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Forecasting Emergency Department Overcrowding

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FORECASTING EMERGENCY DEPARTMENT OVERCROWDING

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Abstract

Objective: *To assess the development, use, and implementation of a predictive two-hour forecasting tool for Emergency Department overcrowding. Validate a forecasted Bed Ratio with the National Emergency Department Overcrowding Scale (NEDOCS) and Bed Ratio (BR) to determine accuracy and benefit of use.*

Methods: *This research study utilized tools that identified overcrowding to establish a reliable two-hour forecasting tool within the Emergency Department. It included the use of the Dixon Forecasting Model (DFM), BR, and the NEDOCS. A combination of two tools, the DFM and BR, was utilized to forecast overcrowding based on current census. This two-hour forecast was validated by the NEDOCS and BR, which have been acknowledged in the identification of real-time overcrowding (Jones, 2006).*

Data Analysis: *The two-hour forecasted BR is moderately correlated with the NEDOCS and BR at the forecasted time. This is evidenced by a correlation coefficient of 0.508 with the NEDOCS and a correlation coefficient of 0.492 with the BR. Further data analysis revealed a strong correlation between the NEDOCS and the BR, as evidenced by a correlation coefficient of 0.949.*

Conclusion: *Results of this study suggest that the DFM can be used in combination with the BR to calculate a two-hour forecasted BR. This data would also indicate that using either BR or NEDOCS in real-time to determine overcrowding is effective. One limitation of the study involves criteria set forth for predicted departures in two hours. Creating an automated forecasting tool for* *departures, similar to the DFM's forecasting of arrivals, could prove beneficial.*

Key words: Emergency Department, Overcrowding, NEDOCS, Bed Ratio, Forecasting

Forecasting Emergency Department Overcrowding

In 2001, the Institute of Medicine (IOM) released *Crossing the Quality Chasm: A New Health System for the 21st Century*. This instrumental piece of literature outlined key components lacking within the current health system. Specifically, the report outlined six aims for improvement to impact the quality of care. These aims focus on care that is safe, timely, effective, efficient, equitable, and patient-focused (IOM, 2001).

Implementation of information technology is one approach to address these six aims. According to Jones, et al. (2009), "The IOM recommends that hospitals utilize information technology and use operations research methods to become more efficient." One way of accomplishing this task is through the use of Electronic Health Records (EHR). This technological advancement allowed for improved efficiency, throughput, and quality data metrics (IOM, 2007).

Over the past decade, healthcare systems have started to utilize their EHRs in an effort to generate analytics (Post, 2013). One area within the current healthcare system that could benefit from this technological advancement is the Emergency Department. Set up for a wide variety of ailments, Emergency Departments serve as an essential access point for patients seeking medical treatment (Weiss, 2004). Emergency departments have been impacted by an increasing demand for care. Emergency Department overcrowding is a major problem that highlights this growing trend (IOM, 2007). The use of predictive analytics could provide a solution for Emergency Department overcrowding.

Overcrowding

According to the IOM (2007), overcrowding is an important issue that needs attention within the current health system. Annually, Emergency Department visits have been growing at an exponential rate. The American Hospital Association (2013) reports that from 1993 to 2013, the number of Emergency Department visits increased by forty-one million. It is essential to note, even though patient volumes are increasing, the number of Emergency Departments available to provide treatment is not (Morganti, 2013). Emergency Departments must maintain efficient throughput in order to meet the demands of incoming patients; failure to meet this demand results in overcrowding (Hoot, 2006). As this continues to be a problem, Emergency Departments are faced with extreme challenges to create a solution for this crisis. Understanding what overcrowding is and how to predict the likelihood of it occurring is necessary for its prevention (Jones, 2006).

Overcrowding in the Emergency Department can put patients at risk for increased length of stay, increased cost of care, and diminished quality of care (IOM, 2007). Through research and data analysis, tools to identify overcrowding in real time have been established. Unfortunately, there is limited research to support forecasting and predicting of overcrowding (Hoot, 2007). Consequently, this study attempted to forecast Emergency Department overcrowding with predictive analytics.

METHODOLOGY

Hypothesis

This study aimed to prove that an established demand indicator of Bed Ratio (BR) can be leveraged with the Dixon Forecasting Model (DFM) to accurately predict Emergency Department overcrowding two hours into the future. In an effort to determine the potential for forecasting Emergency Department overcrowding, this study attempted to disprove the following null hypotheses. H0a, the use of a forecasted BR two hours into the future will not have statistical significance in predicting Emergency Department overcrowding. H0b, a forecasted BR two hours into the future will not have statistical significance when validated with the National Emergency Department Overcrowding Scale (NEDOCS). H0c, a forecasted BR two hours into the future will not have statistical significance when validated with the BR.

Study Design

The following research study was submitted to the Grand Valley State University Internal Review Board for exempt status under Quality Improvement Management. This research study utilized tools that identify overcrowding in real time, along with Emergency Department data, to forecast overcrowding two hours into the future. Tools utilized included the DFM, a subset of Real-time Emergency Analysis of Demand Indicators (READI), and the NEDOCS. For the purpose of this experiment, the READI subset utilized was Bed Ratio (BR). The DFM was utilized to assist in the calculation of a forecasted BR two hours into the future. The forecasted BR was validated in real time by the NEDOCS and BR, which have been acknowledged in the identification of overcrowding (Jones, 2006).

Environment

This quality improvement study was conducted at Spectrum Health’s Butterworth Emergency Department in Grand Rapids, Michigan. The Butterworth Emergency Department has an annual visit volume of 107,000 patients, with an average daily census of 294 visits. Additionally, the Butterworth Emergency Department is a designated Level 1 Trauma Center, Certified Chest Pain Center, and Certified Stroke Center. In order to handle the large volume of presenting patients, the Butterworth Emergency Department has 88 designated care spaces. This includes 49 general care spaces, 14 Rapid Assessment Zone/Express Care spaces, three trauma bay spaces, two triage rooms and 20 hallway care spaces. The Butterworth Emergency Department utilizes an EHR, which was used for collecting and gathering data for this study.

Study Instruments

The DFM, BR, and NEDOCS were used over the course of a two-week interval to collect data for the study. Each tool utilized a varying degree of data, which was logged in a Microsoft Excel 2010 spreadsheet. After this timeframe, the data was collected, reviewed, and analyzed. Through analysis, the potential for a reliable two hour forecasted BR to predict Emergency Department overcrowding was evaluated.

Dixon Forecasting Model. The DFM is a proprietary tool developed by a former Butterworth Emergency Department Data Analyst, Bill Dixon. The tool was developed to assist in balancing labor through budgeted nursing Hours Per Patient Visit (HPPV). A closer look at the tool reveals that the DFM uses historical department census data to create a linear regression model for predicting future department census. This model has been formatted as a tool for data entry to forecast patient arrivals two hours into the future. The study design uses DFM data to calculate predicted arrivals in two-hour intervals. This will be required for calculating a forecasted two-hour BR in order to determine overcrowding.

Bed Ratio. An objective measurement for predicting Emergency Department demand and overcrowding is the READI score (Hoot, 2006). Scores evaluate treatment spaces, patient acuity, and physician productivity. Together these scores are used to give an overall demand of the department. Evaluation of treatment spaces is calculated through a BR. Specifically, this ratio assesses the number of patients and available beds for treatment (Reeder, 2003). Variables to determine a BR include the total number of ED patients, the number of predicted arrivals, the number of predicted departures, and the number of treatment beds. A BR of greater than 1 suggests that there may be an inadequate number of treatment spaces available (Hoot, 2007). In its simplest form, if there are not enough care spaces for presenting patients, then this would indicate overcrowding. The calculation for BR used in this study was based on Hoot (2007):

BR = (Total ED Patients + Predicted Arrivals – Predicted Departures) / Total Number of Treatment Spaces

National Emergency Department Overcrowding Scale. Discussed by Weis, et al. (2004), the NEDOCS is a simple screening tool that can be utilized to determine the degree of Emergency Department overcrowding. The NEDOCS creates a saturation score accounting for a variety of factors including the number of Emergency Department patients, patient beds, admissions, and Emergency Department throughput. Over the past decade, numerous studies have included the NEDOCS tool in an effort to define overcrowding and assess patient throughput. As a result, the tool has changed since initial implementation in 2004. The calculation and scoring scale used for this study are as follows (Bhardwaj, 2010):

*NEDOCS = -20+85.8 * (Total patients/ED Beds) + 600 * (Admits/Hospital Beds) + 13.4 * (ventilators) + .93 * (longest Admits) + 5.64 *(Last Bed Time).*

Scores 0-50 = Not Busy, 51-100 = Busy, 101-140 = Overcrowded, 141-180 = Dangerous, and above 180 = Disaster

Data Collection

Data required for the study instruments previously outlined was collected by the Spectrum Health Butterworth Emergency Department Charge Nurse group. This group consisted of sixteen highly skilled professionals with an expertise in emergency nursing. Charge Nurses were trained how to use each tool, when to use the tool, and how to record data generated by the tools. Data entry for the three tools was collected over the course of two weeks.

Microsoft Excel 2010 was used for data entry and the equation function was used for calculating a forecasted two-hour BR, NEDOCS, and BR. Data collected by the Charge Nurses was entered into established tables for each tool. These tables were saved in a file that included separate tabs for each day of the two-week study. Charge Nurses were also instructed to resave the file after each data entry.

The following times were established for initial data entry: 0100, 0500, 0900, 1300, 1700, and 2100. These timeframes were chosen based on the two-hour forecasting ability of the DFM. Data entered at these times included the total ED patients, two hour predicted arrivals generated by the DFM, two hour predicted departures generated by the Charge Nurse, and the number of treatment spaces available in two hours. As a result, the following equation was created:

Forecasted two-hour BR = (Total ED Patients + DFM Predicted Arrivals – Charge Nurse Predicted Departures) / Total Number of Treatment Spaces Available in two hours.

The forecasted two-hour BR was generated for the following times: 0300, 0700, 1100, 1500, 1900, and 2300. To validate the forecasted two-hour BR, the Charge Nurses then recorded the required information for generating a BR and a NEDOCS into premade table at these times.

For the sake of this study, hallway care spaces were not included as available treatment spaces. The department uses hallway care for overflow and they are not included in the original floor plan. A pre-determined set of criteria was established to assist the Charge Nurses in generating two hour predicted departures. Criteria for potential discharges used by the Charge Nurse group consisted of the following: patients with discharge written, patients with a current inpatient bed assignment, patients with inpatient admission request placed, patients with observation admission request placed, patients with disposition request placed, and any patients that could potentially leave within the next two hours.

Data Analysis

Data was collected from June 17 until June 30, 2015. After the two-week time period, data analysis was completed using Microsoft Excel 2010 Data Analysis Tool Pack. The forecasted two-hour BR was analyzed against NEDOCS and BR. In addition, the NEDOCS and BR were analyzed against each other for validation of overcrowding.

Results

Table 1: Descriptive Statistics of Overcrowding Instruments

	Forecasted two-hour BR	NEDOCS	BR
Mean	0.946	61.696	0.860
Standard Error	0.035	2.6415	0.027
Median	0.930	65	0.873
Mode	1.254	80	0.536
Standard Deviation	0.292	21.942	0.225
Sample Variance	0.085	481.450	0.051
Range	1.385	100	1.071
Minimum	0.107	14	0.393
Maximum	1.492	114	1.464
Count	69	69	69
Confidence Level (95.0%)	0.070	5.2710	0.0541

A total of 69 observations were recorded during the study's two-week timeframe. Microsoft Excel 2010 Data Analysis Tool Pack was utilized to generate descriptive statistics, correlation, and regression analysis. These tests were completed for the two hour forecasted BR, NEDOCS, and BR. Descriptive Statistics generated for all three are listed in Table 1. Analysis indicates that the forecasted two-hour BR is moderately correlated with the NEDOCS and the BR. This is evidenced by a correlation coefficient of 0.508 and 0.492. Further analysis of the NEDOCS and BR shows a strong correlation, as evidenced by coefficient of 0.949 (see Table 2).

Table 2 Correlation Analysis of Overcrowding Instruments

	Forecasted two-hour BR	NEDOCS	BR
Forecasted two-hour BR	1		
NEDOCS	0.509	1	
BR	0.493	0.949	1

Regression analysis shows that a forecasted two-hour BR has statistical significance in predicting future overcrowding. This was validated through the NEDOCS score and is evidenced by a P-value < 0.001. Further regression analysis between the forecasted two-hour BR and the BR also supports significance in predicting future overcrowding. This is evidenced by a P-value < 0.001 (Table 3).

Table 3 Regression Analysis of Overcrowding Instruments

	P-value
Forecasted two-hour BR and BR	1.708 E -05
Forecasted two-hour BR and NEDOCS	8.073 E -06
BR and NEDOCS	2.366 E -35

Limitations

Based on the size and volume of the Butterworth Emergency Department, the timeframe for recording observations is small. Increasing the timeframe or the number of data points could produce more favorable results. The criteria set forth for predicted departures in two hours are variable and subject to Charge Nurse interpretation. Creating an automated forecasting tool for departures, similar to the DFM, could prove beneficial. Lastly, during the recording of data by the Charge Nurse group, timestamps to be recorded were missed due to department needs. It should be noted that the complexity of the Charge Nurse role, coupled with high volumes and acutely ill patients, creates the potential for inaccurate data recording.

In an effort to address these limitations, automation of forecasted departures was initiated. Before the investment of time devoted to extensive historical data entry, a three-day retrospective sample with manual entry of known departure data was completed. Data analysis of this three-day sample showed a statistically significant correlation between the forecasted two-hour BR and BR. This was evidenced by a new correlation coefficient of 0.858 (see Table 4).

Building on this development, construction of a linear regression model for predicting two-hour departures was conducted. First, the most recent thirteen months of departure data was entered into Microsoft Excel 2010. Departure data included admission to the hospital for inpatient status, admission to the hospital for observation status, discharge from the Emergency Department, and patients who expired in the Emergency Department. Next, this was formatted as a tool for data entry. Similar to the DFM, this tool took historical departure data and predicted future departures. Lastly, the tool was integrated into the DFM in order to provide a more accurate forecasted two-hour BR. The modified DFM was used over a thirty-day retroactive time period. In total, this generated 180 points of data, which showed similar results to the three-day sample. As evidenced by a statistically significant correlation of 0.854 in Table 4.

Table 4 Summary of Correlation and Regression Analysis After Integration of Forecasted Two-hour Departures

	Correlation	P-value
3 Day: Forecasted two-hour BR and BR	0.858	5.258 E -06
30 Day: Forecasted two-hour BR and BR	0.854	1.920 E -52

This two-hour timeframe for predicting overcrowding has the potential to impact how Emergency Departments deal with resource allocation. One way to ensure appropriate resource allocation in the Butterworth Emergency Department is through the development of a surge plan. The use of forecasting to assist in development and implementation of surge plans to prevent future overcrowding could prove beneficial (Moseley, 2010). However, with a moderate correlation, forecasting alone will not be sufficient for design and development.

It will be essential to have adequate supplementation when attempting to forecast over long expanses of time. Development of a responsive staffing model will be necessary to safeguard staff and patients. The use and implementation of a flexible staffing model could be advantageous when looking for responsiveness. Additionally, the development of a staffing algorithm and complimentary standard work could supplement decision making. Solutions and supplementation material previously mentioned should be taken into consideration, along with consulting key stakeholders. Further research is needed to determine if these resources coupled with the forecasted two-hour BR have the potential to reduce overcrowding. Scalability of this model will be important for use at Emergency Departments with low annual visit volumes or fluctuating seasonable variances. One final limitation of the study is the use of linear regression. In the future, using a multiple regression model could improve the overall forecasting potential. Further design and development will be needed to determine validity.

CONCLUSION

The results of this study suggest that a recognized demand indicator can be used in combination with the DFM to calculate a reliable forecasted two-hour BR. This data would also indicate that using either BR or NEDOCS in real-time to determine overcrowding is effective. When using a forecasted two-hour BR without forecasting departures, the ability to identify overcrowding is not as strong as real-time identification. Regardless, it is significant in determining the likelihood of overcrowding two hours in the future. This has been validated through analysis with the NEDOCS and BR.

The use of the DFM in conjuncture with an automated tool for forecasting departures is possible. Utilization of this process by Emergency Department mangers is a potential solution for forecasting overcrowding in Emergency Departments. Not only does it show promise as an effective tool, it provides an opportunity to directly impact patient care through proactive measures to eliminate overcrowding. Future development and research is necessary to improve the efficacy of forecasts for this predictive model.

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