OR/OM Colleagues and Co-Authors

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- Edward Wasil, Kogod School of Business
- Gordon Gao, R.H. Smith of Business
Background

- My advanced degrees are in operations research (OR)
- OR is a field which uses advanced analytical methods to help make better decisions
- I have been a member of INFORMS since 1974
- INFORMS sponsors a Conference on Business Analytics & Operations Research each Spring
In Moliere’s play *The Bourgeois Gentleman*, Mr. Jourdain discovers that he has been speaking prose all his life, and didn’t even know it!

Well, Mike, Margrét, and I have been doing business analytics ever since we were graduate students, but we didn’t use that name.

I began working on healthcare applications about six years ago.
Emergence of Healthcare Analytics within INFORMS

Number of Healthcare Talks at INFORMS Annual Meetings

Above numbers courtesy of Brian Denton
There is more healthcare data available than ever before

- Careful analysis of healthcare data can lead to smarter decisions, better quality healthcare, and cost savings

A larger number of healthcare decision makers have MBAs than ever before

- They understand that we can help

A larger number of us in OR/OM are working on healthcare applications than ever before
The Cardiac Surgery service line at the UMMC has 30 beds that are split between the intensive care unit (ICU) and the intermediate care unit (IMC)

At the time of the study, there were 11 ICU beds and 18 IMC beds

One bed was not in use because of insufficient staffing

**Key Question:** What is the best mix of ICU and IMC beds?
Non-Surgical Admissions

Cardiac Surgery

ICU

IMC

Home, local hospital, or other location

Note: IMC beds are less intensive and less expensive than ICU beds
Data Set

- The data set contained detailed information about the length of stay for every cardiac surgery patient for a two-year period (2005-2006)

- 1,675 patients had 1,725 operations and spent more than 17,000 days in the hospital
We used the data to perform a simulation of different mixes of ICU and IMC beds

- We maintained the current staffing level of 80 nurses

- Each mix of ICU and IMC beds was simulated 1,000 times for four months each time
Results

- The 14/12 bed mix enabled a total volume increase of 20%.
- Each cardiac surgery provides a net income of roughly $20,000.
- Staffing levels are constant, so there is no additional cost for nurses.
- The 14/12 bed mix yields an annual increase in profit of $4.58 million.
- This work can be reproduced in other service lines (e.g., neuro) and at other hospitals with similar results.
There is significant variation in the quality of care from one hospital to the next.

We examine how quality varies within hospitals between daytime (6 am-6 pm) and off-hours (6 pm-6 am).

We focus on trauma patients.

- By trauma, we mean sudden physical injury.
Examples
- Car crashes
- Traumatic brain injury
- Gunshot wounds

Trauma is the leading cause of death among Americans ages 1 to 44 (122,000 deaths a year)

Trauma patients are treated at a wide variety of hospitals
- Short treatment cycle
- Clear quality metrics
Data

- National Trauma Data Bank created and maintained by the American College of Surgeons
- Data on over 1.5 million patients from 477 hospitals
- Detailed data: patient demographics, hospital characteristics, treatment characteristics, outcome, payment type, comorbidities, and more
Quality Measures

- Mortality
- Waiting time to surgery
- Length of ICU stay
- Surgical complication rate
- Number of surgeries required
Empirical Analysis

- Regression modeling
- Logistic regression modeling
- The findings focus on an average patient and show how outcomes change if patient arrives in daytime, night, or early am
## Modeling Outcomes

<table>
<thead>
<tr>
<th>Measure</th>
<th>Daytime</th>
<th>Night</th>
<th>Early am</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mortality rate (L1)</td>
<td>0.10</td>
<td>0.104</td>
<td>0.108</td>
</tr>
<tr>
<td>Mortality rate (L2)</td>
<td>0.10</td>
<td>0.104</td>
<td>0.109</td>
</tr>
<tr>
<td>Mortality rate (L3-4)</td>
<td>0.10</td>
<td>0.114</td>
<td>0.131</td>
</tr>
<tr>
<td>Mortality rate (all)</td>
<td>0.10</td>
<td>0.111</td>
<td>0.111</td>
</tr>
<tr>
<td>Complication rate</td>
<td>0.125</td>
<td>0.131</td>
<td>0.135</td>
</tr>
<tr>
<td>Multiple surgery rate</td>
<td>0.786</td>
<td>x</td>
<td>0.806</td>
</tr>
<tr>
<td>Time to surgery (mins.)</td>
<td>182.5</td>
<td>175.4</td>
<td>167.9</td>
</tr>
<tr>
<td>ICU LOS hours</td>
<td>9.78</td>
<td>10.32</td>
<td>10.61</td>
</tr>
</tbody>
</table>
Initial Observations

- Prompt treatment is essential in trauma care (the Golden Hour)

- To our surprise, longer waits for surgery did not occur during off-hours
  - Hospitals are not as busy at night
  - Operating rooms are mainly idle

- Still, outcomes at night/early am were clearly worse than during daytime
Explanation of Outcomes

- Staffing levels differ between daytime and off-hours
- There tend to be generalists on duty overnight
- More resources and specialized resources are available during the daytime
- More experienced physicians prefer to work during the daytime
- Therefore, we expect a higher quality of care during the daytime and the model outcomes confirm this
The differences in resource availability between day and off-hours at small hospitals are greater than at larger hospitals.

Level I trauma centers are required to have certain surgical specialty staff available at all times.

Therefore, we expect to see larger differences in outcome between daytime and off-hours at lower level trauma centers, and smaller, more resource-constrained hospitals.
- Increase in mortality rate compared to daytime

<table>
<thead>
<tr>
<th></th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early am</td>
<td>11.0%</td>
<td>14.3%</td>
<td>30.6%</td>
</tr>
<tr>
<td>Night</td>
<td>10.1%</td>
<td>13.1%</td>
<td>18.9%</td>
</tr>
</tbody>
</table>

- Increase in surgical complication rate compared to daytime

<table>
<thead>
<tr>
<th></th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early am</td>
<td>9.2%</td>
<td>10.8%</td>
<td>31.9%</td>
</tr>
<tr>
<td>Night</td>
<td>4.6%</td>
<td>4.7%</td>
<td>8.2%</td>
</tr>
</tbody>
</table>
Patients who arrive at night or the early morning to trauma centers receive lower quality care than patients who arrive during the day.

The decrease in quality of care is largest at small, resource constrained hospitals and at lower level trauma centers.

There are fewer specialized doctors available off-hours, which leads to lower quality.

Mitigation strategies: Increase staffing levels and mimic the Dr. Cowley Shock Trauma Center.
Many hospital resources are required for surgery
- Operating rooms
- Nurses
- Anesthesia team
- Post-operative beds for recovery

If downstream beds are unavailable, surgery might be postponed or cancelled

Surgeons decide when patients are discharged
- Surgeons are paid to do surgery
Does the utilization of downstream beds affect the discharge decisions of surgeons?

Hypothesis: There is an increased discharge rate on days when post-operative utilization is high.
Data

- Data collected on every surgery performed at a large US hospital from Jan 1, 2007 to May 31, 2007
- 7,808 patients, of which 6,470 were admitted to the hospital and stayed for at least one night
- These patients stayed a total of 35,478 days
- Data provided on age, race, gender, surgical line, date of surgery, discharge date, and surgery type (scheduled vs. emergency)
- Utilization of post-operative beds varies widely
Discharge Rates

- Discharge rates have positive correlation with utilization
We compute two measures of utilization

- Discrete measure – a variable that is 1 when utilization exceeds a given threshold (e.g., 93%), and 0 otherwise
- Continuous measure – a variable that counts the number of beds in use on each day

Compare marginal effect of each bed in use vs. a discrete change in discharge probability when utilization exceeds a threshold
Can’t use logistic regression because observations are correlated -- a patient discharged on the fifth day cannot be discharged on the first four days

Singer and Willet (1993) show how to handle discrete time survival data

For each day, we record whether or not each patient is discharged, and use this as the outcome variable

The outcome variable is regressed on our utilization measures and our control variables

We control for the patient’s age, race, gender, severity, and surgery type
Models and Results

- **Model 1:** \( \text{logit(DISCHARGE)} = \text{AGE} + \text{ELECTIVE} + \text{FULL} + \text{CARDIAC SURGERY} + \text{CARDIOLOGY} + \ldots + \text{DONOR SERVICE} + D1 + D2 + \ldots + D59 + \varepsilon \)

- **Model 2:** \( \text{logit(DISCHARGE)} = \text{AGE} + \text{ELECTIVE} + \text{BEDS} + \text{CARDIAC SURGERY} + \text{CARDIOLOGY} + \ldots + \text{DONOR SERVICE} + D1 + D2 + \ldots + D59 + \varepsilon \)

- When the utilization threshold is exceeded, the odds of discharge for any given patient increase. The estimate for Full is positive and significant for threshold above 91.5%.

- Each additional bed in use increases the odds that a patient will be discharged. The estimate for Beds is positive and significant.
Observations

- Discharge rates increase as utilization increases, regardless of how utilization is measured.

- Either some patients are held too long and discharged when space is needed, or some patients are discharged too early when utilization is high.

- Our results cannot distinguish between these two explanations.
Are patients who are discharged when utilization is high more likely to be readmitted?

Hypothesis: An increase in the discharge rate will lead to some patients with shortened lengths of stay. This will cause an increase in the readmission rate for those patients.
Using the same data set, we apply logistic regression to study the effect that utilization has on the probability of readmission for a specific patient.

- We use readmission within 72 hours as our dependent variable.

- Hypothesized logistic regression model

\[ \text{logit}(\text{READMISSION72}) = \text{AGE} + \text{BLACK} + \text{ASIAN} + \text{HISPANIC} + \text{FULL} + \text{ELECTIVE} + \text{TRANSPLANT} + \text{TRAUMA} + \ldots + \text{NEURO} + \text{MALE} + \varepsilon \]
Results

- Model with Full: Controlling for race, age, gender, and the type of surgery, being discharged from a full post-operative unit increases the odds of readmission by a factor of 2.341

- Model with Beds: Controlling for race, age, gender, and the type of surgery, each bed in use at the time of discharge increases the odds of readmission by a factor of 1.008
Utilization – Readmission Relationship

The discharge rate and readmission rate both increase as utilization increases.
Over the course of a month, patients discharged from a full hospital are much more likely to be readmitted.
The discharge rate rises when utilization is high

This corresponds to an increase in the readmission rate

We conclude that some patients are discharged too soon when utilization is high

Surgeons have an incentive to clear space for their surgeries

Mitigation strategy: Use a checklist before discharging a patient—force the surgeon to think about whether the discharge is for the right reason
Our research team is working with hospitals in Baltimore and Washington, D.C.

There are more opportunities to apply healthcare analytics than we can handle.

Our colleagues at other universities are in the same situation.

The future of healthcare analytics looks very bright.