied days, No. (%)	75 (4.7)	60 (3.3)	0.69	0.489-0.977	.04

^aCI = confidence interval; CICLE = Creating Incentives and Continuity Leading to Efficiency; OR = odds ratio.

^bComparisons of case mix index, length of stay, and hospital charge per admission are based on linear regression modeling adjusted for outliers using Huber-White method of robust regression.

^cOn the basis of the Huber-White method of robust linear regression, the mean length of stay was 0.14 day lower under the CICLE model on adjusting for effects of case mix weight (95% CI, −0.257 to −0.023; $P=.02$).

^dComparisons related to number of hospitalists involved in care, readmission rates, and payer-denied days are based on simple logistic regressions.

Charges

Under the CICLE model, the percent change in mean total hospital charge per hospitalization was 8.5% (from \$7224.33 before to \$6607.79 after initiation of the model; $P<.001$; Table 3). Total hospital charges adjusted for CM-adjusted LOS decreased on average by \$403.39 ($P<.001$; Table 3). The r^2 from regression modeling of total charges revealed that

charges associated with inpatient medications, laboratory testing, and radiology services explained 82.1% of the variance in total hospital charges. The percent decrease in charges associated with inpatient medications was 48.5% under the CICLE model ($P<.001$; Table 3). The proportion of admissions with 1 or more payer-denied days decreased from 4.7% to 3.3% ($P=.04$; Table 2).

TABLE 3. Comparison of Charge Data From the 2 Study Periods: The Traditional Staffing Model and the CICLE Staffing Model^{a-c}

Variable	Traditional model, mean (SD)	CICLE model, mean (SD)	Difference (95% CI)	P value	Difference adjusted for case mix-adjusted length of stay (95% CI)	P value
Total hospital charges	7224.33 (97.39)	6607.79 (91.19)	616.54 (−878.12 to −354.95)	<.001	403.39 (−578.51 to −228.26)	<.001
Inpatient medication charges	214.84 (3.98)	110.75 (3.73)	104.09 (−114.78 to −93.39)	<.001	107.84 (−118.22 to −97.45)	<.001
Inpatient laboratory charges	686.89 (10.37)	641.40 (9.71)	45.49 (−73.34 to −17.64)	.001	35.28 (−61.26 to −9.31)	.008
Inpatient diagnostic imaging charges	453.14 (12.83)	461.63 (12.01)	8.49 (−25.98 to 42.94)	.63	12.56 (−21.60 to 46.74)	.47
Other inpatient charges ^d	5477.22 (77.75)	5145.28 (72.80)	331.94 (−540.77 to −123.10)	.002	173.19 (−305.15 to −41.22)	.01

^aCI = confidence interval; CICLE = Creating Incentives and Continuity Leading to Efficiency.

^bData are presented in US dollars.

^cAll comparisons are based on linear regression modeling adjusted for outliers using Huber method of robust regression.

^dOther inpatient charges include nursing, supplies, ancillary services, etc.

DISCUSSION

Handoffs in patient care have been recognized as being responsible for preventable adverse events²⁷⁻²⁹ and excess resource use^{27,30,31} by the Joint Commission, the Institute of Medicine, and the SHM. As such, transfers of patient care are the subject of increased attention from health care researchers, policymakers, administrators, and patients themselves. Because individual hospitalists cannot remain in the hospital 24 hours a day, 7 days a week, some discontinuity in care is unavoidable in hospital medicine. We propose the CICLE hospitalist staffing model to improve the inpatient continuity of care. The CICLE model has been successful in meeting its objective and is associated with reductions in LOS and health care costs without substantial effect on readmission rates and at zero implementation cost. That said, the trend toward higher readmissions rates noted during the period of improved continuity was a surprising finding to the authorship team.

Discontinuity in inpatient care can result in hazards that are threats to patient safety, can increase unnecessary use of resources, and is thought to diminish patient satisfaction.^{10-12,27-33} Given that some in-hospital handoffs are inevitable, researchers and policymakers are emphasizing initiatives to standardize transfers of care. Nonetheless, in their comprehensive review of the handoff literature, Cohen and Hilligoss³⁴ were unable to point to any reliable evidence linking handoff standardization to substantive gains in measurable patient outcomes. By reducing the number of handoffs and the number of hospitalists involved in any given hospitalization, our CICLE model attacks the inpatient continuity-of-care problem at its very root.

The patient-focused model, a hospitalist scheduling model described by SHM, is also designed to maintain continuity of care.³⁵ Under the patient-focused model, hospitalists work in 2-week blocks during which hospitalists cover their own patients 24 hours per day, for the entire 14 days, but accept new patients only during the first week. Evaluations to measure the effect of the patient-focused model have not been published. Working 14 consecutive days may result in hospitalist fatigue and burnout. Like the patient-focused model, the CICLE model maintains continuity of care; however, with shorter cycles (4 days), it probably lessens the likelihood of fatigue and burnout.

Our work supports the finding of Epstein et al¹² that increased fragmentation of care is associated with longer LOS. The CICLE model guarantees at least 3 days (and usually 4 days) of continuity. Patients whose LOS is longer than 4 days are likely to be subsequently cared for by another single hospitalist, which explains the significant improvement in continuity of care and reductions in handoffs under

the CICLE model. With fewer hospitalists involved with each admission, plans of care are less likely to be questioned and changed midcourse, resulting in more streamlined and cost-effective care. Whereas a new hospitalist may feel uncomfortable discharging a patient that he/she is meeting for the first time, the hospitalist who has cared for a patient from admission onward can appreciate the progress and may have more confidence in discharging the patient as soon as it is appropriate to do so. Furthermore, by protecting physicians from new admissions on day 3 and day 4 of the cycle, physicians have more time to focus on planning safer discharges and patient education for the patients who remain on their service.

Because the model was designed by the hospitalists themselves, buy-in and engagement are deep and genuine. The dedication to ensuring CICLE's success may be greater than what might have been seen with a leadership-designed, top-down initiative. Knowing that they will have a smaller census to care for on the next day is a real incentive for hospitalists to discharge patients as soon as the patients are ready to go home. This reality may influence behaviors and how time is allocated among patients; a hospitalist may choose to spend more time with patient A, preparing the patient for an afternoon discharge, knowing that the smaller census on the following day will allow the hospitalist to connect more deeply and make up the time with another patient tomorrow. If workflow is considered carefully, CICLE can be a win-win for all stakeholders, especially patients.

Several limitations of this study should be considered. First, it was conducted at a single hospital, and thus the results may not be generalizable. Second, the CICLE teams covered a large proportion of admissions cared for by our hospitalist group, but the remaining patients were admitted directly to the red team under the traditional model, thus diluting the effect of the CICLE model. Third, the CICLE model was designed with continuity and efficiency in mind. Hospitalists working within productivity-based compensation models may not be amenable to a scheduling model that effectively encourages lower hospitalist censuses. Our hospitalists are salaried with minimal bonuses tied to clinical productivity. With shorter LOS and no new admissions beyond day 2 of the cycle, individual professional fee bills may decrease. Finally, the retrospective, observational study design may not be as robust as a cluster-randomized trial or a randomized controlled trial, but pre-outcome vs post-outcome comparison is commonly used in quality improvement initiatives when randomized trials are not possible. That said, there are potential biases inherent in our study de-

sign. Our study may have been predisposed to selection-history bias due to changes in hospitalist or patient demographics; however, both sets of demographics were similar across study periods. Individual hospitalists may have matured during the period between the 2 study periods, leading to a potential performance change bias; however, we lost 3 experienced hospitalists and gained 6 with limited experience in hospital medicine. Although our study was vulnerable to circumstantial changes, apart from the CICLE model, we are unaware of any changes in our health care system that could have influenced the outcomes. We have made a full attempt to comply with SQUIRE (Standards for Quality Improvement Reporting Excellence) guidelines³⁶ in reporting about our quality improvement initiative.

CONCLUSION

The CICLE staffing model improves continuity of inpatient care and decreases the number of hospitalists involved with any given admission. The CICLE model is also associated with reduced LOS and health care costs. The benefits are accomplished without substantially affecting readmission rates and at zero implementation cost. In the era of value-driven health care, the CICLE staffing model is a viable option for hospitalist groups that are truly committed to quality patient care, and we encourage policymakers and hospital leaders to support hospitalist groups in further exploring and considering implementation of the CICLE model.

ACKNOWLEDGMENTS

We are indebted to Ramesh Chandra, PhD, Marie Diener-West, PhD, Barbara Brigade, Regina Landis, Tiffani Panek, Angel Sampedro, and all the hospitalists at Johns Hopkins Bayview Medical Center for their involvement in this project.

Abbreviations and Acronyms: CICLE = Combining Incentives and Continuity Leading to Efficiency; CIMS = Collaborative Inpatient Medicine Service; CM = case mix; FTE = full-time equivalent; LOS = length of stay; NPPA = nurse practitioner/physician assistant; SHM = Society of Hospital Medicine

Potential Competing Interests: Dr Wright is a Miller-Coulson Family Scholar; the Miller-Coulson family, through the Johns Hopkins Center for Innovative Medicine, supported his work on this project.

Correspondence: Address to Shalini Chandra, MD, MS, Johns Hopkins University School of Medicine, Johns Hopkins Bayview Medical Center, Sixth Floor, West Tower, Mason Lord Bldg, 5200 Eastern Ave, Baltimore, MD 21224 (schand12@jhmi.edu).

REFERENCES

1. Miller JA. New study finds over half of US hospitals utilize hospitalists. http://www.hospitalmedicine.org/AM/Template.cfm?Section=Press_Releases&Template=/CM/HTMLDisplay.cfm&ContentID=21260. Accessed January 12, 2009.
2. Wachter RM. The state of hospital medicine in 2008. *Med Clin North Am*. 2008;92(2):265-273.
3. Hospitalists prove their worth for capitated providers, plans. *Capitation Manag Rep*. 2002;9(4):62-64, 49.
4. Coffman J, Rundall TG. The impact of hospitalists on the cost and quality of inpatient care in the United States: a research synthesis. *Med Care Res Rev*. 2005;62(4):379-406.
5. Everett GD, Anton MP, Jackson BK, Swigert C, Uddin N. Comparison of hospital costs and length of stay associated with general internists and hospitalist physicians at a community hospital. *Am J Manag Care*. 2004;10(9):626-630.
6. Lindenauer PK, Rothberg MB, Pekow PS, Kenwood C, Benjamin EM, Auerbach AD. Outcomes of care by hospitalists, general internists, and family physicians. *N Engl J Med*. 2007;357(25):2589-2600.
7. Peterson MC. A systematic review of outcomes and quality measures in adult patients cared for by hospitalists vs nonhospitalists. *Mayo Clin Proc*. 2009;84(3):248-254.
8. Srivastava R, Landrigan CP, Ross-Degnan D, et al. Impact of a hospitalist system on length of stay and cost for children with common conditions. *Pediatrics*. 2007;120(2):267-274.
9. Joint Commission. National Patient Safety Goals. 2010. http://www.jointcommission.org/standards_information/npsgs.aspx. Accessed July 14, 2010.
10. Lofgren RP, Gottlieb D, Williams RA, Rich EC. Post-call transfer of resident responsibility. *J Gen Intern Med*. 1990;5(6):501-505.
11. Rich EC, Gifford G, Dowd B. The effects of scheduled intern rotation on the cost and quality of teaching hospital care. *Eval Health Prof*. 1994;17(3):259-272.
12. Epstein K, Juarez E, Epstein A, Loya K, Singer A. The impact of fragmentation of hospitalist care on length of stay. *J Hosp Med*. 2010;5(6):335-338.
13. Arora VM, Faman JM. Care transitions for hospitalized patients. *Med Clin North Am*. 2008;92(2):315-324, viii.
14. Bell CM, Schnipper JL, Auerbach AD, et al. Association of communication between hospital-based physicians and primary care providers with patient outcomes. *J Gen Intern Med*. 2009;24(3):381-386.
15. Gleason KM, McDaniel MR, Feinglass J, et al. Results of the Medications At Transitions and Clinical Handoffs (MATCH) study: an analysis of medication reconciliation errors and risk factors at hospital admission. *J Gen Intern Med*. 2010;25(5):441-447.
16. Halasyamani L, Kripalani S, Coleman E, et al. Transition of care for hospitalized elderly patients: development of a discharge checklist for hospitalists. *J Hosp Med*. 2006;1(6):354-360.
17. Kripalani S, Jackson AT, Schnipper JL, Coleman EA. Promoting effective transitions of care at hospital discharge: a review of key issues for hospitalists. *J Hosp Med*. 2007;2(5):314-323.
18. Kripalani S, LeFevre F, Phillips CO, Williams MV, Basaviah P, Baker DW. Deficits in communication and information transfer between hospital-based and primary care physicians: implications for patient safety and continuity of care. *JAMA*. 2007;297(8):831-841.
19. Pham HH, Grossman JM, Cohen G, Bodenheimer T. Hospitalists and care transitions: the divorce of inpatient and outpatient care. *Health Aff (Millwood)*. 2008;27(5):1315-1327.

20. Snow V, Beck D, Budnitz T, et al. Transitions of Care: Consensus Policy Statement American College of Physicians-Society of General Internal Medicine-Society of Hospital Medicine-American Geriatrics Society-American College of Emergency Physicians-Society of Academic Emergency Medicine. *J Gen Intern Med*. 2009;24(8):971-976.
21. Arora VM, Manjarrez E, Dressler DD, Basaviah P, Halasyamani L, Kripalani S. Hospitalist handoffs: a systematic review and task force recommendations. *J Hosp Med*. 2009;4(7):433-440.
22. The Joint Commission. 2008 National Patient Safety Goals Handbook. Oakbrook Terrace, IL: The Joint Commission; 2009.
23. The Maryland Health Services Cost Review Commission. http://www.hsrc.state.md.us/hsp_Rates4.cfm. Accessed March 12, 2012.
24. Huber PJ. The behavior of maximum likelihood estimates under nonstandard conditions. In: *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*. Vol 1. Berkeley, CA: The University of California Press; Proc. 1967:221-233.
25. White H. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*. 1980;48(4):817-838.
26. Verardi V, Croux C. Robust regression in Stata. *Stata J*. 2009; 9(3):439-453.
27. Joint Commission Resources. Improving Hand-Off Communication. illustrated. Oakbrook Terrace, IL: Joint Commission Resources; 2007:134
28. Kohn LT, Corrigan JM, Donaldson MS. To Err Is Human: Building a Safer Health System: A Report of the Committee on Quality of Health Care in America. Institute of Medicine. Washington, DC: Institute of Medicine; 2000.
29. Arora VM, Manjarrez E, Dressler DD, Basaviah P, Halasyamani L, Kripalani S. Hospitalist handoffs: a systematic review and task force recommendations. *J Hosp Med*. 2009;4(7):433-440.
30. Leape LL, Brennan TA, Laird N, et al. The nature of adverse events in hospitalized patients. *N Engl J Med*. 1991;324(6):377-384.
31. Vincent C. Understanding and responding to adverse events. *N Engl J Med*. 2003;348(11):1051-1056.
32. Andrews LB, Stocking C, Krizek T, et al. An alternative strategy for studying adverse events in medical care. *Lancet*. 1997; 349(9048):309-313.
33. Griffith CH, Wilson JF, Rich EC. Intern call structure and patient satisfaction. *J Gen Intern Med*. 1997;12(5):308-310.
34. Cohen MD, Hilligoss PB. The published literature on handoffs in hospitals: deficiencies identified in an extensive review. *Qual Saf Health Care*. 2010;19(6):493-497.
35. Nelson J. Hospitalist schedules. <http://squire-statement.org>. Accessed March 12, 2012.
36. Ogrinc G, Mooney SE, Estrada C, et al. The SQUIRE (Standards for Quality Improvement Reporting Excellence) guidelines for quality improvement reporting: explanation and elaboration. *Qual Saf Health Care*. 2008;17(suppl 1):i13.