MORTALITY MEASUREMENT IN THE EMR ERA: WHAT REAL TIME LAB AND CLINICAL DATA CAN CONTRIBUTE TO PRECISION AND PREDICTION

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November 3, 2008

TOPICS TO BE COVERED

- Value of readily available enhancements:
  POA coding
  Laboratory data
  Other physiologic data
- Work in progress: use of bed history data combined with laboratory data

WHY SHOULD WE SETTLE FOR THE LOWEST COMMON DENOMINATOR?

- Billing data are driven by need for reimbursement
- High propensity to being "gamed"
- "Coding creep" occurs
- Many diagnoses strongly associated with outcome can be present on admission, e.g., stroke, DVT, pressure ulcers

GLANCE ET AL.: IMPACT OF PRESENT ON ADMISSION CODING ON PERFORMANCE RANKING

- POA coding modifier showed that diagnoses associated with complications were present on admission only 10 – 22% of the time
- Absence of POA coding led to 33 – 40% of low performing hospitals not being detected for these conditions

  CABG

  Coronary angioplasty

  Hip replacement

  AMI
- "Treating complications as pre-existing conditions gives poor-performing hospitals 'credit' for their complications and may cause some hospitals that are delivering low-quality care to be misclassified as average- or high-performing hospitals"

VALUE OF INCORPORATING PHYSIOLOGIC DATA

- Increasingly available, particularly in hospital chains
- Much less expensive than manual chart abstraction
- Have tremendous face validity with clinicians
- Relatively easy to combine with other data
- Can be used either for disease-specific models (e.g., Fine PSI for community acquired pneumonia) or for global risk adjustment (e.g., VA or Kaiser Permanente risk adjustment methodologies)

RELATIVE CONTRIBUTION OF PHYSIOLOGIC DATA TO OVERALL MODEL PERFORMANCE

- Operational use of laboratory data first occurred in the ICU
- Render et al. – 29,377 consecutive first ICU admissions in 17 VA hospitals

  Laboratory data accounted for 74% of model predictive ability

  Diagnosis accounted for 13%
- Zimmerman et al. – 110,558 ICU admissions in 45 U.S. hospitals

  Laboratory data accounted for 65% of model predictive ability

  Diagnosis accounted for 16%

PINE ET AL.: USE OF LABORATORY DATA FOR NON-ICU POPULATIONS

- Quantified effect of adding POA coding, laboratory data, and vital signs data for 5 conditions and 3 procedures
- Not restricted to ICU; N ranged from 5309 for AAA to 200,506 for CHF
- Average effect of adding predictors, as evidenced by change in c statistic:

No risk adjustment	0.50
Administrative model	0.79
POA model	0.84
POA + labs	0.86
POA + labs + VSS	0.88

TABAK ET AL.: DEFINITIVE QUANTIFICATION OF VALUE OF LABORATORY DATA

- Evaluated 6 disease-specific mortality predictive models for pay-for-performance (ischemic & hemorrhagic stroke, pneumonia, CHF, and sepsis)
- 194,903 admissions in 2000-2003 across 71 hospitals that imported laboratory data
- Quantified relative contribution with omega statistic
- Laboratory data were between 2 and 67 times more important in predicting mortality than ICD-9 variables
- Only models where laboratory data were less important were those for stroke, where altered mental status recordings were more important

RESEARCH IN PROGRESS: COMBINING LABORATORY DATA WITH ANOTHER EMR MARKER, BED HISTORY

- 207,922 hospitalizations at 19 Kaiser Permanente hospitals, 11/1/06 – 1/31/08
- All severity scored using laboratory acute physiology score (LAPS) and pre-admission comorbidity point score (COPS)
- Employs time stamps for patient arrival at different units (ward, OR/PAR, TCU, ICU)
- Examines mortality of intra-hospital transfers combined with laboratory testing patterns

CATEGORIZATION OF INTRA-HOSPITAL TRANSFERS TO A HIGHER LEVEL OF CARE

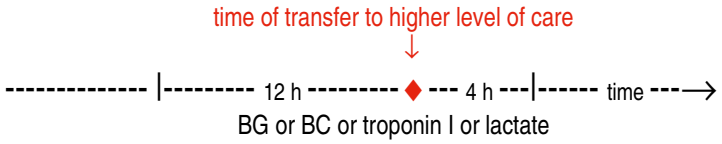
- Post-surgical (OR/PAR → TCU, OR/PAR → ICU)
- Unplanned (ward → TCU, ward → ICU, TCU → ICU)
- Laboratory testing patterns (blood gases, lactate, troponin I, blood culture)

  Not tested during 16 hour (12-4) time window surrounding transfer

  Tested during time window but not before

  Tested before and during time window

Testing patterns



•If index test obtained in 16 hour window (12 hrs before to 4 hours after transfer to higher level of care) patient is considered to have been tested, otherwise patient is considered "not tested"

•If another test is located within 24-48 hours (depending on test type) preceding index test, the patient is considered "previously tested"

•If another test is not located within 24-48 hours preceding index test, the patient is considered "newly tested"

OUTCOMES BASED ON FIRST HOSPITAL UNIT

	Ward	OR/PAR	TCU	ICU
N	119,418	52,137	20,416	15,951
LAPS (median)	18	0	20	28
COPS (median)	79	53	89	81
Mortality (mean,p)	3.9%	0.8%	4.7%	8.9%
Mortality (mean,a)	3.2%	0.5%	4.4%	12.5%

OUTCOMES BASED ON INTRA-HOSPITAL TRANSFER TYPE – I

Group	N (%)		Death Rate	OEMR
Never in TCU or ICU	155,298	(75%)	1.6%	0.57
Direct admit to ICU (all)	15,951	(7.7%)	12.5%	1.41
Experienced unplanned transfer	786	(0.4%)	24.1%	2.03
Direct admit to TCU (all)	20,416	(9.8%)	4.4%	0.94
Experienced unplanned transfer	1,388	(0.7%)	24.1%	2.92

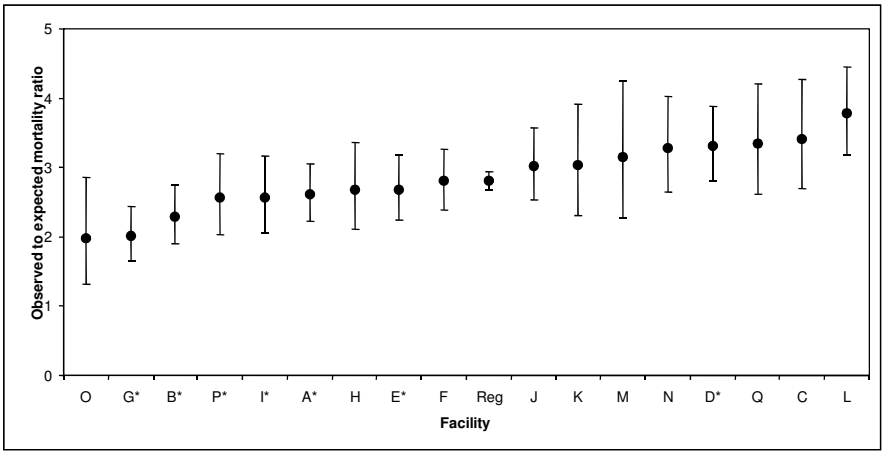
OUTCOMES BASED ON INTRA-HOSPITAL TRANSFER TYPE – II

Group	N (%)		Death Rate	OEMR
Post-surgical transfers to TCU or ICU				
Not Tested	6,458	(3.1%)	1.7%	0.79
Newly Tested	1,385	(0.7%)	6.4%	1.78
Previously Tested	2,452	(1.2%)	6.4%	1.84

OUTCOMES BASED ON INTRA-HOSPITAL TRANSFER TYPE – III

Group	N (%)		Death Rate	OEMR
Unplanned transfer to TCU or ICU				
Not Tested	4,311	(2.1%)	10.2%	1.84
Newly Tested	2,439	(1.2%)	25.4%	3.35
Previously Tested	2,621	(1.3%)	26.6%	3.39

OEMR For Unplanned Transfers in 17 Kaiser Permanente Hospitals



ELAPSED HOSPITAL LENGTH OF STAY AT TIME OF DEATH

Group	ELOS (days) @ time of death (median, mean ± SD)
Ward Patients	3.8, 6.0 ± 8.9
TCU/ICU Direct Admits	4.7, 10.1 ± 19.6
Post-Surgical Transfers	12.9, 21.8 ± 32.2
Unplanned Transfers	10.0, 17.9 ± 26.0

NEXT EMR CHALLENGE: IDENTIFICATION OF DNR/COMFORT CARE PATIENTS

Holloway & Quill:

- Mortality is a good quality measure for individuals with acute illness who are not supposed to die but is a poor quality measure for the majority of patients with multiple chronic diseases who are near the end of their life
- "taken alone, short-term mortality measures essentially treat death as a medical failure and reinforce avoiding death at all costs"
- Careful use of EMRs could permit excluding these patients from analyses (or separating them for different types of analyses)

CONCLUSIONS – I

- Evidence base for use of physiologic data in risk adjustment is overwhelming
- Two entities, the VA system and Kaiser Permanente, are already employing physiologic-based risk adjustment operationally
- Other uses of physiologic data (e.g., multivariable template matching for targeted case-control studies; VA's use of change in serum creatinine) make the use of these data even more compelling
- The important question is not "Should one employ automated physiology-based risk-adjustment?" but, rather, "Is it possible to convince different institutions to standardize data definitions so as to permit larger collaborative studies?"

CONCLUSIONS – II

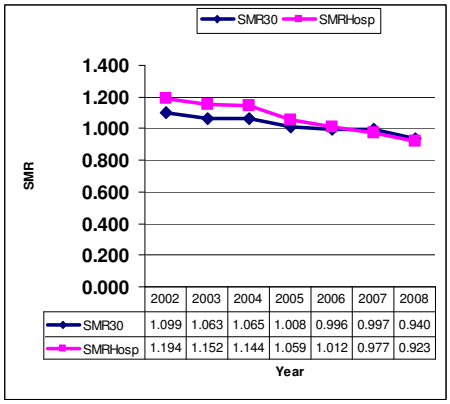
- Entities such as IHI and AHRQ should be creating incentives for use of these data, rather than simply reinforcing the use of administrative data
- Not all hospitals have the capability to employ these data, but for those that do, IHI/AHRQ should encourage creation of networks that collaborate to employ data from EMRs
- Future research using EMRs should emphasize capture of DNR/comfort care orders

Veterans Administration Risk Adjusted Mortality in the ICU

- **Risk model**
  - Diagnosis, comorbid disease, source of admission, worst of 11 lab values (Na, Glu, BUN, Cr, ALB, Bili, WBC, Hct, pH / PaCO2, PaO2
  - Separate models predict death at 30 days and at hospital discharge
- **Advantage in addition of physiologic data**
  - Face validity / improved discrimination calibration to fairly portray risk and outcomes
- **Unexpected advantage of using lab values in model**
  - Ability to create metrics related to labs;
    - Mean hyperglycemia,
    - Hypoglycemic rate/ patient days on hypoglycemic agent,
    - Rate of acute kidney injury (AKI)
  - Ability to link relationships
    - Troponin with mortality in medical patients and/ or beta blocker use
    - CHF readmission rates with ACE AKI

The VA Inpatient Evaluation Center

Aggregate VA ICU Standardized Mortality Rate



	2002	2003	2004	2005	2006	2007	2008
SMR30	1.099	1.063	1.065	1.008	0.996	0.997	0.940
SMRHosp	1.194	1.152	1.144	1.059	1.012	0.977	0.923

Mortality data and VA ICUs

- Multiple mortality measures tell you different things
  - Unadjusted mortality at hospital discharge or at 30 – days for ICU and acute care patients (Are the admission criteria similar; access)
  - Risk adjusted mort at hospital discharge or at 30-days for ICU and Acute care patients (The difference may address issues of alternative access for placement for chronic acute illness/ futile care)
  - Unadjusted mortality of patients transferred from the ward to the ICU (ability to detect and rescue deteriorating patients)
  - Unadjusted mortality graphed against SMR may tell you about risk of underperforming hospital (vulnerability of the healthcare organization and patients)

Use of the VA ICU mortality measures

- Reported every quarter; web based; regional access with national benchmarks stratified by level and type of ICU
- "Boots on the grounds," Targeted site visits, identification of unmeasured variables, Review of low predicted mortality patients who die, use of evidenced based practices, recommendations, follow-up in 6 months.
- Case mix index (ICU pred mort/ all ICU pred mort)
  - Adjusted bed turns, Track severity at ICUs with more limited services
- Targeting groups of patients for ICU LOS reduction (< 2.5% pred mortality)
- Evaluate effectiveness of initiatives
  - ACS, SCIP

The association of hyperglycemia with mortality varies by diagnosis

Even mild renal injury (Cr >0.3 mg/dL) increases mortality risk and LOS

Disease Categories	Mortality Rate N (%)	Odds Ratio (95% CI)	LOS Mean (SD)	OMELOS Mean (SD)
Overall (n, 310,323)	31,912 (10.3)			
No AKI (n, 244,550)	15,106 (6.2)	Reference	4.5 (3.6)	- 0.44 (3.3)
Stage I (n, 52,773)	10,212 (19.4)	2.22 (2.15 – 2.29)	7.1 (6.2)	1.4 (5.7)
Stage II (n, 7,744)	3,359 (43.4)	6.09 (5.74 – 6.46)	10.6 (8.7)	5.2 (8.9)
Stage III (n, 3,271)	2,052 (62.7)	12.51 (11.5 – 13.7)	13.9 (9.9)	10.3 (10.5)
Stage III-D (n, 1,985)	1,183 (59.6)	8.08 (7.24 – 9.03)	16.2 (10.5)	11.2 (10.9)

(CI – confidence limits; AKI – acute kidney injury; OMELOS – observed minus expected length of stay; SD – standard deviation)

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