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Title: Using Queueing Theory to Increase the Effectiveness of ED Provider Staffing

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Abstract: Study Objective: Significant variation in emergency department patient arrival rates necessitates the adjustment of staffing patterns to optimize the timely care of patients. This study evaluates the effectiveness of a queueing model in identifying provider staffing patterns to reduce the fraction of patients who leave without being seen.

Methods: We collected detailed emergency department arrival data from an urban hospital and used a queueing model to gain insights on how to change provider staffing to decrease the proportion of patients who leave without being seen. We then compared this proportion for the same 39 week period before and after the resulting changes.

Results: Despite an increase in patient arrival volume of 6.3%, an increase in provider hours of only 3.1% resulted in a decrease in the proportion of patients who left without being seen by 22.9%. Restricting attention to a 4 day subset of the week during which there was no increase in total provider hours, a reallocation of providers based on the queueing model resulted in a decrease in the fraction of left without being seen of 21.7% while the arrival volume increased by 5.5%.

Conclusion: Timely access to a provider is a critical dimension of emergency department quality performance. In an environment in which emergency departments are often understaffed, analyses of arrival patterns and the use of queueing models can be extremely useful in identifying the most effective allocation of staff.

Author Contribution Form

Please identify the specific contribution(s) of **each** author to the submitted manuscript. The recognised contribution categories are as follows:

1. Study concept and design
2. Acquisition of the data
3. Analysis and interpretation of the data
4. Drafting of the manuscript
5. Critical revision of the manuscript for important intellectual content
6. Statistical expertise
7. Obtained funding
8. Administrative, technical, or material support
9. Study supervision

Author	**Contribution**
Linda V. Green	1, 2, 3, 4, 5, 6, 9
João Soares	3, 8
James F. Giglio	5, 8
Robert A Green	1, 2, 3, 4, 5, 6

LG and RG conceived the study. LG and JS developed the mathematical equations for the time-varying delay probabilities that were used to evaluate alternative staffing schedules. JS programmed and ran the queueing models and LG used the output from the models to develop suggested staffing changes. JG and RG implemented the staffing changes after interpretation of the queueing model results. RG performed the statistical analysis. LG and RG drafted the manuscript with contributions from JG.

* Cover Letter

Academic Emergency Medicine
Cover Letter for Submissions

To: Academic Emergency Medicine
From: Robert Green, MD
Subject: Cover Letter

Title of Article

Using Queueing Theory to Increase the Effectiveness of ED Provider Staffing.

Description

The paper describes a research study that used queueing theory to identify provider staffing levels to improve service performance in an inner city 25,000 visit emergency room. A unique feature of the study was that the queueing method used was developed by one of the authors in order to better match staffing to the kind of strongly time-varying arrival pattern that is found in emergency departments as well as many other service systems. The staffing levels suggested by the queueing model were used to reallocate provider hours and resulted in a significant decrease in the fraction of patients who left without being seen.

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There were no grants or compensation for this study This is a controlled trial with a "before-after" design and has not been previously published in any form.

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Using Queueing Theory to Increase the Effectiveness of ED Provider Staffing

Study Objective: Significant variation in emergency department patient arrival rates necessitates the adjustment of staffing patterns to optimize the timely care of patients**.** This study evaluates the effectiveness of a queueing model in identifying provider staffing patterns to reduce the fraction of patients who leave without being seen.

Methods: We collected detailed emergency department arrival data from an urban hospital and used a queueing model to gain insights on how to change provider staffing to decrease the proportion of patients who leave without being seen. We then compared this proportion for the same 39 week period before and after the resulting changes.

Results: Despite an increase in patient arrival volume of 6.3%, an increase in provider hours of only 3.1% resulted in a decrease in the proportion of patients who left without being seen by 22.9%. Restricting attention to a 4 day subset of the week during which there was no increase in total provider hours, a reallocation of providers based on the queueing model resulted in a decrease in the fraction of left without being seen of 21.7% while the arrival volume increased by 5.5%.

Conclusion: Timely access to a provider is a critical dimension of emergency department quality performance. In an environment in which emergency departments are often understaffed, analyses of arrival patterns and the use of queueing models can be extremely useful in identifying the most effective allocation of staff.

INTRODUCTION

Several national reports have documented a growing demand for care from emergency departments and a simultaneous decrease in the number of operating emergency departments. The result has been increased crowding, prolonged waiting times to be treated by an emergency provider (i.e. physician or physician assistant), and high percentages of patients leaving emergency departments without being seen.[1, 2] A recent study found that in 2001, 7.7% of the 36.6 million adults in the U.S. who sought care in a hospital emergency department reported trouble in receiving emergency care, and that over half of these cited long waiting times as a cause.[3]

Timely access to an emergency provider is a critical dimension of quality for emergency departments. Yet, hospitals often struggle to provide adequate staffing to handle increasing demands for care. Constrained provider capacity relative to demand volume is exacerbated by the extreme variability in demand during each 24 hour period experienced by a typical emergency department. This time-of-day pattern, as reported in the National Hospital Ambulatory Medical Care Survey for 2002 is distinguished by a relatively low level of demand during the night followed by a precipitous increase starting at about 8 or 9 A.M., a peak at about noon, and persistently high levels until late evening. [4] In addition, though the general pattern of demand is similar across the week, individual days are likely to experience different overall volumes as well as slight differences in the exact timing of peaks and valleys. In particular, emergency departments are likely to have fewer visits on weekends than on weekdays.

Among the foremost challenges in determining emergency department provider schedules is trying to match staffing levels to accommodate these changing demand levels. This is a difficult task for several reasons. First, even in the case of constant demand levels over the day, statistical fluctuations in individual patient arrival times and the variability in the time needed by a provider to treat patients can create long delays even when overall average staff capacity is greater than average demand. Second, the magnitude of delays is a non-linear function of the demand or staffing level, and is thus impossible to predict without the use of a queueing model.[5] In an environment with time-varying demands, delays are likely to be even greater, particularly if staffing is not carefully adjusted based on the actual fluctuation of the arrival rate over the day. Furthermore, the level of staffing in any given interval affects delays in other staffing intervals and the interaction effects are not predictable without the use of a model. [6, 7] Finally, staff levels at any given time may be constrained by organizationally mandated shift lengths as well as by the preferences of individual providers.

The primary goal of this study is to demonstrate the benefit of using a queueing model to construct emergency department provider staffing schedules that result in a more effective allocation of provider hours over the day and over the week. In particular, we illustrate how data analysis and queueing models can be used to identify staffing changes that can decrease the delays in being seen by a provider and thus, the fraction of patients who leave without being seen, without necessarily increasing capacity.

METHODS

Study design and setting

We conducted a controlled trial with a "before-after" design. The study examined the response of one emergency department measure of performance, LWBS, to a provider staffing reallocation based on queueing theory. The study site is an urban emergency department in the Inwood neighborhood of northern Manhattan and has an annual census of approximately 25,000 patients. The population is 61% Hispanic, 18% African American, and 17% White. Twenty-five percent of patients arrive via ambulance. The admission rate for patients seen by a provider is 23%. At the time that the study began, staffing levels and shift schedules were identical for all days of the week using 55 provider-hours per day. This study was granted an exemption from full review by the institutional review board.

Queueing model description

Many organizations, such as banks, airlines, telecommunications companies, and police departments, routinely use queueing models to help determine capacity levels needed to respond to experienced demands in a timely fashion. Queueing models have also been used in the hospital setting, primarily with respect to determining the impact of bed capacity on patient delays.[5, 8, 9] The most commonly used model is the M/M/s queueing model.[10] This model assumes a single queue with unlimited waiting room that feeds into s identical servers (e.g. providers). Arrivals occur according to a time-homogeneous Poisson process with a constant rate and the service duration (e.g. provider time associated with a patient) has an exponential distribution. (These two assumptions are often called Markovian, hence the use of the two "M's" in the notation used for the model). Many real arrival and demand processes have been empirically shown to be very well approximated by a Poisson process. Among these are demands for emergency services such as police, fire and ambulance, arrivals to banks and other retail establishments, and arrivals of telephone calls to customer service call centers. Consequently, the Poisson process is the most commonly used arrival process in modeling service systems.

One advantage of using the M/M/s model is that given an arrival rate, an average service duration and the number of servers, closed form expressions for performance measures such as the probability of a positive delay or the mean delay can be easily obtained. The delay is measured from the time of the demand for service (e.g. patient registered in the emergency department) to the time at which service begins (e.g. a provider is available to treat that patient). It is important to note that the model's delay predictions pertain only to waiting times due to provider unavailability and do not include any other possible delays prior to seeing a provider such as registration and triage times, which would have to be estimated independently.

Since the M/M/s model assumes that the arrival rate does not change over the day, actual service systems that have time-varying demands typically use this type of model as part of a SIPP (stationary independent period by period) approach to determine how to vary staffing to meet changing demand. The SIPP approach begins by dividing the workday into staffing periods, e.g. one, two, four or eight hours. Then a series of M/M/s models are constructed, one for each staffing period. Each of these period-specific models is independently solved for the minimum number of servers needed to meet the service target in that period. The service target might be a desired maximum mean delay or probability of delay standard. However, recent research has shown that the SIPP approach is often unreliable, and that a simple modification, called Lag SIPP, is often more effective in identifying staffing levels that achieve the desired performance standard.[7] This is because in many service systems with time-varying arrival rates, the time of peak congestion significantly lags the time of the peak in the arrival rate.[6] While the standard SIPP approach ignores this phenomenon, the Lag SIPP method incorporates an estimation of this lag and thus does a better job of identifying staffing levels to limit delays.

In this study, we used the Lag SIPP methodology to identify provider staffing levels to achieve a given delay standard. Statistical analyses on the number of emergency department patient arrivals each half-hour by day of week for the 2002 calendar year yielded strong support for the assumption of time-varying Poisson arrivals used by the queueing model. The delay standard we choose was that no more than 20% of patients wait more than one hour before being seen by a provider. The use of one hour is consistent with the time standards associated with emergent and urgent patient groups used in the National Hospital Ambulatory Medical Care Survey.[4] The 20% criterion reflects the approximate percentage of non-urgent arrivals at the study institution.

Data collection and processing

Data was extracted from the hospital's admission database (Eagle 2000, Siemens Inc., Malvern, PA), using SAS version 9.1.3 (SAS Institute Inc. Cary, NC). Emergency department hourly arrival data during 2002 were grouped by day of week. These data were used to construct the arrival rates needed as input to the queueing model. The queueing model also requires an average provider service time per patient, which must include the times of all activities related to a patient. These activities include direct patient care, review of x-rays and lab tests, phone calls, charting, and speaking with other providers or consults. At the time of the study, provider service times were not recorded. The only reference we were able to find in the literature that includes such data reports an average service time of 24 minutes based on a prospective time study.[11] For the purposes of our study, we used an average service time of 30 minutes based, in part, on the existing literature, but also on productivity data and observation from the study site.

Two 39 week periods - one before the staffing changes (August 26th, 2002 – May 25th, 2003) and one after the staffing changes (September 1st 2003 – May 30th 2004) - were studied. Matching weeks were chosen to better control for seasonal variation in both volume and disease states. The intervals are not aligned by exact date as to control for number of total days as well as days of the week. These date intervals result in exactly 39 complete weeks for both the before and after time intervals. The two periods of study are not contiguous; they are separated by a 14 week intervening period during which the staffing changes had started but were not yet fully implemented.

For the performance analysis phase, patient disposition, arrival mode, age, gender and length of stay were extracted from the Eagle 2000 registration database. Percent left without being seen (LWBS) was defined as the total patients who left without being seen divided by the total number of registered patients during the specified time period. Since patients are generally triaged before registration, it is possible that some LWBS patients were not captured in our data collection.

Outcome measures

A critical measure of emergency department performance related to provider staffing and patient throughput is the time from triage to the time to be seen by a provider. This measure was not recorded at the time of this study. Instead we used the strongly related measure - the proportion of patients who leave without being seen (LWBS). Previous studies have established a strong link between long emergency department delays and LWBS.[12, 13] In addition, the proportion of LWBS is itself an important measure of emergency department performance and quality of care. Several studies have concluded that patients who LWBS are sick and do require emergency care. One study has shown that up to 11% of patients who leave without being seen are hospitalized within a week and 46% of patients were judged to require immediate medical attention.[14]

Primary Data Analysis

We constructed a multivariate logistic regression model using LWBS (0 or 1) as the dependent variable. The main independent variable was an indicator variable designating the original or new staffing (0 or 1). Daily mean total emergency department length of stay values, daily total visit values, daily percent admit values, age and mode of arrival were used in a logistic regression model to assess the relationship between the staffing change and the odds of LWBS. There was no change in nursing or tech staffing during the study period and thus these variables were not included in the model. The model was applied to obtain odds ratios (ORs) with 95% confidence intervals (CIs) before and after adjustment for these potentially confounding factors. Statistical analysis was conducted using SAS version 9.1.3 (SAS Institute Inc. Cary, NC).

RESULTS

Queueing Model Analyses, Recommendations and Resulting Insights

An examination of the hourly average arrival rates by day of week revealed that while the daily pattern of peaks and valleys was quite consistent, the overall average volume varied from a low of 63 patients per day on Saturdays to a high of 72 per day on Mondays. While this degree of variation indicated that the current policy of identical staffing levels for all days of the week was likely suboptimal, it was deemed impractical to have a different provider schedule every day. So we decided to use queueing analyses to develop two schedules: weekday and weekend. Figure 1 shows the aggregated average hourly emergency department visit rates for weekdays and weekends. We used these average hourly arrival rates and the estimated average provider time per patient of 30 minutes as input to the Lag SIPP routine to estimate staffing levels, based on two-hour staffing intervals, to achieve a maximum probability of 20% that a patient would wait more than one hour to be seen by a provider during any staffing interval.

The modeling results indicated that a total of 58 provider-hours were needed on weekdays to achieve the desired service standard, which represented an increase of 3 hours over the existing staffing level of 55 provider-hours. Model runs for the weekend indicated that the target performance standard could be achieved with a total of 53 provider-hours. In both these cases, the queueing analyses suggested that the existing staffing pattern over the course of the day needed to be changed (See Figure 2 for the original staffing pattern.). Specifically, it indicated that some provider hours should be switched from the middle of the night to much earlier in the day. This suggested change was further supported by the realization that more patients are impacted by staffing levels during high arrival rate intervals than during low demand levels. Therefore, implementing adequate staffing levels during the late morning, afternoon and evening hours would have a greater positive effect on emergency department delays and LWBS levels than doing so during the middle of the night. A more subtle change suggested by the model was that the increase in staffing level to handle the morning surge in demand needed to occur earlier than in the original schedule. The insights gained from these analyses became the guiding principles in developing new provider schedules.

Development of New Schedules

The entire weekly staffing schedule was deconstructed and rebuilt based on the results of the queueing analyses. The resulting staffing requirement of 58 hours on weekdays to achieve the performance standard of provider contact within 1 hour for 80% of patients translated into 15 more hours a week relative to the 55 hours per weekday which was then available. Though the study results aided in obtaining a 3% staffing increase, this additional 12 hours still fell short of the recommended levels. The queueing model, however, facilitated a more logical placement of providers throughout the week and the day.

Weekdays

Figure 2 shows the weekday staffing levels both before and after the change was made. The second provider on the overnight shift, 10pm-6am, was moved to a daytime shift, 2pm-10pm. In addition, the noon–8pm shift was moved to a 10am-6pm shift based on the model results indicating a need to increase staffing earlier in the day. To better handle the high afternoon and evening volumes, an additional 4 hours were added to the 2pm-10pm shift resulting in a 12 hour shift from 2pm – 2am. Eight of these 20 additional hours (5 weekdays * 4 hours/day) were obtained by decreasing staffing on weekends based on the modeling results (see below), and the 12 remaining additional hours represent the 3 % increase in staffing placed into the emergency department. The net result of these changes resulted in 59 provider-hours for weekdays – one above the model-based recommendation for the average weekday. The specific changes are illustrated in Figure 2.

Weekends

The second provider on overnight shifts (10pm-6am) was eliminated. The noon – 8pm shift was extended to midnight. This resulted in a net removal of 4 hours of provider time on both Saturday and Sunday.

The 4 day subset (Saturday, Sunday, Monday and Tuesday)

As noted above, 4 hours were moved from each of Saturday and Sunday and 4 hours were added to each of the weekdays. Therefore, by limiting the analysis to the weekend days and the two busiest weekdays, we could analyze the effect of reallocation of hours, both between days and within each day, without the confounding effect of the additional provider hours added to the schedule.

35,536 patients arrived to seek care in the emergency department during the 78 weeks examined. There was a 6.3% increase in visits during the implementation phase compared to the baseline period. Demographic characteristics of the patients in each group are shown in Table 1.

Table 2 contains our results on LWBS. Considering the entire week, the fraction of LWBS decreased from 8.3% to 6.4% despite the significant increase in emergency department visits. Isolating the 4 day subset of the week for which there was no increase in provider hours, the proportion of LWBS declined from 9.2% to 7.2%. This latter improvement is particularly noteworthy given that the number of visits for this subset increased 5.5% between the before and after time periods.

The weekends, when net provider hours were decreased by 7.3%, experienced an increase from 6.7% to 8.2% in the proportion of LWBS. Weekday performance, when net provider hours were augmented by 7.3%, improved significantly, with a drop in the proportion of LWBS from 8.9% to 5.8%.

DISCUSSION

Analytic models, such as queueing models, can never capture all characteristics of an actual operational setting. However, as has been demonstrated over many years and in an extremely broad variety of settings, models can be invaluable in providing decision support that greatly improves performance, particularly in complex environments. This study supports the usefulness of queueing models in guiding emergency department provider scheduling decisions. This is particularly true in emergency departments where resources are tight relative to demand, since in such situations, even small changes in staffing can have a dramatic impact on delays. Our study also demonstrates the need to collect and examine arrival patterns and to adjust daily staffing levels to assure that schedules are appropriate for what might be significantly different levels and patterns of demand across the week.

This work also highlights the importance of setting delay standards in order to obtain meaningful estimates of how much capacity is needed. An analytic model, in combination with a carefully developed, clinically appropriate delay standard, can provide an objective evaluation of what additional resources are required in order to meet a given standard of quality care. In the emergency department setting, timely treatment is most essential for emergent and urgent patients. So, ideally, the standard used would reflect the time urgency associated with these types of patients and the queueing model would be priority based, reflecting the actual dynamics of the triage system. This was not done in this initial study because the patient information system did not accurately identify the triage status of patients. Future work to identify the best way to schedule additional provider hours that will become available this coming year will use the improved patient information system to produce a more refined analysis to reflect the triage classification.

LIMITATIONS

As mentioned previously, we did not have access to all of the data that is required for a queueing model. In particular, we had no data on the time providers spend with patients and had to estimate this based on the existing literature, observation and judgment. We also did not have the ability to collect data on delays that patients experienced in being seen by a provider. Therefore, we could not directly validate the estimates produced by the queueing model. A new information system, implemented subsequent to this study, will enable the collection of these data in the future. In addition, due to constraints on the timing of provider shifts and personal preferences, the staffing schedules that were implemented were somewhat different than those that most closely aligned with the model's suggestions. It is possible that our results would have been different had these constraints not existed.

We believe that the queueing model, by providing a more rigorous and scientific basis for predicting patient delays in being seen by a provider, identified staffing schedules which reduced these delays and hence reduced the fraction of LWBS. It is possible that LWBS decreased during the post-staffing change period due to other factors such as shorter waits for lab results or increased availability of inpatient beds. Such changes would have resulted in fewer patients in the emergency department, reduced provider time per patient, and hence shorter patient waits to be seen by a physician and a reduced fraction of LWBS. However, given the increased ED volume and no known change in the operations of other parts of the hospital that would directly affect ED length of stay, we think that it is more likely that the change in physician staffing was the major factor in reduction of LWBS.

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Figure 1.

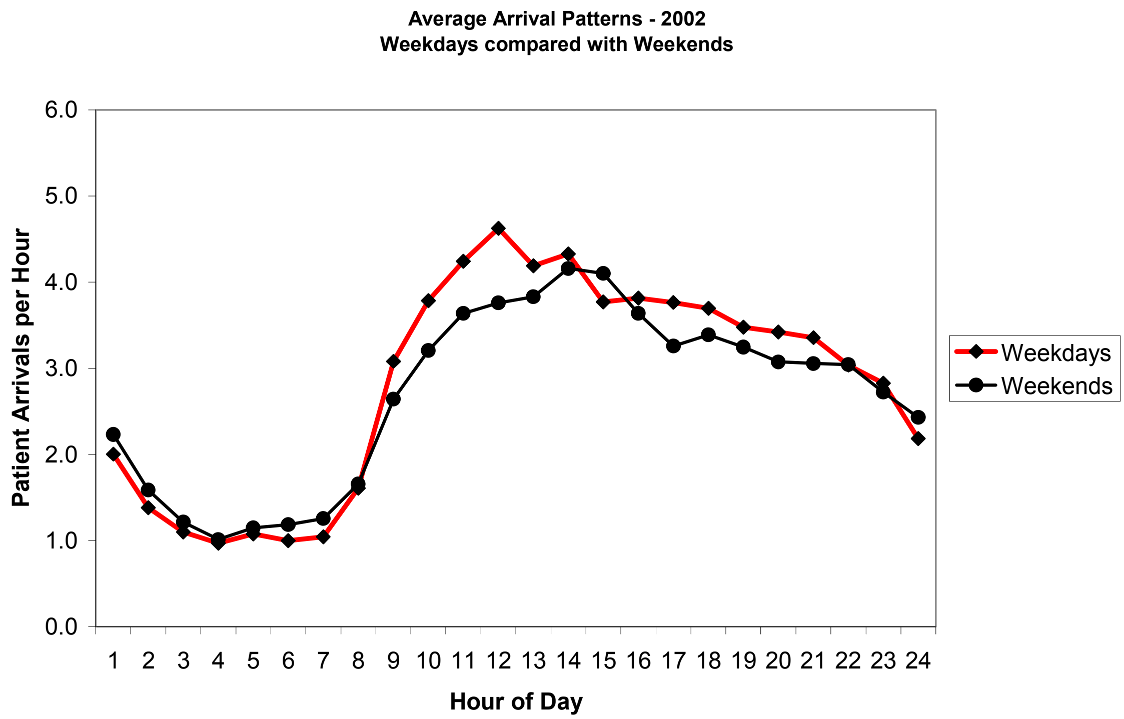
Average Arrival Patterns - 2002
Weekdays compared with Weekends
6.0
5.0
4.0
3.0
2.0
1.0
0.0
Patient Arrivals per Hour
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour of Day
Weekdays
Weekends

Figure 2.
Example of Staff Changes for Weekdays

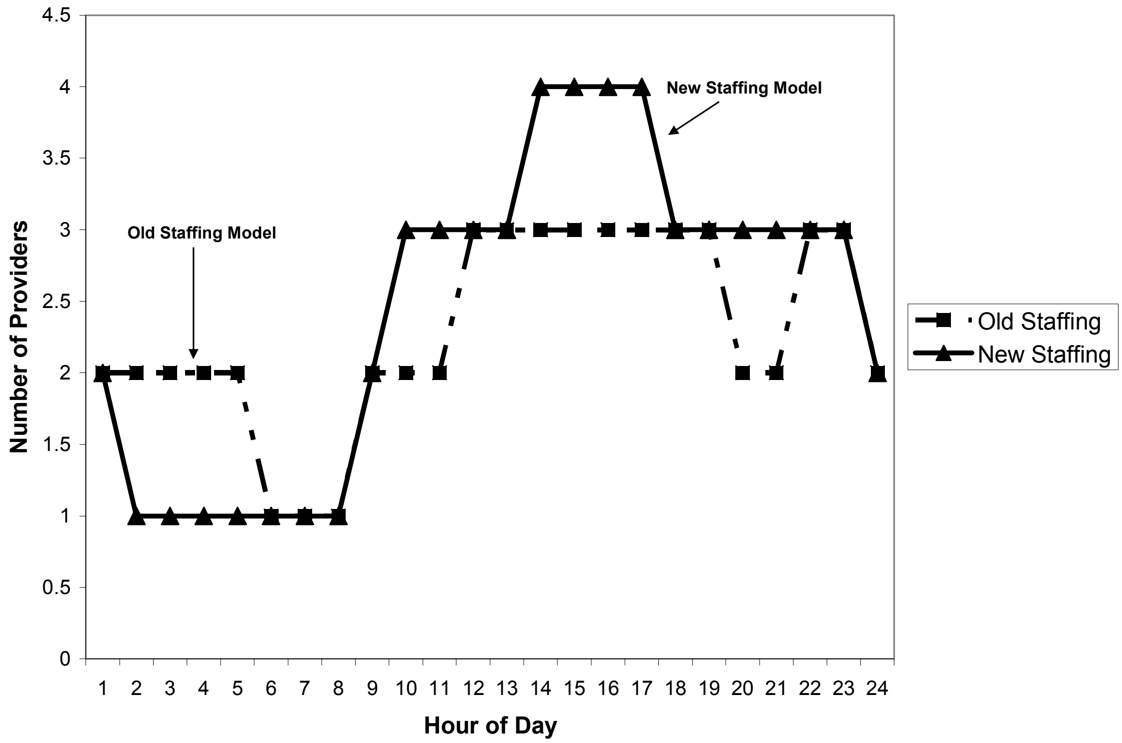

Table 1

Demographic, arrival mode, dispositon and LOS characteristics before and after staffing change

	Before New Staffing Implementation (n=17,229)	**After New Staffing Implementation (n=18,307)**
Male (%)	38.7	39.6
Age (Mean)	43.6	43.7
Arrival by Ambulance (%)	25.2	25.4
Admissions (%)	22.6	21.7
Total ED Length of Stay (Hrs.)	4.1	3.9

Table 2

Results - before and after staffing change

Variable	Before New Staffing	After New Staffing	Percent Change	Crude Odds Ratio	Adjusted Odds Ratio
{full 7 day week}					
Visits	17,229	18,307	6.3%		
Provider Hours/day (mean)	55	57	3.1%		
Left without Being Seen (%)	8.3	6.4	-22.9%	**0.75 (0.70 - 0.82)**	**0.74 (0.68 - 0.81)**
{Limited to Sat-Tues}					
Visits	10,007	10,555	5.5%		
Provider Hours/day (mean)	55	55	0.0%		
Left without Being Seen (%)	9.2	7.2	-21.7%	**0.77 (0.70 - 0.85)**	**0.79 (0.71 - 0.89)**
{Limited to Weekdays}					
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Visits	4,725	4,923	4.2%		
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*LWBS is presented as both the relative percent change between time periods and the crude and adjusted odds ratio

Using Queueing Theory to Increase the Effectiveness of ED Provider Staffing

Study Objective: Significant variation in emergency department patient arrival rates necessitates the adjustment of staffing patterns to optimize the timely care of patients**.** This study evaluates the effectiveness of a queueing model in identifying provider staffing patterns to reduce the fraction of patients who leave without being seen.

Methods: We collected detailed emergency department arrival data from an urban hospital and used a queueing model to gain insights on how to change provider staffing to decrease the proportion of patients who leave without being seen. We then compared this proportion for the same 39 week period before and after the resulting changes.

Results: Despite an increase in patient arrival volume of 6.3%, an increase in provider hours of only 3.1% resulted in a decrease in the proportion of patients who left without being seen by 22.9%. Restricting attention to a 4 day subset of the week during which there was no increase in total provider hours, a reallocation of providers based on the queueing model resulted in a decrease in the fraction of left without being seen of 21.7% while the arrival volume increased by 5.5%.

Conclusion: Timely access to a provider is a critical dimension of emergency department quality performance. In an environment in which emergency departments are often understaffed, analyses of arrival patterns and the use of queueing models can be extremely useful in identifying the most effective allocation of staff.

INTRODUCTION

Several national reports have documented a growing demand for care from emergency departments and a simultaneous decrease in the number of operating emergency departments. The result has been increased crowding, prolonged waiting times to be treated by an emergency provider (i.e. physician or physician assistant), and high percentages of patients leaving emergency departments without being seen.[1, 2] A recent study found that in 2001, 7.7% of the 36.6 million adults in the U.S. who sought care in a hospital emergency department reported trouble in receiving emergency care, and that over half of these cited long waiting times as a cause.[3]

Timely access to an emergency provider is a critical dimension of quality for emergency departments. Yet, hospitals often struggle to provide adequate staffing to handle increasing demands for care. Constrained provider capacity relative to demand volume is exacerbated by the extreme variability in demand during each 24 hour period experienced by a typical emergency department. This time-of-day pattern, as reported in the National Hospital Ambulatory Medical Care Survey for 2002 is distinguished by a relatively low level of demand during the night followed by a precipitous increase starting at about 8 or 9 A.M., a peak at about noon, and persistently high levels until late evening. [4] In addition, though the general pattern of demand is similar across the week, individual days are likely to experience different overall volumes as well as slight differences in the exact timing of peaks and valleys. In particular, emergency departments are likely to have fewer visits on weekends than on weekdays.

Among the foremost challenges in determining emergency department provider schedules is trying to match staffing levels to accommodate these changing demand levels. This is a difficult task for several reasons. First, even in the case of constant demand levels over the day, statistical fluctuations in individual patient arrival times and the variability in the time needed by a provider to treat patients can create long delays even when overall average staff capacity is greater than average demand. Second, the magnitude of delays is a non-linear function of the demand or staffing level, and is thus impossible to predict without the use of a queueing model.[5] In an environment with time-varying demands, delays are likely to be even greater, particularly if staffing is not carefully adjusted based on the actual fluctuation of the arrival rate over the day. Furthermore, the level of staffing in any given interval affects delays in other staffing intervals and the interaction effects are not predictable without the use of a model. [6, 7] Finally, staff levels at any given time may be constrained by organizationally mandated shift lengths as well as by the preferences of individual providers.

The primary goal of this study is to demonstrate the benefit of using a queueing model to construct emergency department provider staffing schedules that result in a more effective allocation of provider hours over the day and over the week. In particular, we illustrate how data analysis and queueing models can be used to identify staffing changes that can decrease the delays in being seen by a provider and thus, the fraction of patients who leave without being seen, without necessarily increasing capacity.

METHODS

Study design and setting

We conducted a controlled trial with a "before-after" design. The study examined the response of one emergency department measure of performance, LWBS, to a provider staffing reallocation based on queueing theory. The study site is an urban emergency department in the --------------- and has an annual census of approximately 25,000 patients. The population is 61% Hispanic, 18% African American, and 17% White. Twenty-five percent of patients arrive via ambulance. The admission rate for patients seen by a provider is 23%. At the time that the study began, staffing levels and shift schedules were identical for all days of the week using 55 provider-hours per day. This study was granted an exemption from full review by the institutional review board.

Queueing model description

Many organizations, such as banks, airlines, telecommunications companies, and police departments, routinely use queueing models to help determine capacity levels needed to respond to experienced demands in a timely fashion. Queueing models have also been used in the hospital setting, primarily with respect to determining the impact of bed capacity on patient delays.[5, 8, 9] The most commonly used model is the M/M/s queueing model.[10] This model assumes a single queue with unlimited waiting room that feeds into s identical servers (e.g. providers). Arrivals occur according to a time-homogeneous Poisson process with a constant rate and the service duration (e.g. provider time associated with a patient) has an exponential distribution. (These two assumptions are often called Markovian, hence the use of the two "M's" in the notation used for the model). Many real arrival and demand processes have been empirically shown to be very well approximated by a Poisson process. Among these are demands for emergency services such as police, fire and ambulance, arrivals to banks and other retail establishments, and arrivals of telephone calls to customer service call centers. Consequently, the Poisson process is the most commonly used arrival process in modeling service systems.

One advantage of using the M/M/s model is that given an arrival rate, an average service duration and the number of servers, closed form expressions for performance measures such as the probability of a positive delay or the mean delay can be easily obtained. The delay is measured from the time of the demand for service (e.g. patient registered in the emergency department) to the time at which service begins (e.g. a provider is available to treat that patient). It is important to note that the model's delay predictions pertain only to waiting times due to provider unavailability and do not include any other possible delays prior to seeing a provider such as registration and triage times, which would have to be estimated independently.

Since the M/M/s model assumes that the arrival rate does not change over the day, actual service systems that have time-varying demands typically use this type of model as part of a SIPP (stationary independent period by period) approach to determine how to vary staffing to meet changing demand. The SIPP approach begins by dividing the workday into staffing periods, e.g. one, two, four or eight hours. Then a series of M/M/s models are constructed, one for each staffing period. Each of these period-specific models is independently solved for the minimum number of servers needed to meet the service target in that period. The service target might be a desired maximum mean delay or probability of delay standard. However, recent research has shown that the SIPP approach is often unreliable, and that a simple modification, called Lag SIPP, is often more effective in identifying staffing levels that achieve the desired performance standard.[7] This is because in many service systems with time-varying arrival rates, the time of peak congestion significantly lags the time of the peak in the arrival rate.[6] While the standard SIPP approach ignores this phenomenon, the Lag SIPP method incorporates an estimation of this lag and thus does a better job of identifying staffing levels to limit delays.

In this study, we used the Lag SIPP methodology to identify provider staffing levels to achieve a given delay standard. Statistical analyses on the number of emergency department patient arrivals each half-hour by day of week for the 2002 calendar year yielded strong support for the assumption of time-varying Poisson arrivals used by the queueing model. The delay standard we choose was that no more than 20% of patients wait more than one hour before being seen by a provider. The use of one hour is consistent with the time standards associated with emergent and urgent patient groups used in the National Hospital Ambulatory Medical Care Survey.[4] The 20% criterion reflects the approximate percentage of non-urgent arrivals at the study institution.

Data collection and processing

Data was extracted from the hospital's admission database (Eagle 2000, Siemens Inc., Malvern, PA), using SAS version 9.1.3 (SAS Institute Inc. Cary, NC). Emergency department hourly arrival data during 2002 were grouped by day of week. These data were used to construct the arrival rates needed as input to the queueing model. The queueing model also requires an average provider service time per patient, which must include the times of all activities related to a patient. These activities include direct patient care, review of x-rays and lab tests, phone calls, charting, and speaking with other providers or consults. At the time of the study, provider service times were not recorded. The only reference we were able to find in the literature that includes such data reports an average service time of 24 minutes based on a prospective time study.[11] For the purposes of our study, we used an average service time of 30 minutes based, in part, on the existing literature, but also on productivity data and observation from the study site.

Two 39 week periods - one before the staffing changes (August 26th, 2002 – May 25th, 2003) and one after the staffing changes (September 1st 2003 – May 30th 2004) - were studied. Matching weeks were chosen to better control for seasonal variation in both volume and disease states. The intervals are not aligned by exact date as to control for number of total days as well as days of the week. These date intervals result in exactly 39 complete weeks for both the before and after time intervals. The two periods of study are not contiguous; they are separated by a 14 week intervening period during which the staffing changes had started but were not yet fully implemented.

For the performance analysis phase, patient disposition, arrival mode, age, gender and length of stay were extracted from the Eagle 2000 registration database. Percent left without being seen (LWBS) was defined as the total patients who left without being seen divided by the total number of registered patients during the specified time period. Since patients are generally triaged before registration, it is possible that some LWBS patients were not captured in our data collection.

Outcome measures

A critical measure of emergency department performance related to provider staffing and patient throughput is the time from triage to the time to be seen by a provider. This measure was not recorded at the time of this study. Instead we used the strongly related measure - the proportion of patients who leave without being seen (LWBS). Previous studies have established a strong link between long emergency department delays and LWBS.[12, 13] In addition, the proportion of LWBS is itself an important measure of emergency department performance and quality of care. Several studies have concluded that patients who LWBS are sick and do require emergency care. One study has shown that up to 11% of patients who leave without being seen are hospitalized within a week and 46% of patients were judged to require immediate medical attention.[14]

Primary Data Analysis

We constructed a multivariate logistic regression model using LWBS (0 or 1) as the dependent variable. The main independent variable was an indicator variable designating the original or new staffing (0 or 1). Daily mean total emergency department length of stay values, daily total visit values, daily percent admit values, age and mode of arrival were used in a logistic regression model to assess the relationship between the staffing change and the odds of LWBS. There was no change in nursing or tech staffing during the study period and thus these variables were not included in the model. The model was applied to obtain odds ratios (ORs) with 95% confidence intervals (CIs) before and after adjustment for these potentially confounding factors. Statistical analysis was conducted using SAS version 9.1.3 (SAS Institute Inc. Cary, NC).

RESULTS

Queueing Model Analyses, Recommendations and Resulting Insights

An examination of the hourly average arrival rates by day of week revealed that while the daily pattern of peaks and valleys was quite consistent, the overall average volume varied from a low of 63 patients per day on Saturdays to a high of 72 per day on Mondays. While this degree of variation indicated that the current policy of identical staffing levels for all days of the week was likely suboptimal, it was deemed impractical to have a different provider schedule every day. So we decided to use queueing analyses to develop two schedules: weekday and weekend. Figure 1 shows the aggregated average hourly emergency department visit rates for weekdays and weekends. We used these average hourly arrival rates and the estimated average provider time per patient of 30 minutes as input to the Lag SIPP routine to estimate staffing levels, based on two-hour staffing intervals, to achieve a maximum probability of 20% that a patient would wait more than one hour to be seen by a provider during any staffing interval.

The modeling results indicated that a total of 58 provider-hours were needed on weekdays to achieve the desired service standard, which represented an increase of 3 hours over the existing staffing level of 55 provider-hours. Model runs for the weekend indicated that the target performance standard could be achieved with a total of 53 provider-hours. In both these cases, the queueing analyses suggested that the existing staffing pattern over the course of the day needed to be changed (See Figure 2 for the original staffing pattern.). Specifically, it indicated that some provider hours should be switched from the middle of the night to much earlier in the day. This suggested change was further supported by the realization that more patients are impacted by staffing levels during high arrival rate intervals than during low demand levels. Therefore, implementing adequate staffing levels during the late morning, afternoon and evening hours would have a greater positive effect on emergency department delays and LWBS levels than doing so during the middle of the night. A more subtle change suggested by the model was that the increase in staffing level to handle the morning surge in demand needed to occur earlier than in the original schedule. The insights gained from these analyses became the guiding principles in developing new provider schedules.

Development of New Schedules

The entire weekly staffing schedule was deconstructed and rebuilt based on the results of the queueing analyses. The resulting staffing requirement of 58 hours on weekdays to achieve the performance standard of provider contact within 1 hour for 80% of patients translated into 15 more hours a week relative to the 55 hours per weekday which was then available. Though the study results aided in obtaining a 3% staffing increase, this additional 12 hours still fell short of the recommended levels. The queueing model, however, facilitated a more logical placement of providers throughout the week and the day.

Weekdays

Figure 2 shows the weekday staffing levels both before and after the change was made. The second provider on the overnight shift, 10pm-6am, was moved to a daytime shift, 2pm-10pm. In addition, the noon–8pm shift was moved to a 10am-6pm shift based on the model results indicating a need to increase staffing earlier in the day. To better handle the high afternoon and evening volumes, an additional 4 hours were added to the 2pm-10pm shift resulting in a 12 hour shift from 2pm – 2am. Eight of these 20 additional hours (5 weekdays * 4 hours/day) were obtained by decreasing staffing on weekends based on the modeling results (see below), and the 12 remaining additional hours represent the 3 % increase in staffing placed into the emergency department. The net result of these changes resulted in 59 provider-hours for weekdays – one above the model-based recommendation for the average weekday. The specific changes are illustrated in Figure 2.

Weekends

The second provider on overnight shifts (10pm-6am) was eliminated. The noon – 8pm shift was extended to midnight. This resulted in a net removal of 4 hours of provider time on both Saturday and Sunday.

The 4 day subset (Saturday, Sunday, Monday and Tuesday)

As noted above, 4 hours were moved from each of Saturday and Sunday and 4 hours were added to each of the weekdays. Therefore, by limiting the analysis to the weekend days and the two busiest weekdays, we could analyze the effect of reallocation of hours, both between days and within each day, without the confounding effect of the additional provider hours added to the schedule.

35,536 patients arrived to seek care in the emergency department during the 78 weeks examined. There was a 6.3% increase in visits during the implementation phase compared to the baseline period. Demographic characteristics of the patients in each group are shown in Table 1.

Table 2 contains our results on LWBS. Considering the entire week, the fraction of LWBS decreased from 8.3% to 6.4% despite the significant increase in emergency department visits. Isolating the 4 day subset of the week for which there was no increase in provider hours, the proportion of LWBS declined from 9.2% to 7.2%. This latter improvement is particularly noteworthy given that the number of visits for this subset increased 5.5% between the before and after time periods.

The weekends, when net provider hours were decreased by 7.3%, experienced an increase from 6.7% to 8.2% in the proportion of LWBS. Weekday performance, when net provider hours were augmented by 7.3%, improved significantly, with a drop in the proportion of LWBS from 8.9% to 5.8%.

DISCUSSION

Analytic models, such as queueing models, can never capture all characteristics of an actual operational setting. However, as has been demonstrated over many years and in an extremely broad variety of settings, models can be invaluable in providing decision support that greatly improves performance, particularly in complex environments. This study supports the usefulness of queueing models in guiding emergency department provider scheduling decisions. This is particularly true in emergency departments where resources are tight relative to demand, since in such situations, even small changes in staffing can have a dramatic impact on delays. Our study also demonstrates the need to collect and examine arrival patterns and to adjust daily staffing levels to assure that schedules are appropriate for what might be significantly different levels and patterns of demand across the week.

This work also highlights the importance of setting delay standards in order to obtain meaningful estimates of how much capacity is needed. An analytic model, in combination with a carefully developed, clinically appropriate delay standard, can provide an objective evaluation of what additional resources are required in order to meet a given standard of quality care. In the emergency department setting, timely treatment is most essential for emergent and urgent patients. So, ideally, the standard used would reflect the time urgency associated with these types of patients and the queueing model would be priority based, reflecting the actual dynamics of the triage system. This was not done in this initial study because the patient information system did not accurately identify the triage status of patients. Future work to identify the best way to schedule additional provider hours that will become available this coming year will use the improved patient information system to produce a more refined analysis to reflect the triage classification.

LIMITATIONS

As mentioned previously, we did not have access to all of the data that is required for a queueing model. In particular, we had no data on the time providers spend with patients and had to estimate this based on the existing literature, observation and judgment. We also did not have the ability to collect data on delays that patients experienced in being seen by a provider. Therefore, we could not directly validate the estimates produced by the queueing model. A new information system, implemented subsequent to this study, will enable the collection of these data in the future. In addition, due to constraints on the timing of provider shifts and personal preferences, the staffing schedules that were implemented were somewhat different than those that most closely aligned with the model's suggestions. It is possible that our results would have been different had these constraints not existed.

We believe that the queueing model, by providing a more rigorous and scientific basis for predicting patient delays in being seen by a provider, identified staffing schedules which reduced these delays and hence reduced the fraction of LWBS. It is possible that LWBS decreased during the post-staffing change period due to other factors such as shorter waits for lab results or increased availability of inpatient beds. Such changes would have resulted in fewer patients in the emergency department, reduced provider time per patient, and hence shorter patient waits to be seen by a physician and a reduced fraction of LWBS. However, given the increased ED volume and no known change in the operations of other parts of the hospital that would directly affect ED length of stay, we think that it is more likely that the change in physician staffing was the major factor in reduction of LWBS.

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Figure 1.

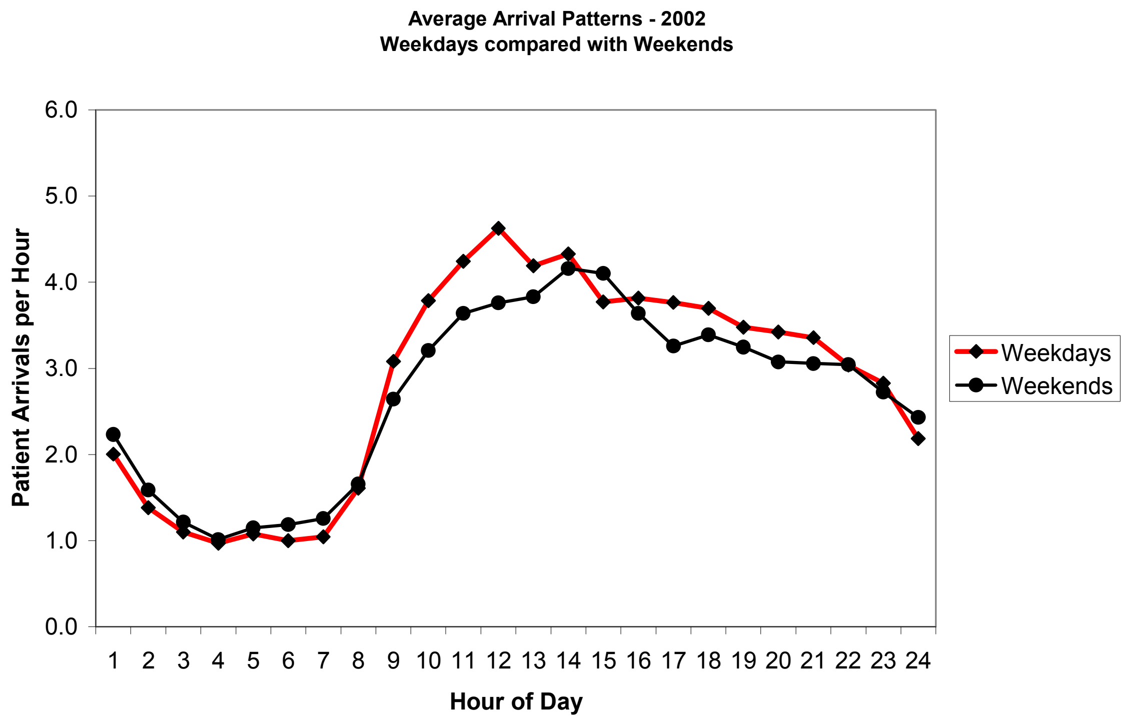
Average Arrival Patterns - 2002
Weekdays compared with Weekends
6.0
5.0
4.0
3.0
2.0
1.0
0.0
Patient Arrivals per Hour
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour of Day
Weekdays
Weekends

Figure 2.
Example of Staff Changes for Weekdays

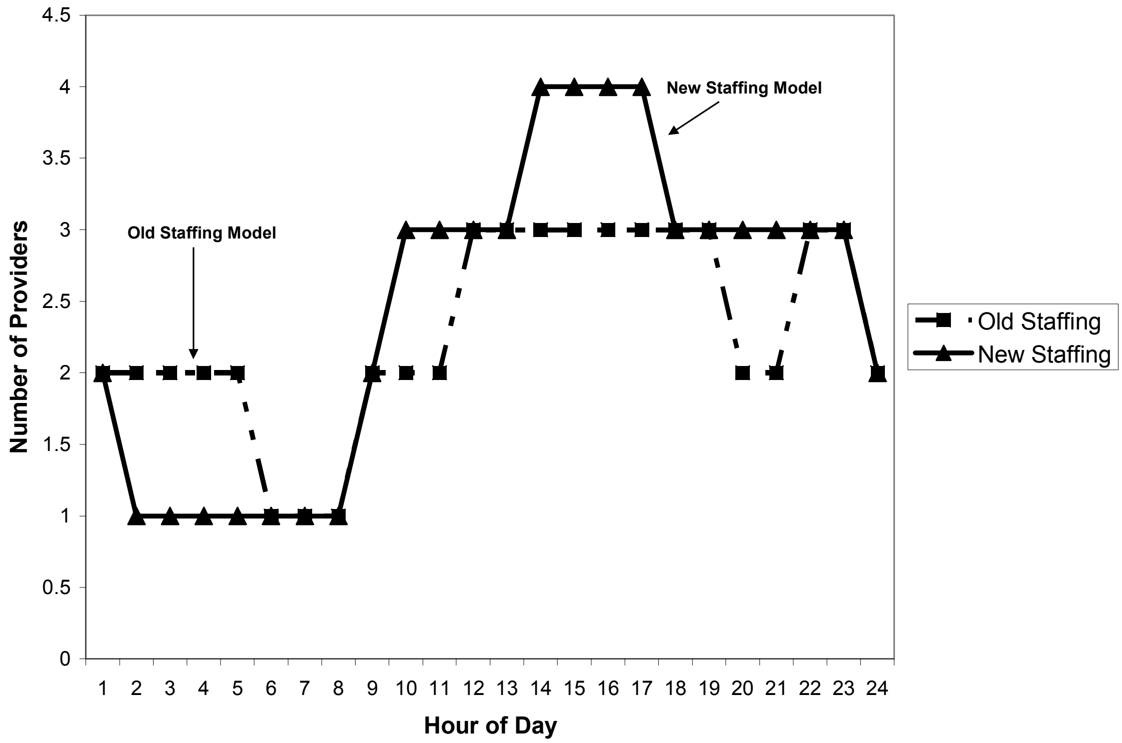

Table 1

Demographic, arrival mode, dispositon and LOS characteristics before and after staffing change

	Before New Staffing Implementation (n=17,229)	**After New Staffing Implementation (n=18,307)**
Male (%)	38.7	39.6
Age (Mean)	43.6	43.7
Arrival by Ambulance (%)	25.2	25.4
Admissions (%)	22.6	21.7
Total ED Length of Stay (Hrs.)	4.1	3.9

Table 2

Results - before and after staffing change

Variable	Before New Staffing	After New Staffing	Percent Change	Crude Odds Ratio	Adjusted Odds Ratio
{full 7 day week}					
Visits	17,229	18,307	6.3%		
Provider Hours/day (mean)	55	57	3.1%		
Left without Being Seen (%)	8.3	6.4	-22.9%	**0.75 (0.70 - 0.82)**	**0.74 (0.68 - 0.81)**
{Limited to Sat-Tues}					
Visits	10,007	10,555	5.5%		
Provider Hours/day (mean)	55	55	0.0%		
Left without Being Seen (%)	9.2	7.2	-21.7%	**0.77 (0.70 - 0.85)**	**0.79 (0.71 - 0.89)**
{Limited to Weekdays}					
Visits	12,504	13,384	7.0%		
Provider Hours/day (mean)	55	59	7.3%		
Left without Being Seen (%)	8.9	5.8	-34.8%	**0.62 (0.57 - 0.69)**	**0.60 (0.54 - 0.66)**
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Visits	4,725	4,923	4.2%		
Provider Hours/day (mean)	55	51	-7.3%		
Left without Being Seen (%)	6.7	8.2	22.4%	**1.23 (1.06 - 1.43)**	**1.17 (1.01 - 1.37)**

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