Automated analysis of electronic medical record data reflects the pathophysiology of operative complications

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Purpose. *We hypothesized that a novel algorithm that uses data from the electronic medical record (EMR) from multiple clinical and biometric sources could provide early warning of organ dysfunction in patients with high risk for postoperative complications and sepsis. Operative patients undergoing colorectal procedures were evaluated.*

Methods. *The Rothman Index (RI) is a predictive model based on heuristic equations derived from 26 variables related to inpatient care. The RI integrates clinical nursing observations, bedside biometrics, and laboratory data into a continuously updated, numeric physiologic assessment, ranging from 100 (unimpaired) to −91. The RI can be displayed within the EMR as a graphic trend, with a decreasing trend reflecting physiologic dysfunction. Patients undergoing colorectal procedures between June and October 2011 were evaluated to determine correlation of initial RI, average inpatient RI, and lowest RI to incidence of complications and/or postoperative sepsis. Patients were stratified by color-coded RI risk group (100-65, blue; 64-40, yellow; <40 red). One-way or repeated-measures analysis of variance was used to compare groups by age, number of complications, and presence of sepsis defined by discharge* International Classification of Diseases, *9*[th] *Revision, codes. Mean direct cost of care and duration of stay also was calculated for each group.*

Results. *The overall incidence of perioperative complications in the 124 patient cohort was 51% (*n = *64 patients). The 261 complications sustained by this group represented 82 distinct diagnoses. The 10 patients with sepsis (8%) experienced a 40% mortality. Analysis of initial RI for the population stratified by number of complications and/or sepsis demonstrated a risk-related difference. With progressive onset of complications, the RI decreased, suggesting worsening physiologic dysfunction and linear increase in direct cost of care.*

Conclusion. *These findings demonstrate that EMR data can be automatically compiled into an objective metric that reflects patient risk and changing physiologic state. The automated process of continuous update reflects a physiologic trajectory associated with evolving organ system dysfunction indicative of postoperative complications. Early intervention based on these trends may guide preoperative counseling, enhance pre-emptive management of adverse occurrences, and improve cost-efficiency of care. (Surgery 2013;154:918-26.)*

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In 1998, the Institute of Medicine reported that every year approximately 98,000 patients died from medical errors in U.S. hospitals.[1] Because a major driver of these errors was poor communication among providers, a primary recommendation of this report was implementation of computerized order entry and the institution of an electronic medical record (EMR) to replace the illegible hieroglyphics that often characterized the written bedside chart.[2-4] Almost two decades later, practically every major health care facility is in the process of adopting EMR technology.

Concomitant with the evolution and propagation of the EMR has been the development of multiple

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clinical registries designed to compile specific and standardized data elements intended to define best practice, monitor clinical outcomes, and measure clinical performance. Among these are the National Surgical Quality Improvement Program, the National Trauma Databank, and the registry of the Commission on Cancer. The overarching mission of these and similar registries is quality improvement. The universal characteristic of these data-management systems is the mandate for use of validated, structured data elements. Unfortunately, very few of these elements are contained in currently available EMR products. Rather than automatically exporting critical data required for continuous quality improvement, current EMR technology simply serves as a repository of information to be extracted by registrars for subsequent entry into appropriate registries.

Continued evolution of the EMR will eventually automate the collection of valid, relevant, structured data and will compile relevant data in a manner that defines best practice and assists immediate clinical decision support. The Rothman Index (RI), developed to be such an automated assessment system, is a general measure of individual patient condition that uses 26 clinical variables related to inpatient care and routinely available in the EMR. These include vital signs, laboratory results, cardiac rhythms, and nursing assessments, all of which are incorporated in a heuristic model to compute a number that reflects a general assessment of a hospitalized patient's current physiologic condition. We hypothesized that such a novel algorithm, using only EMR data from multiple clinical and biometric sources, could provide early warning of organ dysfunction in patients with high risk for postoperative complications and sepsis. Patients undergoing colorectal resections were evaluated.

METHODS

Index computation. The RI integrates clinical nursing observations, bedside biometrics, and laboratory data (Table I) into a continuously updated, numeric, physiologic assessment, ranging from 100 (unimpaired) to −91.[5] The RI can be displayed as a graph within the EMR with decreasing trend warning of physiologic dysfunction. The RI recalculates automatically every time any new data are generated from the clinical patient monitoring or laboratory systems. It is fully automated and requires no additional data entry activities that digress from the normal workflow of clinical care. The clinical component combines new values with existing values of the other variables; however, no data point can be older than 15 hours. The laboratory component of the index is based on values obtained within 48 hours of the RI recalculation.

To compute the patient's overall condition, the independent single variable risk is summed over the 26 variables. Single-variable risk for each patient at a point in time is estimated by evaluating the 1-year postdischarge mortality corresponding to the current value of that variable. Laboratory variables are included in the computation when they are available but are aged-out during a 48-hour period. Twenty-four hours after measurement, the laboratory variables are given 50% of their original weight, and after 48 hours they are excluded.

Twelve of the 26 RI variables directly reflect clinical patient assessment performed by nursing personnel. These data are collected in the course of the routine clinical care process that requires a "head-to-toe" or "body system" patient examination performed at least once per nursing shift and recorded in the EMR in one of two ways. If charting by exception, the nurse answers a master question for each physiologic system, such as "*Is the patient's respiratory function within normal limits?*" Alternatively, the nurse may answer a series of questions, such as, "*What are the breath sounds?*" or "*What color are the nail beds?*" etc. The answer to a master question is "pass" or "fail." When there are multiple questions per assessment, the entire category fails if any answer reflects a deviation from normal. Assessment questions may vary between hospitals but share the aim of noting a non-normal status of the physiologic system. Example definitions of standards for each nursing assessment are shown in Table II.

An RI of 100 means unimpaired, 65 is the acuity generally seen with patients discharged to a skilled nursing facility, 40 corresponds to the level of a common physiologic scoring system (Modified Early Warning System [MEWS]) of 4, which indicates consideration of transfer to intensive care unit (ICU), 0 is the lowest score generally supported on a regular ward; negative values are often seen in the ICU.[6] To alert caregivers of status and potential change, the background of the RI graph is blue any time the RI is greater than 65. Between 64 and 40 the display is yellow, and for patients with greatest physiologic derangement whose scores decrease to less than 40, the display background is red (Fig 1).

Index assessment. The primary purpose of this investigation was to assess the correlation of the RI as an indicator of physiologic status to preoperative morbidity and postoperative complications. Our

Table I. Components of the Rothman Index

Vital signs	*Nursing assessments (head-to-toe)*	*Nursing assessments (other)*	*Laboratory tests (blood)*	*Cardiac monitoring*
Temperature	Cardiac	Braden score	Creatinine	Heart pattern, eg
Diastolic blood pressure	Respiratory		Sodium	Asystole
Systolic blood pressure	Gastrointestinal		Chloride	Sinus rhythm
Pulse oximetry	Genitourinary		Potassium	Sinus bradycardia
Respiration rate	Neurologic		BUN	Sinus tachycardia
Heart rate	Skin		WBC	Atrial fibrillation
	Safety		Hemoglobin	Atrial flutter
	Peripheral Vascular			Heart block
	Food/nutrition			Junctional rhythm
	Psychosocial			Paced
	Musculoskeletal			Ventricular fibrillation
				Ventricular tachycardia

BUN, Blood urea nitrogen; *WBC*, white blood cells.

Table II. Nursing assessment standards

Cardiac	*Pulse regular, rate 60–100 beats/min, skin warm and dry. Blood pressure <140/90 mm Hg, and no symptoms of hypotension.*
Food/nutrition	No difficulty with chewing, swallowing or manual dexterity. Patient consuming >50% of daily diet ordered as observed or stated.
Gastrointestinal	Abdomen soft and nontender. Bowel sounds present. No nausea or vomiting. Continent. Bowel pattern normal as observed or stated
Genitourinary	Voids without difficulty. Continent. Urine clear, yellow to amber as observed or stated. Urinary catheter patent if present.
Musculoskeletal	Independently able to move all extremities and perform functional activities as observed or stated (includes assistive devices).
Pain	Without pain or visual analogue pain scale <4 or experiencing chronic pain that is managed effectively.
Neurologic	Alert, oriented to person, place, time, and situation. Speech is coherent.
Peripheral/vascular	Extremities are normal or pink and warm. Peripheral pulses palpable. Capillary refill <3 s. No edema, numbness or tingling.
Psychosocial	Behavior appropriate to situation. Expressed concerns and fears being addressed. Adequate support system.
Respiratory	Respiratory rate 12–24 breaths/min at rest, quiet and regular. Bilateral breath sounds clear. Nail beds and mucous membranes pink. Sputum clear, if present.
Safety/fall risk	Safety/fall risk factors not present. Patient is not a risk to self or others.
Skin/tissue	Skin clean, dry and intact with no reddened areas. Patient is alert, cooperative and able to reposition self independently. Braden scale >15.

hypothesis was that a lesser RI correlates with increased numbers of inpatient complications, including sepsis, and that this inverse correlation also applied to duration of stay and inpatient charges. Institutional review board approval was obtained for retrospective analysis of deidentified patient data reflecting care of 124 operative patients at a major teaching hospital. Electronic clinical records and administrative billing data of patients undergoing colon resection by either laparoscopic or open technique between June 1 and October 31, 2011, were evaluated to determine the correlation of initial RI, mean RI during hospitalization, and lowest inpatient RI, to incidence of complications and/or postoperative sepsis. The initial RI was used to define the relationship from the perspective of the physiologic starting point of inpatient care. The average RI reflected the patients' status across the continuum of care, and the lowest RI was used to evaluate the relationship of pathophysiologic nadir to outcome.

Patients were categorized by the three separate, color-coded risk cohorts defined previously. Each risk cohort was then stratified by number of complications defined by discharge *International Classification of Diseases*, 9th Revision, Clinical Modification codes. Because sepsis occurred independently

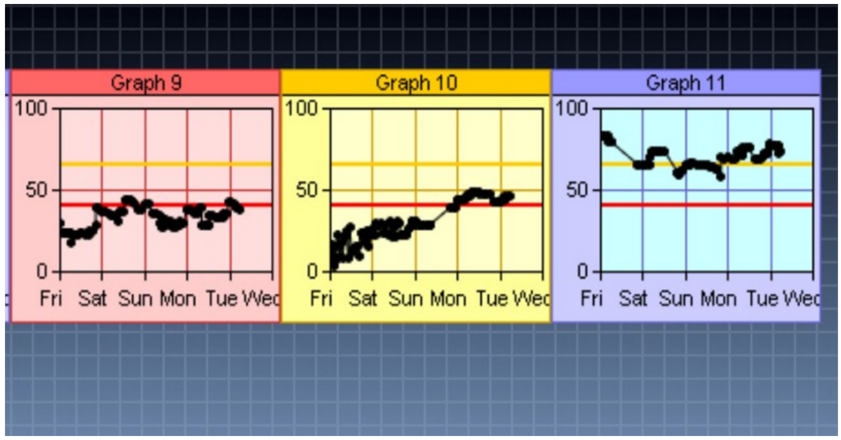

Fig 1. Typical unit-based display of three patients, each of whom have differing physiologic status as depicted by the background color of each graph. Note improvement trends in graphs 10 and 11.

Table III. Complications listed by AHRQ-defined Clinical Classification Software (CCS) diagnoses

CSS description	*No. complications*
238: Complications of surgical procedures or medical care	48
E Codes: Adverse effects of medical care	27
145: Intestinal obstruction without hernia	24
55: Fluid and electrolyte disorders	21
60: Acute posthemorrhagic anemia	16
131: Respiratory failure; insufficiency; arrest (adult)	14
2: Septicemia (includes 10 severe sepsis)	11
244:- Other injuries and conditions due to external causes	10
Multiple: Other	90
Total	261

AHQR, Agency for Health Quality Research.

from the number of concomitant other complications, this group was analyzed separately. Independent variables were patient age and color-coded risk strata. Dependent variables were number of complications, cost, and duration of stay. One-way analysis of variance was used to compare patient age, number of complications reported, direct costs, and duration of stay for each risk group. Tukey-Kramer multiple comparisons were used to assess differences between groups. Alpha was set at .05.

RESULTS

The study group consisted of patients undergoing 74 laparoscopic and 54 open colon resections. Perioperative complications were recorded in 64 patients (51%). The 261complications sustained by this group are listed in Table III, obtained from the diagnosis categories from the Agency for Health Quality Research. From the perspectives of admission status as defined by initial RI, a patient's overall condition as defined by average RI, and physiologic nadir defined by lowest RI, there were no differences between each color-coded risk level and patient age. As an automated reflection of both physiologic and laboratory derangement, however, the RI did correlate with risk as defined by number of complications, direct cost, and duration of inpatient stay, each of which differed significantly for all three RI measures. Pairwise comparison of the three color-coded risk cohorts varied in significance, as depicted in Table IV; the greatest risk (red background) category, however, was statistically different from the other cohorts for all three RI measures.

Table V summarizes the cohorts by incidence of complication, and includes the group of 10 patients with severe sepsis (8% of population) who experienced 40% mortality. Presence of sepsis with its attendant physiologic derangement was associated with an even more dramatic decrease in RI. Repeated-measures analysis of variance demonstrated no difference among initial, mean, and lowest RI for each group, and difference among the RI stratified by number of complications and sepsis. The initial RI reflecting admission physiologic status was almost twice both the average and lowest RI, illustrating the pathophysiologic effect of sepsis and its reflection by the RI.

DISCUSSION

These data demonstrate that RI correlates with physiologic derangement and risk associated with one of the most problematic areas of surgical care.

Table IV. Relationship of RI to incidence of perioperative complications and cost

RI score cohort	Patients	Avg no. complications	Avg ACT Total cost	ALOS	Avg age
Earliest RI score					
Red (R)	10	5.11	$136,368	33.20	56.3
Yellow (Y)	15	3.64	$56,225	16.33	66.1
Blue (B)	99	4.00	$29,248	8.31	57.5
ANOVA		NS	$P < .0001$	$P < .0001$	$P = .1099$
Average RI score					
Red	14	7.08	$158,434	36.14	59.9
Yellow	22	4.81	$49,287	16.64	65.8
Blue	88	2.62	$20,457	6.00	56.4
ANOVA		$P < .00001$	$P < .00001$	$P < .0001$,	$P = .0302$*
Pairwise Tukey-Kramer		R-Y < .01 R-B < .001, Y-B < .001	R-Y, R-B < .001 Y-B < .01	all <.001	R-Y, R-B ns,* Y_B < .05
Lowest RI score					
Red	33	6.04	$98,106	25.61	62.3
Yellow	28	3.24	$26,425	8.64	62.7
Blue	63	2.30	$17,861	4.97	54.6
ANOVA		$P < .00001$	$P < .0001$	$P < .0001$	$P = .0140$
Pairwise Tukey-Kramer		R-Y < .01 R-B, Y-B < .001	R-Y R-B < .001 Y-B < .01	R-Y, R-B < .01 Y-B ns*	R-Y ns,* R-B, Y-B < .05

*Nonsignificant pair differences.
ACT, Actual; *ALOS*, average length of stay; *ANOVA*, analysis of variance; *ns*, nonsignificant; *RI*, Rothman Index.

Table V. RI and complications, including sepsis

Category	Avg earliest RI	Avg average RI	Avg lowest RI
0	85.06	81.27	85.64
1–5	71.43	69.50	72.23
>5	56.44	49.61	66.67
Sepsis	64.13	38.39	36.97

RI, Rothman Index.

We chose to evaluate colorectal resection procedures because they reflect an operative intervention that is increasing in incidence, rapidly has transitioned to minimally invasive approaches, and by nature of risk for anastomotic leak, are associated commonly with surgical-site infections and potentially sepsis. As an objective metric that reflects patient risk and changing physiologic state, the automated process of continuous RI update can define changing physiologic state and potentially describe the trajectory associated with evolving organ system dysfunction indicative of postoperative complications. Figure 2 illustrates two such examples involving patients who developed postoperative sepsis. The arrows indicate the day of operation. One case demonstrates a precipitous decrease (red background), whereas the other defines a more gradual decrease (yellow background). Both trends raise the question of potential pre-emption if the care teams had been able to recognize the trend and intervene earlier.

Such a capability provides three immediate benefits. First, it is totally automated and, as described previously, gradually evolves to a clinical assessment driven by both nursing and physician evaluations. There are no additional workflow tasks associated with the gathering and computation of this index. Second, this change in physiologic status should provide early warning of impending organ dysfunction, which often manifests itself by subtle clinical changes well before objective evidence in associated laboratory values. By nature of its design, the RI recalculates every time a change in a component metric is recorded. Regardless of the absolute number or color code class displayed, the very fact that a number of indices are being calculated and displayed is an indication of physiologic change either positively or negatively. Finally, the RI appears to be a useful process for risk-stratification. Assessment of these data focused on the initial RI as an indicator of admission physiologic state. The data clearly show that lower scores portend more problematic care. Documentation of such changes will become an extremely important issue both for performance assessment and public reporting.

The core strategy of the Patient Protection and Affordable Care Act of 2009 is expansion of health care coverage, definition of quality through collection of objective data, then control of cost by determination of value defined as the ratio of

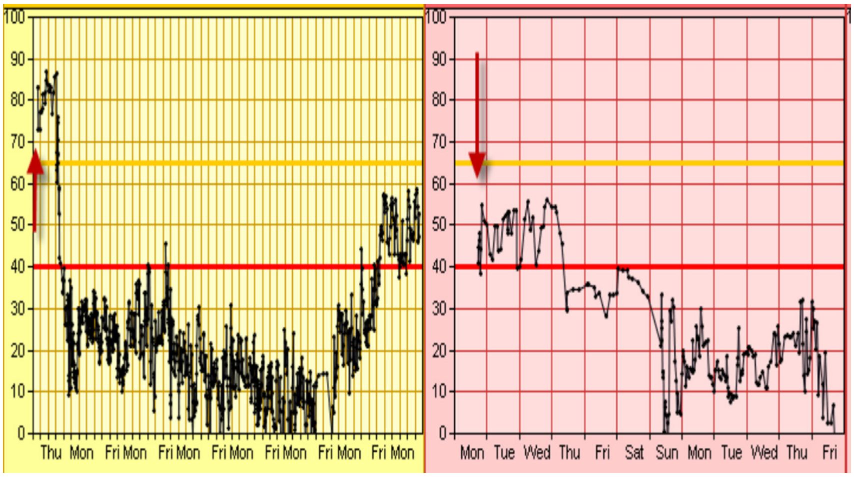

Fig 2. RI trajectory and sepsis. Vertical lines correspond to midnight. RI of 100 means unimpaired, 65 is the acuity generally seen with patients discharged to a skilled nursing facility, 40 corresponds to MEWS of 4 and indicates consideration of transfer to ICU, 0 is the lowest score generally supported on a regular ward, negative values are often seen in the ICU.

optimal quality divided by appropriate expense.[7-9] Reliable, structured data with standardized definitions will drive this process. Unfortunately, the current state of EMR technology does not provide this level of data quality or provide direct surveillance of issues related to patient safety.

Currently, most EMR systems do capture large amounts of clinical data that will eventually become available for computational purposes. The RI already provides such an opportunity to use a wide range of clinical variables for automated determination of the acuity of a hospitalized patient's condition. Even more importantly, this automation eliminates the burden of complexity or miscalculation on the part of clinicians.[10-13] This background process of automated assessment of overall physiologic status varies from the many tools currently designed to identify or predict specific conditions such as cardiopulmonary arrest, mortality, or transfer to the ICU. Moreover, these scoring systems are often specific to an ICU environment, as, for example are PRISM, Acute Physiology and Chronic Health Evaluation (ie, APACHE) III, and Sequential Organ Failure Assessment score (ie, SOFA).[13-18]

These assessment systems generally use one of two approaches. Clinicians compute patient acuity based on a set of criteria such as the Modified Early Warning Score (MEWS).[6] Alternatively, clinicians rely on models using standard regression methods.[19,20] Many of these external assessment methodologies originate from Delphian definition of variables and associated risk developed by consensus of recognized experts. [6,21-23] For example, the Behavior/Neuro subscore used in the cardiac children's hospital early warning score model is assigned a value of 0 when the patient state is "playing/sleeping appropriately," a value of 1 when "sleepy, somnolent when not disturbed," a value of 2 when "irritable, difficult to console," and a value of 3 when displaying "reduced response to pain." These are 4 of more than 40 values in the model, which have similarly assigned risk weightings.[23] While these expert distinctions form the basis of the model, in general these risk functions do not have any rigorous validation.

Regression model development is a more rigorous approach in which a proposed predictive model is validated using an independent test set. Both expert-generated rules systems and regression models have limitations of specificity and positive predictive value. For example, to identify 44% of transfers to ICU in advance by 12 hours, MEWS generates 69 false positives for every correctly identified event. A similar system espoused by Escobar et al[20] generates 34 false positives.

For these reasons the RI applies a different perspective. The RI provides a general assessment of a hospitalized patient's current condition, rather than attempting to forecast particular events.[24,25] Its constituent 26 clinical variables are all commonly available in the EMR including vital signs, laboratory results, cardiac rhythms, and nursing assessments. Leveraging the EMR in this manner realizes the vision of a continuously updated patient condition score, independent of specific events, diseases, procedures or environments, and incorporating sufficient clinical variables to provide sensitivity to patient risk across the spectrum of acuity from the unimpaired to the gravely ill.[13]

Viewed against the current environment of clinical data management systems that are not yet able to drive the global transition of health care to the level of efficacy, cost effectiveness, and value that is clearly needed, systems like the RI provide a real and present application of EMR technology that uses routinely gathered clinical data to provide a fully automated method of constant surveillance of a hospitalized patient's overall physiologic status. Our EMR approach accomplishes this task with no additional input from providers nor any changes in the standard workflow of inpatient clinical care.

A limitation of this study is that it is a retrospective uncontrolled analysis of discharge claims data. Despite this, our study clearly demonstrates that this automated system running in the background of the normal process of clinical care does reflect gradations of physiologic state that relate to potential for perioperative morbidity and mortality. Clearly, the next stage of validation will be prospective analysis of clinical data to define pre- and postoperative trends of RI. This approach will assess its ability to serve as an early warning of impending organ dysfunction, and to determine if it is able to identify a point of "optimization" of a patient in preparation for elective surgical repair.

In summary, the RI reflects a status, not an event. Early intervention determined by trends in the RI will guide preoperative counseling, enhance preemptive management of adverse occurrences, and improve cost efficiency of care. Better and more timely evidence of patient status related to these costly and often devastating complications will improve overall operative quality as well as costs.

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DISCUSSION

Dr Frederick Luchette (Maywood, IL): All of us in the audience that work with EMRs know that the only thing we've received to date is an increase in our workload, without any benefit. But what you've done today with this proof of concept study is demonstrated how the information entered into the EMR can actually be harnessed to assist the clinicians with patient care. I think this is particularly relevant as more of the traditional nursing activities of patient care are being performed by less-skilled and knowledgeable nurse's aides.

So I have three questions for you, Joe.

First, it is curious that the RI does not include comorbidities as variables but does include nursing physical examination. Some of the nursing variables seem redundant to me, such as the ones labeled safety, psychological, and neurologic. What physiologic information do these variables provide? And would the fidelity of the RI be improved with the inclusion of comorbidities, which we all know are well known to influence morbidity and mortality in our surgical patients?

You included 82 distinct complications. What kinds of complications were studied for the stratification? Were they mainly arhythmias, electrolyte disturbances, or anemia? How significant are they with regard to quality care and patient safety?

Finally, what percent of the colectomies were emergent and elective? I would assume that the emergent colectomies were admitted to the ICU, with intensive nursing, so what is the benefit of the RI in the ICU setting?

Dr Joseph Tepas, III: The issue regarding the comorbidities and the nursing, one of the observations of the individuals who built this was that watching the care of their mother—and I think all of us in this room would agree with this—that, unfortunately, we still tend to work in silos. Watch a resuscitation. You have the nurses talking to the nurses. You have the doctors yelling at the nurses and essentially talking to each other.

The one thing that is constant in our health care system today, sad to say, is that the nurses, by definition and by policy, do a head-to-toe assessment every time they come on shift. And that's the only reliable thing. We all sitting in this room know the horror stories of patients being seen on rounds and someone forgets to check the wound or misses things. So that's the purpose of having that in there.

And you raise a very interesting question about whether this represents a specific comorbidity. What this represents is a set of trained eyes looking at what the patient actually looks like lying in bed. And that, I think, is going to turn out to be a very significant additional adjunct.

The issue regarding complications—I actually did get the list of complications, and I did the analysis across the board. And there was no difference in trends between those that had one to five and those that didn't. So that information wasn't in there.

I looked at laparoscopic versus open, but I cannot answer the question regarding emergent. I suspect that that group of patients that came in the door with the lowest were probably emergent, versus the ones that were average of 85 coming in the door, were elective. But I didn't look at that data.

Dr Carol E.H. Scott-Conner (Iowa City, IA): I'm struck by the potential this has to operationalize and close the loop so that you start actually intervening in patients in a systematic fashion at the early sign of deterioration.

And sort of by loose analogy, quite a few years ago, our hospital, and probably many of yours, instituted what were called rapid response teams. And they're often triggered by the nurses. Patient just doesn't look right—please come. We have been able to avoid a lot of emergent intubations by identifying a patient who is going downhill. So this sort of puts this sort of gestalt on a statistical basis.

I would like to ask you to speculate, if you would, as to how you would then operationalize a kind of surgical response, probably operation-specific. The response might be different for a colon patient than for an esophagectomy, but a way in which once you've identified this down slope, before they get to the red zone, you can do something that might change the course of events.

Dr Joseph Tepas, III: Your insight is spot on. And that first display, when I described the RI, is exactly what the display looks like at the center where our rapid response team sits. And if they see a change in color, for example, they query it.

Now, we are going forth in rolling this and implementing this system at the University of Florida in a data-driven manner because this is a great concept, but it needs proof. The nurses asked the same question. They've got a green graduate nurse sitting up there on the floor with a patient that's status postcolectomy, how far does it need to dip? Should it dip at all? And when do I call for help? And we are actually doing a prospective analysis.

The first part of this, however, to answer your question, which gets to the slide with the change, is, I had them give me, from our Rothman server, blinded data, and, concurrently, the rapid response team data, blended the two together. I have no idea who the patients were, didn't know where they were. And I had one question: Did this thing really change? And the interesting assessment of that, which is what I used to literally accept implementation of this and pay these guys, was that when you did a circle of an hour around a rapid response event, you saw two things: You saw a dip, and you saw an increase in the number of computations. Remember, every time things change, this recalculates.

So this is sitting out there as a warning system, both from trend, color, but also just, hey, something is going on here, because things keep changing. So it's coming.

Dr Gerald Larson (Louisville, KY): My information is that in 2012, approximately 44% of our hospitals in the United States have the EMR. And there are three or four different programs or systems out there that are being used. Would this RI be applicable to all of them?

Two, I'm most comfortable and familiar with the Veterans Affairs (VA) EMR, the CPRS program, which I actually think, for me, works quite well. Would the RI work in the VA programs?

Dr Joseph Tepas, III: Yes. It is actually system agnostic. It was developed initially for the Allscripts Eclipsys program, works in Cerner, works in EPIC. I think it works in the VA. The basic topography—not to bore you with geek details—is that it essentially ports over from the data server into its own server. And it's the development of that interface. And then it pushes it out. This is an add-on. And as we go forward and look at what tools are going to help us learn the tool of the EMR, this is just one of the first. There will be many more.

And just to add one more comment to it, the other issue is that the American Heart Association, the American Medical Association, and the American Medical Informatics Association have pushed back against the fed because you're absolutely right. And we look at the cost per bed of what it has taken to install the EMR, it has been enormous.

So the good news is there's a ton of digital data that we can start to give our patients by way of an interface network when they travel. The bad news is it's unstructured textual data that's almost useless. And we have to fix that problem.

The College of Surgeons has begun doing this with Epic, and with other because we want this automatically to drive all of the registries which are what really define how well we do.

Dr Mark Talamonti (Evanston, IL): This presentation is really convincing that we can use the EMR to improve patient care and support clinical decisions. One question I have about this, though, is it seems to be real-time monitoring of events that are happening on the floor but still somewhat subjected to the interpretation of nurses entering data into the EMR, and abnormal labs being ordered, computed tomography scans, and so forth.

One of the things that we're trying to look at is standardizing clinical care with clinical pathways. And then when the patients deviate off the pathway, using that as the yellow flag, red flag alert, so that it's less subjective, more objective. And we can identify those patients who are starting this trend, as you say, downward spiral.

Can I have your perspective on clinical standardization pathways and how that might even be more effective than a RI, which is still somewhat dependent upon good data in, good data out, rather than setting up the parameters by which you raise the red flag and say something is going wrong here?

Dr Joseph Tepas, III: That's an excellent question and that actually kind of reflects my mindset when I first heard about this thing. And I actually did work with them to develop a pediatric Rothman, because I'm actually a pediatric surgeon.

But the answer to your question really relates to the fact that 12 of these 26 elements are clinical observations. How in the heck do you take clinical observations and turn them into a binary number that goes into a heuristic logistic regression analysis? That's the model. That was the question.

And it's done in a manner that, essentially, each of those 12 things either meets the standards of the patient being in good shape or not by the nursing system, or not. And so that's how that part works.

But probably the most important response that I can make is unlike, say, MEWS or The Cardiac Children's Hospital Early Warning Score, or the pediatric trauma score that are designed to identify a specific diagnosis, this is the physiologic status. And so the way we are using this—because we are starting Surgical Unit-based Safety Program or Comprehensive Unit-based Safety Program for surgical safety—is this is another thing that lets us see whether our clinical pathways are following the course anticipated or need to be revised.

I think, as we go forward, we'll get better at understanding that. And quite frankly, as time goes by, some of these factors may change.

Dr Scott Melvin (Columbus, OH): You almost implied that this is predictive in nature, that, based on the trend, you can predict what's going to happen next. It's easy to describe that if you look at patients who code, but what about everybody else who had deviations and then does okay, they have abnormal observations but yet it's not predictable?

Dr Joseph Tepas, III: I agree, that's the wrong word to use, predictive. It should be reflective, because predictive implies that there would be no interaction or intervention. So this is an early warning of a physiologic status. I suspect, in the absence of intervention, the patient would continue to deteriorate.

Dr Michael G. Sarr (Rochester, MN): Three focused questions, Joe. First, is sepsis independent from your scores of zero, one to five, or greater than five?

Dr Joseph Tepas, III: The reason that I put sepsis in there is that, in my role as leading the Florida surgical care initiative, as you know, sepsis, especially sepsis after colorectal surgery, is a major driver of bad outcome, surgical-site infection. And so I asked them specifically, give me the sepsis data. And it's mixed and matched, as you can see in there.

Dr Michael G. Sarr (Rochester, MN): You showed us a profile of a very sharp decrease, with a red arrow. Now, did you look at each of those cases to see if that decreases preceded the intervention by the clinical team or occurred concurrently?

Dr Joseph Tepas, III: Actually, my collaborators, who represent the institution from which these data came, did do that. And there was evidence of intervention delayed in both cases.

Dr Michael G. Sarr (Rochester, MN): Third, is this a great tool for turnover?

Dr Joseph Tepas, III: Yes. Actually, anticipate your residents turning over, looking at a display, and saying, "Oh, we need to look at Mrs. Jones."