

# Intra-Hospital Transfers to a Higher Level of Care: Contribution to Total Hospital and Intensive Care Unit (ICU) Mortality and Length of Stay (LOS)

Gabriel J. Escobar, MD<sup>1</sup>  
 John D. Greene, MA<sup>1</sup>  
 Marla N. Gardner, BA<sup>1</sup>  
 Gregory P. Marelich, MD, FCCM<sup>2</sup>  
 Bryon Quick, MD<sup>3</sup>  
 Patricia Kipnis, PhD<sup>1,4</sup>

<sup>1</sup>Hospital Operations Research, Division of Research, Oakland, California.

<sup>2</sup>Critical Care, Kaiser Permanente Medical Center, Sacramento, California.

<sup>3</sup>Intensive Care Unit, Kaiser Permanente Medical Center, Oakland, California.

<sup>4</sup>Management, Information and Analysis, Kaiser Foundation Health Plan, Oakland, California.

This work was supported by a grant from the Kaiser Foundation Health Plan Inc., Kaiser Foundation Hospitals, Inc., and The Permanente Medical Group, Inc. ("Early Detection of Impending Physiologic Deterioration in Hospitalized Patients"). In addition, development work for some of the computer algorithms we employed was funded by the Sidney Garfield Memorial Fund.

Disclosure: Nothing to report.

**BACKGROUND:** Patients who experience intra-hospital transfers to a higher level of care (eg, ward to intensive care unit [ICU]) are known to have high mortality. However, these findings have been based on single-center studies or studies that employ ICU admissions as the denominator.

**OBJECTIVE:** To employ automated bed history data to examine outcomes of intra-hospital transfers using all hospital admissions as the denominator.

**DESIGN:** Retrospective cohort study.

**SETTING:** A total of 19 acute care hospitals.

**PATIENTS:** A total of 150,495 patients, who experienced 210,470 hospitalizations, admitted to these hospitals between November 1st, 2006 and January 31st, 2008.

**MEASUREMENTS:** Predictors were age, sex, admission type, admission diagnosis, physiologic derangement on admission, and pre-existing illness burden; outcomes were: 1) occurrence of intra-hospital transfer, 2) death following admission to the hospital, 3) death following transfer, and 4) total hospital length of stay (LOS).

**RESULTS:** A total of 7,868 hospitalizations that began with admission to either a general medical surgical ward or to a transitional care unit (TCU) had at least one transfer to a higher level of care. These hospitalizations constituted only 3.7% of all admissions, but accounted for 24.2% of all ICU admissions, 21.7% of all hospital deaths, and 13.2% of all hospital days. Models based on age, sex, preadmission laboratory test results, and comorbidities did not predict the occurrence of these transfers.

**CONCLUSIONS:** Patients transferred to higher level of care following admission to the hospital have excess mortality and LOS. *Journal of Hospital Medicine* 2011;6:74–80. © 2011 Society of Hospital Medicine.

**KEYWORDS:** failure to rescue, hospital mortality, intensive care unit, intra-hospital transfer, patient outcomes, transitional care unit.

Additional Supporting Information may be found in the online version of this article.

Considerable research and public attention is being paid to the quantification, risk adjustment, and reporting of inpatient mortality.<sup>1–5</sup> Inpatient mortality is reported as aggregate mortality (for all hospitalized patients or those with a specific diagnosis<sup>3,6</sup>) or intensive care unit (ICU) mortality.<sup>7,8</sup> While reporting aggregate hospital or aggregate ICU mortality rates is useful, it is also important to develop reporting strategies that go beyond simply using data elements found in administrative databases (eg, diagnosis and procedure codes) to quantify practice variation. Ideally, such strategies would permit delineating processes of care—particularly those potentially under the control of hospitalists,

not only intensivists—to identify improvement opportunities. One such process, which can be tracked using the bed history component of a patient's electronic medical record, is the transfer of patients between different units within the same hospital.

Several studies have documented that risk of ICU death is highest among patients transferred from general medical-surgical wards, intermediate among direct admissions from the emergency department, and lowest among surgical admissions.<sup>9–11</sup> Opportunities to reduce subsequent ICU mortality have been studied among ward patients who develop sepsis and are then transferred to the ICU,<sup>12</sup> among patients who

experience cardiac arrest,<sup>13,14</sup> as well as among patients with any physiological deterioration (eg, through the use of rapid response teams).<sup>15–17</sup> Most of these studies have been single-center studies and/or studies reporting only an ICU denominator. While useful in some respects, such studies are less helpful to hospitalists, who would benefit from better understanding of the types of patients transferred and the total impact that transfers to a higher level of care make on general medical-surgical wards. In addition, entities such as the Institute for Healthcare Improvement recommend the manual review of records of patients who were transferred from the ward to the ICU<sup>18</sup> to identify performance improvement opportunities. While laudable, such approaches do not lend themselves to automated reporting strategies.

We recently described a new risk adjustment methodology for inpatient mortality based entirely on automated data preceding hospital admission and not restricted to ICU patients. This methodology, which has been externally validated in Ottawa, Canada, after development in the Kaiser Permanente Medical Care Program (KPMCP), permits quantification of a patient's pre-existing comorbidity burden, physiologic derangement at the time of admission, and overall inpatient mortality risk.<sup>19,20</sup> The primary purpose of this study was to combine this methodology with bed history analysis to quantify the in-hospital mortality and length of stay (LOS) of patients who experienced intra-hospital transfers in a large, multihospital system. As a secondary goal, we also wanted to assess the degree to which these transfers could be predicted based on information available prior to a patient's admission.

## Materials and Methods

This project was approved by the Northern California KPMCP Institutional Review Board for the Protection of Human Subjects.

The Northern California KPMCP serves a total population of approximately 3.3 million members. Under a mutual exclusivity arrangement, physicians of The Permanente Medical Group, Inc., care for Kaiser Foundation Health Plan, Inc. members at facilities owned by Kaiser Foundation Hospitals, Inc. All Northern California KPMCP hospitals and clinics employ the same information systems with a common medical record number and can track care covered by the plan but delivered elsewhere. Databases maintained by the KPMCP capture admission and discharge times, admission and discharge diagnoses and procedures (assigned by professional coders), bed histories, inter-hospital transfers, as well as the results of all inpatient and outpatient laboratory tests. The use of these databases for research has been described in multiple reports.<sup>21–24</sup>

Our setting consisted of all 19 hospitals owned and operated by the KPMCP, whose characteristics are summarized in the Supporting Information Appendix available to interested readers. These include the 17 described in our previous report<sup>19</sup> as well as 2 new hospitals (Antioch and Manteca) which are similar in size and type of population

served. Our study population consisted of all patients admitted to these 19 hospitals who met these criteria: 1) hospitalization began from November 1st, 2006 through January 31st, 2008; 2) initial hospitalization occurred at a Northern California KPMCP hospital (ie, for inter-hospital transfers, the first hospital stay occurred within the KPMCP); 3) age  $\geq 15$  years; and 4) hospitalization was not for childbirth.

We defined a “linked hospitalization” as the time period that began with a patient's admission to the hospital and ended with the patient's discharge (home, to a nursing home, or death). Linked hospitalizations can thus involve more than 1 hospital stay and could include a patient transfer from one hospital to another prior to definitive discharge. For linked hospitalizations, mortality was attributed to the admitting KPMCP hospital (ie, if a patient was admitted to hospital A, transferred to B, and died at hospital B, mortality was attributed to hospital A). We defined total LOS as the exact time in hours from when a patient was first admitted to the hospital until death or final discharge home or to a nursing home, while total ICU or transitional care unit (TCU, referred to as “stepdown” unit in some hospitals) LOS was calculated for all individual ICU or TCU stays during the hospital stay.

## Intra-Hospital Transfers

We grouped all possible hospital units into four types: general medical-surgical ward (henceforth, “ward”); operating room (OR)/post-anesthesia recovery (PAR); TCU; and ICU. In 2003, the KPMCP implemented a mandatory minimum staffing ratio of one registered nurse for every four patients in all its hospital units; in addition, staffing levels for designated ICUs adhered to the previously mandated minimum of one nurse for every 2 patients. So long as they adhere to these minimum ratios, individual hospitals have considerable autonomy with respect to how they staff or designate individual hospital units. Registered nurse-to-patient ratios during the time of this study were as follows: ward patients, 1:3.5 to 1:4; TCU patients, 1:2.5 to 1:3; and ICU patients, 1:1 to 1:2. Staffing ratios for the OR and PAR are more variable, depending on the surgical procedures involved. Current KPMCP databases do not permit accurate quantification of physician staffing. All 19 study hospitals had designated ICUs, 6 were teaching hospitals, and 11 had designated TCUs. None of the study hospitals had “closed” ICUs (units where only intensivists admit patients) and none had continuous coverage of the ICU by intensivists. While we were not able to employ electronic data to determine who made the decision to transfer, we did find considerable variation with respect to how intensivists covered the ICUs and how they interfaced with hospitalists. Staffing levels for specialized coronary care units and non-ICU monitored beds were not standardized. All study hospitals had rapid response teams as well as “code blue” teams during the time period covered by this report. Respiratory care practitioners were available to patients in all hospital units, but considerable

variation existed with respect to other services available (eg, cardiac catheterization units, provision of noninvasive positive pressure ventilation outside the ICU, etc.).

This report focuses on intra-hospital transfers to the ICU and TCU, with special emphasis on nonsurgical transfers (due to space limitations, we are not reporting on the outcomes of patients whose first hospital unit was the OR; additional details on these patients are provided in the Supporting Information Appendix). For the purposes of this report, we defined the following admission types: direct admits (patients admitted to the ICU or TCU whose first hospital unit on admission was the ICU or TCU); and non-surgical transfers to a higher level of care. These latter transfers could be of 3 types: ward to ICU, ward to TCU, and TCU to ICU. We also quantified the effect of inter-hospital transfers.

### Independent Variables

In addition to patients' age and sex, we employed the following independent variables to predict transfer to a higher level of care. These variables are part of the risk adjustment model described in greater detail in our previous report<sup>19</sup> and were available electronically for all patients in the cohort. We grouped admission diagnoses into 44 broad diagnostic categories (Primary Conditions), and admission types into 4 groups (emergency medical, emergency surgical, elective medical, and elective surgical). We quantified patients' degree of physiologic derangement using a Laboratory-based Acute Physiology Score (LAPS) using laboratory test results prior to hospitalization. We quantified patients' comorbid illness burden using a Comorbidity Point Score (COPS) based on patients' pre-existing diagnoses over the 12-month period preceding hospitalization. Lastly, we assigned each patient a predicted mortality risk (%) and LOS based on the above predictors,<sup>19</sup> permitting calculation of observed to expected mortality ratios (OEMRs) and observed minus expected LOS (OMELOS).

### Statistical Methods

All analyses were performed in SAS.<sup>25</sup> We calculated standard descriptive statistics (medians, means, standard deviations) and compared different patient groupings using *t* and chi-square tests. We employed a similar approach to that reported by Render et al.<sup>7</sup> to calculate OEMR and OMELOS.

To determine the degree to which transfers to a higher level of care from the ward or TCU would be predictable using information available at the time of admission, we performed 4 sets of logistic regression analyses using the above-mentioned predictors in which the outcome variables were as follows: 1) transfer occurring in the first 48 hours after admission (time frame by which point approximately half of the transferred patients experienced a transfer) among ward or TCU patients and 2) transfer occurring after 48 hours among ward or TCU patients. We evaluated the discrimination and calibration of these models using the same methods described in our original report (measuring the area under

the receiver operator characteristic curve, or *c* statistic, and visually examining observed and expected mortality rates among predicted risk bands as well as risk deciles) as well as additional statistical tests recommended by Cook.<sup>19,26</sup>

### Results

During the study period, a total of 249,129 individual hospital stays involving 170,151 patients occurred at these 19 hospitals. After concatenation of inter-hospital transfers, we were left with 237,208 linked hospitalizations. We excluded 26,738 linked hospitalizations that began at a non-KPMCP hospital (ie, they were transported in), leaving a total of 210,470 linked hospitalizations involving 150,495 patients. The overall linked hospitalization mortality rate was 3.30%.

Table 1 summarizes cohort characteristics based on initial hospital location. On admission, ICU patients had the highest degree of physiologic derangement as well as the highest predicted mortality. Considerable inter-hospital variation was present in both predictors and outcomes; details on these variations are provided in the Supporting Information Appendix.

Table 2 summarizes data from 3 groups of patients: patients initially admitted to the ward, or TCU, who did not experience a transfer to a higher level of care and patients admitted to these 2 units who did experience such a transfer. Patients who experienced a transfer constituted 5.3% (6,484/121,237) of ward patients and 6.7% (1,384/20,556) of TCU patients. Transferred patients tended to be older, have more acute physiologic derangement (higher LAPS), a greater pre-existing illness burden (higher COPS), and a higher predicted mortality risk. Among ward patients, those with the following admission diagnoses were most likely to experience a transfer to a higher level of care: gastrointestinal bleeding (10.8% of all transfers), pneumonia (8.7%), and other infections (8.2%). The diagnoses most likely to be associated with death following transfer were cancer (death rate among transferred patients, 48%), renal disease (death rate, 36%), and liver disease (33%). Similar distributions were observed for TCU patients.

Table 3 compares outcomes among ward and TCU patients who did and did not experience a transfer to a higher level of care. The table shows that transferred patients were almost 3 times as likely to die, even after controlling for severity of illness, and that their hospital LOS was 9 days higher than expected. This increased risk was seen in all hospitals and among all transfer types (ward to ICU, ward to TCU, and TCU to ICU).

Table 3 also shows that, among decedent patients, those who never left the ward or TCU died much sooner than those who died following transfer. Among direct admits to the ICU, the median LOS at time of death was 3.9 days, with a mean of  $9.4 \pm$  standard deviation of 19.9 days, while the corresponding times for TCU direct admits were a median and mean LOS of 6.5 and  $11.7 \pm 19.5$  days.

**TABLE 1. Characteristics of Study Cohort Based on Patients' Admission Hospital Unit**

	Ward	TCU	ICU	All*
n	121,237	20,556	16,001	210,470
Admitted via emergency department, n (%)	99,909 (82.4)	18,612 (90.5)	13,847 (86.5)	139,036 (66.1)
% range across hospitals <sup>†</sup>	55.0-94.2	64.7-97.6	49.5-97.4	53.6-76.9
Male, n (%)	53,744 (44.3)	10,362 (50.4)	8,378 (52.4)	94,451 (44.9)
Age in years (mean ± SD)	64.5 ± 19.2	69.0 ± 15.6	63.7 ± 17.8	63.2 ± 18.6
LAPS (mean ± SD)	19.2 ± 18.0	23.3 ± 19.5	31.7 ± 25.7	16.7 ± 19.0
COPS (mean ± SD)	90.4 ± 64.0	99.2 ± 65.9	94.5 ± 67.5	84.7 ± 61.8
% predicted mortality (mean ± SD)	4.0 ± 7.1	4.6 ± 7.3	8.7 ± 12.8	3.6 ± 7.3
Observed in-hospital deaths (n, %)	3,793 (3.1)	907 (4.4)	1,995 (12.5)	6,952 (3.3)
Observed to expected mortality ratio <sup>‡</sup>	0.79 (0.77-0.82)	0.95 (0.89-1.02)	1.43 (1.36-1.49)	0.92 (0.89-0.94)
Total hospital LOS, days (mean ± SD)	4.6 ± 7.5	5.3 ± 10.0	7.8 ± 14.0	4.6 ± 8.1

NOTE: See text for description of unit characteristics and staffing.

**Abbreviations:** COPS, Comorbidity Point Score; ICU, Intensive Care Unit; LAPS, Laboratory Acute Physiology Score; LOS, length of stay; SD, standard deviation; TCU, Transitional Care Unit.

\*Number includes 52,676 excluded surgical patients described in the Supporting Information Appendix.

<sup>†</sup>See Supporting Information Appendix for details on inter-hospital variation.

<sup>‡</sup>Numbers in parentheses are 95% confidence intervals. Total ratio for cohort is <1.0 because risk adjustment is based on an earlier calibration dataset (the 2002-2005 Kaiser Permanente hospital cohort described in citation 19).

**TABLE 2. Characteristics of Ward and Transitional Care Unit (TCU) Patients Who Did and Did Not Experience Transfer to a Higher Level of Care**

	Patients Initially Admitted to Ward, Remained There	Patients Initially Admitted to TCU, Remained There	Patients Transferred to Higher Level of Care	All
n	114,753	19,172	7,868	141,793
Male, n (%)	50,586 (44.1)	9,626 (50.2)	3,894 (49.5)	64,106 (45.2)
Age (mean ± SD)	64.3 ± 19.4	69.0 ± 15.7	68.1 ± 16.1	65.2 ± 18.8
LAPS (mean ± SD)	18.9 ± 17.8	22.7 ± 19.1	26.7 ± 21.0	19.8 ± 18.3
COPS (mean ± SD)	89.4 ± 63.7	98.3 ± 65.5	107.9 ± 67.6	91.7 ± 64.4
% predicted mortality risk (mean ± SD)	3.8 ± 7.0	4.4 ± 7.0	6.5 ± 8.8	4.1 ± 7.1
Admission diagnosis of pneumonia, n (%)	5,624 (4.9)	865 (4.5)	684 (8.7)	7,173 (5.1)
Admission diagnosis of sepsis, n (%)	1,181 (1.0)	227 (1.2)	168 (2.1)	1,576 (1.1)
Admission diagnosis of GI bleed, n (%)	13,615 (11.9)	1,448 (7.6)	851 (10.8)	15,914 (11.2)
Admission diagnosis of cancer, n (%)	2,406 (2.1)	80 (0.4)	186 (2.4)	2,672 (1.9)

**Abbreviations:** COPS, Comorbidity Point Score; GI, Gastrointestinal; LAPS, Laboratory Acute Physiology Score; SD, Standard Deviation.

Table 4 summarizes outcomes among different patient subgroups that did and did not experience a transfer to a higher level of care. Based on location, patients who experienced a transfer from the TCU to the ICU had the highest crude death rate, but patients transferred from the ward to the ICU had the highest OEMR. On the other hand, if one divides patients by the degree of physiologic derangement, patients with low LAPS who experienced a transfer had the highest OEMR. With respect to LOS, patients transferred from the TCU to the ICU had the highest OMELOS (13.4 extra days).

Transfers to a higher level of care at a different hospital, which in the KPMCP are usually planned, experienced lower mortality than transfers within the same hospital. For ward to TCU transfers, intra-hospital transfers had a mortality of 12.1% while inter-hospital transfers had a mortality of 5.7%. Corresponding rates for ward to ICU transfers were 21.7%

and 11.2%, and for TCU to ICU transfers the rates were 25.9% and 12.5%, respectively.

Among patients initially admitted to the ward, a model to predict the occurrence of a transfer to a higher level of care (within 48 hours after admission) that included age, sex, admission type, primary condition, LAPS, COPS, and interaction terms had poor discrimination, with an area under the receiver operator characteristic (c statistic) of only 0.64. The c statistic for a model to predict transfer after 48 hours was 0.66. The corresponding models for TCU admits had c statistics of 0.67 and 0.68. All four models had poor calibration.

## Discussion

Using automated bed history data permits characterizing a patient population with disproportionate mortality and LOS: intra-hospital transfers to special care units (ICUs or TCUs).

**TABLE 3. Outcomes of Ward and Transitional Care Unit (TCU) Patients Who Did and Did Not Experience Transfer to a Higher Level of Care**

	Patients Initially Admitted to Ward, Remained There	Patients Initially Admitted to TCU, Remained There	Patients Transferred to Higher Level of Care
n	114,753	19,172	7,868
Admitted to ICU, n (%)	0 (0.0)	0 (0.0)	5,245 (66.7)
Ventilated, n (%)	0 (0.0)	0 (0.0)	1,346 (17.1)
Died in the hospital, n (%)	2,619 (2.3)	572 (3.0)	1,509 (19.2)
Length of stay, in days, at time of death (mean ± SD)	7.0 ± 11.9	8.3 ± 12.4	16.2 ± 23.7
Observed to expected mortality ratio (95% CI)	0.60 (0.57-0.62)	0.68 (0.63-0.74)	2.93 (2.79-3.09)
Total hospital length of stay, days (mean ± SD)	4.0 ± 5.7	4.4 ± 6.9	14.3 ± 21.3
Observed minus expected length of stay (95% CI)	0.4 (0.3-0.4)	0.8 (0.7-0.9)	9.1 (8.6-9.5)
Length of stay, in hours, at time of transfer (mean ± SD)			80.8 ± 167.2

Abbreviations: CI, confidence interval; ICU, intensive care unit; SD, standard deviation.

**TABLE 4. Death Rates and Hospital Length of Stay Among Ward and Transitional Care Unit (TCU) Patients**

	n (%)*	Death Rate (%)	OEMR <sup>†</sup>	LOS (mean ± SD)	OMELOS <sup>‡</sup>
Never admitted to TCU or ICU	157,632 (74.9)	1.6	0.55 (0.53-0.57)	3.6 ± 4.6	0.04 (0.02-0.07)
Direct admit to TCU	18,464 (8.8)	2.9	0.66 (0.61-0.72)	4.2 ± 5.8	0.60 (0.52-0.68)
Direct admit to ICU	14,655 (7.0)	11.9	1.38 (1.32-1.45)	6.4 ± 9.4	2.28 (2.14-2.43)
Transferred from ward to ICU	5,145 (2.4)	21.5	3.23 (3.04-3.42)	15.7 ± 21.6	10.33 (9.70-10.96)
Transferred from ward to TCU	3,144 (1.5)	11.9	1.99 (1.79-2.20)	13.6 ± 23.2	8.02 (7.23-8.82)
Transferred from TCU to ICU	1,107 (0.5)	25.7	2.94 (2.61-3.31)	18.0 ± 28.2	13.35 (11.49-15.21)
Admitted to ward, COPS ≥80, no transfer to ICU or TCU	55,405 (26.3)	3.4	0.59 (0.56-0.62)	4.5 ± 5.9	0.29 (0.24-0.34)
Admitted to ward, COPS ≥80, did experience transfer to ICU or TCU	4,851 (2.3)	19.3	2.72 (2.55-2.90)	14.2 ± 20.0	8.14 (7.56-8.71)
Admitted to ward, COPS <80, no transfer to ICU or TCU	57,421 (27.3)	1.1	0.55 (0.51-0.59)	3.4 ± 4.2	0.23 (0.19-0.26)
Admitted to ward, COPS <80, did experience transfer to ICU or TCU	3,560 (1.7)	9.8	2.93 (2.63-3.26)	12.0 ± 19.0	7.52 (6.89-8.15)
Admitted to ward, LAPS ≥20, no transfer to ICU or TCU	46,492 (22.1)	4.2	0.59 (0.56-0.61)	4.6 ± 5.4	0.16 (0.12-0.21)
Admitted to ward, LAPS ≥20, did experience transfer to ICU or TCU	4,070 (1.9)	21.4	2.37 (2.22-2.54)	14.8 ± 21.0	8.76 (8.06-9.47)
Admitted to ward, LAPS <20, no transfer to ICU or TCU	66,334 (31.5)	0.9	0.55 (0.51-0.60)	3.5 ± 4.9	0.32 (0.28-0.36)
Admitted to ward, LAPS <20, did experience transfer to ICU or TCU	4,341 (2.1)	9.5	4.31 (3.90-4.74)	11.8 ± 18.1	7.12 (6.61-7.64)

Abbreviations: COPS, Comorbidity Point Score; ICU, intensive care unit; LAPS, Laboratory Acute Physiology Score; LOS, length of stay; OEMR, Observed to expected mortality ratio; OMELOS, Observed minus expected length of stay; SD, standard deviation.

\* Percentage refers to % among all hospital admissions.

<sup>†</sup> Numbers in parentheses are the 95% confidence intervals.

<sup>‡</sup> Numbers in parentheses are the 95% confidence intervals.

Indeed, the largest subset of these patients (those initially admitted to the ward or TCU) constituted only 3.7% of all admissions, but accounted for 24.2% of all ICU admissions, 21.7% of all hospital deaths, and 13.2% of all hospital days. These patients also had very elevated OEMRs and OMELOS. Models based on age, sex, preadmission laboratory test results, and comorbidities did not predict the occurrence of these transfers.

We performed multivariate analyses to explore the degree to which electronically assigned preadmission severity scores could predict these transfers. These analyses found that, compared to our ability to predict inpatient or 30-day mortality at the time of admission, which is excellent, our ability to predict the occurrence of transfer after admission is much more limited. These results highlight the limitations of severity scores that rely on automated data, which may not have

adequate discrimination when it comes to determining the risk of an adverse outcome within a narrow time frame. For example, among the 121,237 patients initially admitted to the ward who did not experience an intra-hospital transfer, the mean LAPS was 18.9, while the mean LAPS among the 6,484 ward patients who did experience a transfer was 25.5. Differences between the mean and median LAPS, COPS, and predicted mortality risk among transferred and non-transferred patients were significant ( $P < 0.0001$  for all comparisons). However, examination of the distribution of LAPS, COPS, and predicted mortality risk between these two groups of patients showed considerable overlap.

Our methodology resembles Silber et al.'s<sup>27,28</sup> concept of "failure to rescue" in that it focuses on events occurring after hospitalization. Silber et al. argue that a hospital's quality can be measured by quantifying the degree to which

patients who experience new problems are successfully “rescued.” Furthermore, quantification of those situations where “rescue” attempts are unsuccessful is felt to be superior to simply comparing raw or adjusted mortality rates because these are primarily determined by underlying case mix. The primary difference between Silber et al.’s approach and ours is at the level of detail—they specified a specific set of complications, whereas our measure is more generic and would include patients with many of the complications specified by Silber et al.<sup>27,28</sup>

Most of the patients transferred to a higher level of care in our cohort survived (ie, were “rescued”), indicating that intensive care is beneficial. However, the fact that these patients had elevated OEMRs and OMELOS indicates that the real challenge facing hospitalists involves the timing of provision of a beneficial intervention. In theory, improved timing could result from earlier detection of problems, which is the underlying rationale for employing rapid response teams. However, the fact that our electronic tools (LAPS, COPS) cannot predict patient deteriorations within a narrow time frame suggests that early detection will remain a major challenge. Manually assigned vital signs scores designed for this purpose do not have good discrimination either.<sup>29,30</sup> This raises the possibility that, though patient groups may differ in terms of overall illness severity and mortality risk, differences at the individual patient level may be too subtle for clinicians to detect. Future research may thus need to focus on scores that combine laboratory data, vital signs, trends in data,<sup>31,32</sup> and newer proteomic markers (eg, procalcitonin).<sup>33</sup> We also found that most transfers occurred early (within <72 hours), raising the possibility that at least some of these transfers may involve issues around triage rather than sudden deterioration.

Our study has important limitations. Due to resource constraints and limited data availability, we could not characterize the patients as well as might be desirable; in particular, we could not make full determinations of the actual reasons for patients’ transfer for all patients. Broadly speaking, transfer to a higher level of care could be due to inappropriate triage, appropriate (preventive) transfer (which could include transfer to a more richly staffed unit for a specific procedure), relentless progression of disease despite maximal therapy, the occurrence of management errors, patient and family uncertainty about goals of care or inadequate understanding of treatment options and prognoses, or a combination of these factors. We could not make these distinctions with currently available electronic data. This is also true of postsurgical patients, in whom it is difficult to determine which transfers to intensive care might be planned (eg, in the case of surgical procedures where ICU care is anticipated) as opposed to the occurrence of a deterioration during or following surgery. Another major limitation of this study is our inability to identify “code” or “no code” status electronically. The elapsed LOS at time of death among patients who experienced a transfer to a higher level of care (as compared to patients who died in the ward without ever experiencing intra-hospital transfer)

suggests, but does not prove, that prolonged efforts were being made to keep them alive. We were also limited in terms of having access to other process data (eg, physician staffing levels, provision and timing of palliative care). Having ICU severity of illness scores would have permitted us to compare our cohort to those of other recent studies showing elevated mortality rates among transfer patients,<sup>9–11</sup> but we have not yet developed that capability.

Consideration of our study findings suggests a possible research agenda that could be implemented by hospitalist researchers. This agenda should emphasize three areas: detection, intervention, and reflection.

With respect to detection, attention needs to be paid to better tools for quantifying patient risk at the time a decision to admit to the ward is made. It is likely that such tools will need to combine the attributes of our severity score (LAPS) with those of the manually assigned scores.<sup>30,34</sup> In some cases, use of these tools could lead a physician to change the locus of admission from the ward to the TCU or ICU, which could improve outcomes by ensuring more timely provision of intensive care. Since problems with initial triage could be due to factors other than the failure to suspect or anticipate impending instability, future research should also include a cognitive component (eg, quantifying what proportion of subsequent patient deteriorations could be ascribed to missed diagnoses<sup>35</sup>). Additional work also needs to be done on developing mathematical models that can inform electronic monitoring of ward (not just ICU) patients.

Research on interventions that hospitalists can use to prevent the need for intensive care or to improve the “rescue” rate should take two routes. The first is a disease-specific route, which builds on the fact that a relatively small set of conditions (pneumonia, sepsis, gastrointestinal bleeding) account for most transfers to a higher level of care. Condition-specific protocols, checklists, and “bundles”<sup>36</sup> tailored to a ward environment (as opposed to the ICU or to the entire hospital) might prevent deteriorations in these patients, as has been reported for sepsis.<sup>37</sup> The second route is to improve the overall capabilities of rapid response and “code blue” teams. Such research would need to include a more careful assessment of what commonalities exist among patients who were and were not successfully “rescued” by these teams. This approach would probably yield more insights than the current literature, which focuses on whether rapid response teams are a good thing or not.

Finally, research also needs to be performed on how hospitalists reflect on adverse outcomes among ward patients. Greater emphasis needs to be placed on moving beyond “trigger tool” approaches that rely on manual chart review. In an era of expanding use of electronic medical record systems, more work needs to be done on how to harness these to provide hospitalists with better quantitative and risk-adjusted information. This information should not be limited to simply reporting rates of transfers and deaths. Rather, finer distinctions must be provided with respect of the type of patients (ie, more diagnostic detail), the clinical

status of patients (ie, more physiologic detail), as well as the effects of including or excluding patients in whom therapeutic options may be limited (ie, “do not resuscitate” and “comfort care” patients) on reported rates. Ideally, researchers should develop better process and outcomes measures that could be tested in collaborative networks that include multiple nonacademic general medical-surgical wards.

#### Acknowledgements

The authors thank Drs. Paul Feigenbaum, Alan Whippy, Joseph V. Selby, and Philip Madvig for reviewing the manuscript and Ms. Jennifer Calhoun for formatting the manuscript.

#### Address for correspondence and reprint requests:

Gabriel J. Escobar, MD, 2000 Broadway Ave., 021 R10, Oakland, California 94612; Telephone: 510-891-3502; Fax: 510-891-3508; E-mail: gabriel.escobar@kp.org Received 10 December 2009; revision received 29 April 2010; accepted 23 May 2010.

#### References

1. Kohn LT, Corrigan JM, Donaldson MS. *To Err is Human: Building a Safer Health System*. Washington, D. C.: National Academy Press; 2000.
2. Institute for Healthcare Improvement. Protecting 5 million lives from harm. Available at: <http://www.ihf.org/IHI/Programs/Campaign>. Accessed June 2010.
3. Hofer TP, Hayward RA. Identifying poor-quality hospitals. Can hospital mortality rates detect quality problems for medical diagnoses? *Med Care*. 1996;34(8):737–753.
4. Dimick JB, Welch HG, Birkmeyer JD. Surgical mortality as an indicator of hospital quality: the problem with small sample size. *JAMA*. 2004;292(7):847–851.
5. State of California Office of Statewide Health Planning and Development. AHRQ - Inpatient quality indicators (IQIs) hospital inpatient mortality indicators for California. Available at: [http://www.oshpd.ca.gov/HID/Products/PatDischargeData/AHRQ/iqi-imi\\_overview.html](http://www.oshpd.ca.gov/HID/Products/PatDischargeData/AHRQ/iqi-imi_overview.html). Accessed June 2010.
6. Pine M, Jordan HS, Elixhauser A, et al. Enhancement of claims data to improve risk adjustment of hospital mortality. *JAMA*. 2007;297(1):71–76.
7. Render ML, Kim HM, Deddens J, et al. Variation in outcomes in Veterans Affairs intensive care units with a computerized severity measure. *Crit Care Med*. 2005;33(5):930–939.
8. Zimmerman JE, Kramer AA, McNair DS, Malila FM. Acute Physiology and Chronic Health Evaluation (APACHE) IV: hospital mortality assessment for today's critically ill patients. *Crit Care Med*. 2006;34(5):1297–1310.
9. Barnett MJ, Kaboli PJ, Sirio CA, Rosenthal GE. Day of the week of intensive care admission and patient outcomes: a multisite regional evaluation. *Med Care*. 2002;40(6):530–539.
10. Ensminger SA, Morales JJ, Peters SG, et al. The hospital mortality of patients admitted to the ICU on weekends. *Chest*. 2004;126(4):1292–1298.
11. Luyt CE, Combes A, Aegerter P, et al. Mortality among patients admitted to intensive care units during weekday day shifts compared with “off” hours. *Crit Care Med*. 2007;35(1):3–11.
12. Lundberg JS, Perl TM, Wiblin T, et al. Septic shock: an analysis of outcomes for patients with onset on hospital wards versus intensive care units. *Crit Care Med*. 1998;26(6):1020–1024.
13. Schein RM, Hazday N, Pena M, Ruben BH, Sprung CL. Clinical antecedents to in-hospital cardiopulmonary arrest. *Chest*. 1990;98(6):1388–1392.
14. Franklin C, Mathew J. Developing strategies to prevent in-hospital cardiac arrest: analyzing responses of physicians and nurses in the hours before the event. *Crit Care Med*. 1994;22(2):244–247.
15. MERIT Study Investigators. Introduction of the medical emergency team (MET) system: a cluster-randomized controlled trial. *Lancet*. 2005;365(9477):2091–2097.
16. Institute for Healthcare Improvement. *The “MERIT” Trial of Medical Emergency Teams in Australia: An Analysis of Findings and Implications*. Boston, MA: 2005. Available on [www.ihf.org](http://www.ihf.org)
17. Winters BD, Pham J, Pronovost PJ. Rapid response teams--walk, don't run. *JAMA*. 2006;296(13):1645–1647.
18. Griffin F, Resar R. *IHI Global Trigger Tool for Measuring Adverse Events*. 2nd ed. Cambridge, Massachusetts: Institute for Healthcare Improvement; 2009.
19. Escobar G, Greene J, Scheirer P, Gardner M, Draper D, Kipnis P. Risk adjusting hospital inpatient mortality using automated inpatient, outpatient, and laboratory databases. *Medical Care*. 2008;46(3):232–239.
20. van Walraven C, Escobar GJ, Greene JD, Forster AJ. The Kaiser Permanente inpatient risk adjustment methodology was valid in an external patient population. *J Clin Epidemiol*. 2010;63(7):798–803.
21. Selby JV. Linking automated databases for research in managed care settings. *Ann Intern Med*. 1997;127(8 Pt 2):719–724.
22. Go AS, Hylek EM, Chang Y, et al. Anticoagulation therapy for stroke prevention in atrial fibrillation: how well do randomized trials translate into clinical practice? *JAMA*. 2003;290(20):2685–2692.
23. Escobar G, Shaheen S, Breed E, et al. Richardson score predicts short-term adverse respiratory outcomes in newborns  $\geq 34$  weeks gestation. *J Pediatr*. 2004;145(6):754–760.
24. Escobar GJ, Fireman BH, Palen TE, et al. Risk adjusting community-acquired pneumonia hospital outcomes using automated databases. *Am J Manag Care*. 2008;14(3):158–166.
25. *Statistical Analysis Software* [computer program]. Version 8. Cary, NC: SAS Institute, Inc.; 2000.
26. Cook NR. Use and misuse of the receiver operating characteristic curve in risk prediction. *Circulation*. 2007;115(7):928–935.
27. Silber JH, Williams SV, Krakauer H, Schwartz JS. Hospital and patient characteristics associated with death after surgery. A study of adverse occurrence and failure to rescue. *Med Care*. 1992;30(7):615–629.
28. Silber JH, Rosenbaum PR, Ross RN. Comparing the contributions of groups of predictors: which outcomes vary with hospital rather than patient characteristics? *J Am Stat Assoc*. 1995;90(429):7–18.
29. Naeem N, Montenegro H. Beyond the intensive care unit: A review of interventions aimed at anticipating and preventing in-hospital cardiopulmonary arrest. *Resuscitation*. 2005;67(1):13–23.
30. Subbe CP, Gao H, Harrison DA. Reproducibility of physiological track-and-trigger warning systems for identifying at-risk patients on the ward. *Intensive Care Med*. 2007;33(4):619–624.
31. Ferreira FL, Bota DP, Bross A, Melot C, Vincent JL. Serial evaluation of the SOFA score to predict outcome in critically ill patients. *JAMA*. 2001;286(14):1754–1758.
32. Kuzniewicz M, Draper D, Escobar GJ. Incorporation of Physiologic Trend and Interaction Effects in Neonatal Severity of Illness Scores: An Experiment Using a Variant of the Richardson Score. *Intensive Care Med*. 2007;33(9):1602–1608.
33. Clec'h C, Ferriere F, Karoubi P, et al. Diagnostic and prognostic value of procalcitonin in patients with septic shock. *Crit Care Med*. 2004;32(5):1166–1169.
34. Hucker TR, Mitchell GP, Blake LD, et al. Identifying the sick: can biochemical measurements be used to aid decision making on presentation to the accident and emergency department. *Br J Anaesth*. 2005;94(6):735–741.
35. Redelmeier DA. Improving patient care. The cognitive psychology of missed diagnoses. *Ann Intern Med*. 2005;142(2):115–120.
36. Robb E, Jarman B, Suntharalingam G, Higgins C, Tennant R, Elcock K. Using care bundles to reduce in-hospital mortality: quantitative survey. *BMJ*. 2010;340:c1234.
37. Sebat F, Musthafa AA, Johnson D, et al. Effect of a rapid response system for patients in shock on time to treatment and mortality during 5 years. *Crit Care Med*. 2007;35(11):2568–2575.