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THE IMPACT OF SYSTEM FACTORS ON PATIENT PERCEPTIONS OF QUALITY OF CARE

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ABSTRACT

The Hospital Value-Based Purchasing (VBP) Program is a Center for Medicare and Medicaid Services (CMS) initiative that rewards hospitals with incentive payments for the quality of care they provide to patients with Medicare instead of the quantity of procedures they perform. Although the VBP program has direct implications toward both patients and hospitals, no research has been reported in the literature addressing how hospitals can enhance patients' experience of care. This research uses systems modeling to improve the patient experience of care considering the eight dimensions in the Hospital VBP. A case study is presented that considers three intensive care units from a hospital located in central Texas. The simulation results show that strategies such as having a quick patient discharge process greatly benefit the hospital in terms of how patients perceive quality of care as measured by the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey.

1 INTRODUCTION

Delivering patient-centered care is an important component of a high-quality healthcare system (Baker 2001). In 2010 the Hospital Value-Based Purchasing (VBP) was established to link Medicare's payment system to a value-based system that focuses on the patient. Under the VBP, healthcare systems are evaluated not only on the patient outcomes but also on the patient experience of care while in the hospital. The VBP program uses the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey to measure patient experience of care. The results of the survey are used to incentivize hospitals that perform according to the VBP goals. The best hospital performers are incentivized up to 1% of their annual earnings. That incentive amount is expected to double by 2017. Therefore, it is imperative for hospitals to consider new strategies to serve patients while considering both, patient outcomes and patient experience of care.

The HCAHPS survey is a 27-part questionnaire that is currently used as the standard tool to quantify patient's experience. The survey takes into account eight different dimensions including nurse communication, doctor communication, cleanliness and quietness, responsiveness of hospital staff, pain management, communication about medicine, discharge information, and overall rating. Currently, we know little about the relationship between hospital performance and patient satisfaction (Tsai et al. 2015). As national policy efforts, such as VBP are implemented, understanding the potential tradeoffs between patient satisfaction and measures of efficiency of hospital system factors become very important.

In this paper, a discrete-event simulation is developed to model the patient interactions with doctors and nurses in three intensive care units (ICUs) of a hospital located in Central Texas. The objective of the study is to provide insights about the impact of hospital system factors on the patient experience of care as measured by the HCAPHPS survey. The system factors considered in this study include patient communication with the hospitalists and nurses, patient waiting to time to see hospitalists, patient waiting time for discharge, nurse workload and interaction with patients, and hospitalist workload. Section 4 provides a detailed explanation of how these system factors are linked to patient quality of care.

The rest of the paper is organized as follows. In Section 2, we review closely related work. We derive our simulation model and provide a description of the input data in Section 3. We report on a computational study in Section 4 and provide a discussion of the results in Section 5. Section 6 presents some concluding remarks and future research opportunities.

2 RELATED WORK

Discrete-event simulation has being adopted in multiple healthcare settings to study patient management services; see (Jun et al. 1999), (Cayirli and Veral 2003), and (Gupta and Denton 2008). This technique can be used to forecast the impact of system changes and to investigate the relationship between variables in the system. For instance, (Walter 1973) develop a discrete event simulation model of a hospital radiology department to predict the effects of scheduling policies on the efficiency of the appointment system. The author discusses the performance of the system in terms of the average patient queuing time and doctor idle time during the day. (Vanden-Bosch and Dietz 2000) proposed a combination of simulation, heuristics, and approximate solutions to reduce a combination of patients' expected waiting times and doctor's overtime. (LaGanga and Lawrence 2007) carried out a computer simulation study to estimate providers' over-time and patient waiting times. Their model represents a single provider with deterministic service times and a target overbooking level. They concluded that overbooking can lead to greater throughput without significantly higher waiting times. (Pérez et al. 2010) and (Pérez et al. 2011) used simulation to model patient service management in nuclear medicine clinics while considering both patient and manager perspectives. Their results provide insights regarding resource allocation policies and patient admissions schedules. (Mocarzel et al. 2013), (Sowle et al. 2014), and (Walker et al. 2015) developed a discrete-event simulation model to study the front desk operation of an outpatient clinic. The simulation model captured the processes occurring at front desk including answering phone calls, patient check-in and check-out, and documentation. The study concluded that patient waiting time can be reduced by creating balanced schedule of new and existing patients. Simulation modeling has been used extensively to understand and improve the performance of in healthcare setting such as hospitals, clinics, and emergency rooms. However, this is the first simulation study that uses the measurements considered in the HCAHPS survey as part of the evaluation of the performance of the system.

3 DISCRETE EVENT SIMULATION

Healthcare decision makers need reliable tools to support them in decision making and to understand the system impact of changes in policies before implementation. Discrete-event simulation has shown to be an effective tool in healthcare for the evaluation of interventions. In addition, discrete-event simulation enables communication and the discussion of ideas, as well as the analysis of scenarios.

A discrete-event simulation model was developed to study the effect of system changes on the patient experience care. The abstraction of the model was based on the operation of a hospital located in the Central Texas. The practical setting under study involves three areas of the hospital: the intensive care unit (ICU), the progressive care unit (PCU), and the medical surgical unit (MSU). The simulation model abstraction considers several resources for each of the areas which include physicians/hospitalists, nurses, beds, and performance measures. We start this section by describing these entities in the context of the model abstraction. The simulation model was implemented using the Rockwell Software Arena simulation package.

3.1 Model Abstraction

We conceptualize the three medical units (ICU, PCU, and MSU) involving doctors, nurses, beds, and patients. The three medical units are mostly resource independent and the only type of resources shared by them are the doctors/hospitalists. Each medical unit has a specific number of nurses and beds. Patients are assigned to one of the areas when admitted.

There are four hospitalists on staff. Typically, two are present per day. Each physician makes rounds on average once a day. The hospitalist will begin his or her day at the ICU followed by the PCU before arriving at the medical surgical unit. Patient round visits take approximately 10 minutes. The hospitalists' assignments to patients is primarily influenced by the number of patients in the area. Rounding is not done in a set pattern and it is mostly dictated by which nurse is available.

Nurses have 12 hour shifts that run from 7:00 am to 7:00 pm and from 7:00 pm to 7:00 am. Primary nurses are in charge of the patients and they are supposed to check on each patient statues at least one time per hour. When hospitalists are in their area, nurses are encouraged to visit their patient with the hospitalists. The charge nurse can round with the hospitalist if needed. The maximum patient to nurse ratio for each of the areas is: 1:2 in the ICU, and 6:1in the PSU and MSU. Normally nurses are assigned to specific patients each day. There are 10 beds in the ICU, 34 beds in the PCU and 23 bed in the MSU.

3.2 Physicians/Hospitalists

The hospitalist behavior can be abstracted by describing three major activities: checking patient records in the computer, discussing patient information with nurses, and visiting with the patient. These activities follow no set order. Figure 1 shows a flowchart of the major activities performed by the hospitalist. These activities are the same for the three medical units considered in the simulation model.

Figure 1 shows the sequence of activities and decisions made by the hospitalists in the intensive care units. The hospitalists are modeled as entities in the simulation. Two physicians are scheduled per day and they both arrive in the morning to check on their patients (rounds) following a normally distributed time with a mean at 10:27AM and standard deviation of 1 hour and 40 minutes. Patients are assigned to hospitalist at the time of admission and the hospitalist is in charge of that patient until he or she is discharged. The hospitalists perform round visits to their patient in the three medical units on the same day.

When the physician arrives to one of the medical units, he or she will check which patients are under his/her responsibility and the nurses that are assigned to them. After checking the patient records, the physician will start visiting with his patients sequentially base on the room number. Hospitalists are encouraged by the health institution to visit patients with a nurses. However, the hospitalist will either seize a nurse, seize the charge nurse, or enter the room alone and the chances for each decision are .816, .034, and .149 respectively. If the physician decides to wait for the nurse before entering the room, he will wait on average 1 minute and 23 seconds. The physician will repeat this process before visiting with each patient and will also suffer random disruptions to perform other activities (check files, make phone calls and speak with staff). The chart below describes the time distribution in minutes for both clerical duties and speaking with the nurses on staff when task is undertaken. The accompanying percentages are how often the physician will perform the task between seeing each patient. Table 1 and Table 2 present the probability distributions used to model the behavior of the physicians in the intensive care units. Table 3 presents the average cycle time for the physicians in the three intensive care units.

Table 1: Probability distribution hospitalist interaction with the system.

Medical Unit	Time at computer (minutes)	% of time access computer after visiting a patient	Time talking with nurse (minutes)	% of time talking to nurse after visiting a patient
ICU	1 + GAMM(11.9, 1.14)	81%	LOGN(2.95, 3.08)	19%
MSU	0.04 + LOGN(2.61, 2.37)	29%	0.16 + 5.84 * BETA(0.442, 0.366)	24%
PCU	LOGN(7.33, 9.86)	60%	LOGN(2.32, 1.5)	50%

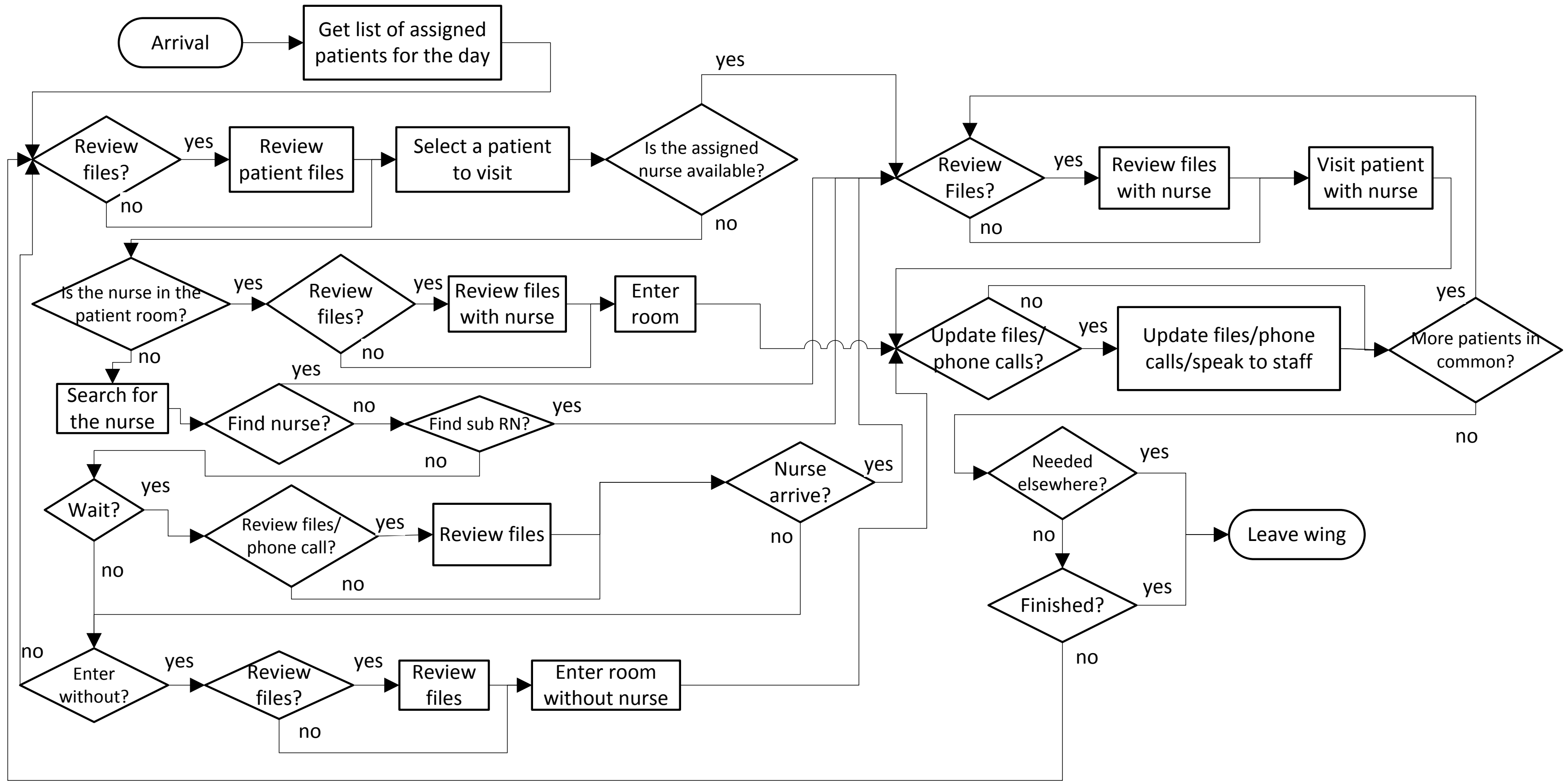

Figure 1: Doctor's sequence of activities in the intensive care units.

Table 2: Probability distribution for hospitalist visit with patient.

Medical Unit	Hospitalist visit time with patient (minutes)
ICU	LOGN(4.48, 5.74)
PCU	GAMM(3.16, 2.35)
MSU	0.999 + EXPO(7.07)

Table 3: Average hospitalist cycle time per medical unit.

Medical Unit	Average hospitalist cycle time per medical unit (minutes)
ICU	58.82
PCU	101.58
MSU	43.57

3.3 Nurses

Nurse behavior is abstracted in the simulation model as a resource that is seized by the hospitalists and the patients in the system. Nurses are assigned to one of the medical units following a nurse to patient ratio of 1:2 for the ICU and 1:6 for the PCU and MSU. A nurse is only assigned to one of the medical units and is in charge of only a group of patients. Nurses perform multiple activities as part of their daily routine. However, for the purpose of the simulation model, only those activities taking most of their time were modeled.

Nurses are in charge of admitting a patient into their areas. Once a patient is assigned to one of the medical units, a nurse and a bed will be seized for about 15 minutes to allow for an initial consultation with the patient admitted. The nurse will be in charge of her admitted patients for as long as they are staying in the medical unit. After the initial consultation, nurses are released by the patients and will be able to continue performing other duties. Nurses will be seized by each of his or her patients every hour for about 5 minutes which represents their hourly rounding schedule. The dynamic of the nurse activities will continue until the hospitalists arrive to their medical unit to check on their patients (rounds). At that point the nurses' priority is to accompany the hospitalists in their rounds. Nurses are not always readily available to round with their hospitalist because they are often performing other duties. Hospitalists will seize nurses according to their patients list which will require multiple nurses. The list of patients assigned to the hospitalist does not match the list of patients assigned to any of the nurses. If the nurse is not available, then the hospitalist will perform one of the following three actions according to the probabilities discussed earlier: wait for the nurse to become available, seize the charge nurse (sub RN) or go into the room alone. Once the hospitalists complete their rounding, the nurses will resume their routine of rounding every hour.

3.4 Patients

The patients are abstracted as entities in the simulation model. The following attributes will be assigned to the patients at the time of admission: arrival time and length of stay. Each patient is admitted to one of the medical units and they are randomly assigned to one of their empty beds and to one of their nurses. The patient will seize a nurse every hour to simulate hourly rounding within the wing and will hold the nurse for about 15 minutes. Patients will see a hospitalist every day and their consultation time with the hospitalist is modeled using the distributions provided in Table 4. At the end of the consultation, the hospitalist will decide if the patient can be discharged which will depend on the current length of stay of the patient.

Table 4: Patient probability distributions (IA=inter-arrival time).

Medical Unit	Patient arrival rate (patients/ month)	Patient length of stay (days)
ICU	μ= 19, σ= 3.76 IA=1.57 (days/patient)	0.5+lognormal (3.4,2.83)
PCU	μ=133, σ=10.44 IA=0.36 (days/patient)	0.5 + lognormal(4.26, 3.14)
MSU	μ=81, σ=14.13 IA=0.23 (days/patient)	0.5+lognormal (3.74,2.03)

3.5 Model Implementation, Verification, and Validation

To compare our baseline model, some data needed to be gathered from the hospital. Data was collected in two ways for two months. The first method was through observation. This method involved gaining a better understanding of the flow of the system and the time distributions from when the physician was meeting the patient, proportion of meeting the patient with nurse, with a charge nurse, or without a nurse, time on the computer, time speaking with nurses, time entering the system, time in system and time on the phone. The team collected about 300 data points for each process. The other set of data came from hospital records from November 2014-April 2015. This data contained times patients were discharged and admitted, the proportion of where the patients were assigned, the patient duration of stay, their assigned physician and their assigned wing. These data values were used to verify and validate the model. Table 5 compares the results of the simulation with those obtained from observing the system.

Table 5: Simulation validation results.

Statistic	Clinic Number	Simulation (Average, half-width)
1- Avg. patient discharge time	14.51	14.87 ± 0.18
2- Avg. patient cycle time ICU days	3.97	4.03 ± 0.37
3- Avg. patient cycle time PCU days	4.76	4.68 ± 0.17
4- Avg. patient cycle time MSU days	4.23	4.46 ± 0.16
5- Avg. rate visiting without nurse	0.15	0.16 ± 0.01
6- Avg. hospitalist cycle time hours.	3.40	3.14 ± 0.25
7- Avg. hospital waiting time for nurse mins.	1.38	1.50 ± 0.19
8- Avg. number of patients served per day	14.07	16.01 ± 1.01

4 EXPERIMENTATION

The main goal of the simulation model is to study the performance of the three medical units and to understand the system factors that can improve patient perceptions of quality of service as measured by the HCAPHS survey. The simulation study will consider *four areas* that were identified using the current literature and expert opinion.

1 Patient communication with the hospitalists and nurses

Based on our consultation with the experts at the hospital, doctor communication with the patient is one of the most important indicators of quality of care as perceived by the patients. Patients prefer to have the nurse present at the time of the hospitalist visit. Having the nurse present allow them to have a backup consultation when hospitalists leave the medical unit. For example, the nurse can help in answering questions and can also explain the patient condition to the patient's relatives. For that reason, the hospitalists should avoid visiting the patients without the patient's assigned nurse.

2 Patient waiting to time to see hospitalists and for discharge

The time it takes to see the physician for the first consultation is related to patient satisfaction, an increase in waiting time is shown to reduce patient satisfaction (Michael et al. 2013). Patient discharge times are also associated with patient dissatisfaction. Most of the patients do not want to wait to the end of the day to be discharged, especially if they are told with anticipation that they are going to be discharged. Therefore, hospitalists are encouraged to arrive early in the day to sign release authorizations and discharge patients.

3 Nurse balance workload and patient interaction

Nurse and patient interactions have been found to be the strongest indicator of patient satisfaction by a large margin (Brosey and March 2015). Therefore, is important that the nurse participate in the hospitalist visits with the patients and also that they check on patients continuously. In addition, based in our consultation with the experts, it is important to keep a balanced workload between the hospital medical units. When nurses are not significantly utilized (low volume of patients in the medical unit), they can be discharged to be on call for the rest of the day. When a nurse spends several days of the week on call, there is a decrease in the nurse morale toward his or her employee because they do not get paid, which reflects on his or her treatment to the patient. Keeping the nurses on site increases their morale (job security) and improve the quality of service provided to the patient.

4 Hospitalist workload

Hospitalist usually visit multiple hospitals and see multiple patients during the week. Therefore, it is important to minimize any bottleneck in the system that will keep them out of their schedule (for example waiting and searching for a nurse to perform a patient visit). Hospitalist morale is also improved when their waiting time for nurses is eliminated and when their cycle time in the hospital is minimized. A high hospitalist morale also reflects on the service provided to the patient.

4.1 Design of Experiment

This section provides a discussion and analysis of the statistical experiments performed with the simulation model. A total of 16 experiments were conducted with twenty replications each. The experiments include five main factors (hospitalist strategy, hospitalist capacity, hospitalist arrival time, and patient demand) and 8 responses (patient waiting time for the hospitalist first consultation, patient discharge time, patient cycle time, rate of times the hospitalist visits the patient without a nurse, hospitalist cycle time, hospitalist waiting time for the nurse, number of patients served per day). Figure 2 presents the input output transformations for our system. Table 6 provides the levels for each factors in our study.

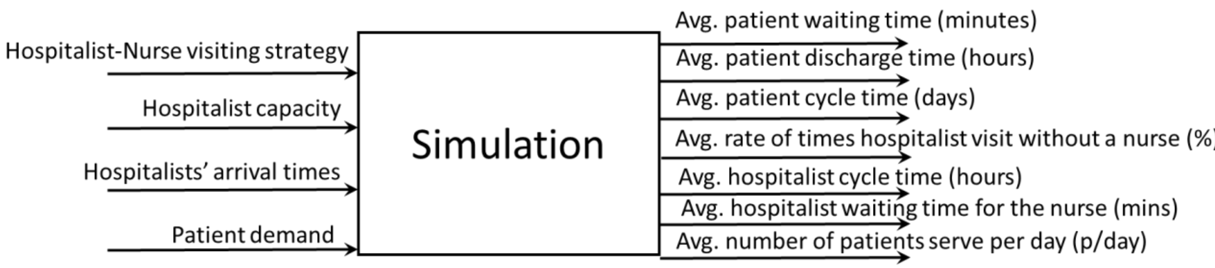

Figure 2: Input output transformation for the simulation experiments.

Table 6: Experimental design.

Factors	Levels	
	Normal (N)	High (H)
hospitalist strategy	Wait for nurse to become available to visit the patient	No wait - nurse will be available to visit patient
hospitalist capacity	2	3
hospitalist arrival time	current (around 11:00 am)	8:00 am
patient demand	current	10% more

5 RESULTS

The computational results are presented in Tables 7 and 8. The tables display the mean outcome of the response and its respected confidence interval for 20 replications and each replication was run for 34 days. The tables contain all of the possible combinations of factors, the letter N represents the normal level in the hospital and letter H represents the high level tested within the simulation. The order of each factor does not change. For example, NHHN represents the Normal nurse waiting strategy, high level of capacity (3 doctors preforming rounds each day), the high level of arrival times (constant 8:00 AM) and a normal level of demand.

Table 7: Average values and confidence interval for each patient response.

				patient waiting		patient discharge		patient cycle ICU		patient cycle PCU		patient cycle MSU	
Strategy	Capacity	Arrivals	Demand	average	half width	average	half width	average	half width	average	half width	average	half width
N	N	N	N	12.72	0.66	14.80	0.14	3.76	0.35	4.68	0.21	4.48	0.23
N	N	N	H	13.25	0.88	14.94	0.10	4.09	0.31	4.78	0.14	4.59	0.17
N	N	H	N	14.12	0.50	11.71	0.11	3.97	0.30	4.69	0.17	4.24	0.28
N	N	H	H	15.08	0.74	11.80	0.18	3.99	0.42	4.81	0.19	4.75	0.18
N	H	N	N	13.09	0.76	14.22	0.09	4.31	0.64	4.77	0.22	4.38	0.14
N	H	N	H	12.96	0.76	14.37	0.11	3.78	0.40	4.64	0.20	4.48	0.17
N	H	H	N	14.60	0.48	11.23	0.13	3.96	0.36	4.45	0.14	4.52	0.16
N	H	H	H	14.58	0.43	11.31	0.08	3.84	0.42	4.73	0.18	4.51	0.08
H	N	N	N	11.39	0.28	14.93	0.17	3.42	0.28	4.43	0.18	4.36	0.14
H	N	N	H	11.45	0.63	15.32	0.26	3.96	0.28	4.60	0.19	4.34	0.21
H	N	H	N	13.05	0.34	11.87	0.12	3.71	0.18	4.42	0.26	4.24	0.22
H	N	H	H	14.02	0.53	12.01	0.09	3.58	0.39	4.69	0.17	4.48	0.33
H	H	N	N	12.72	0.38	14.19	0.10	3.72	0.46	4.63	0.16	4.38	0.15
H	H	N	H	12.58	0.77	14.33	0.08	3.66	0.23	4.68	0.19	4.43	0.16
H	H	H	N	14.48	0.57	11.17	0.11	3.89	0.19	4.57	0.19	4.33	0.18
H	H	H	H	14.68	0.26	11.32	0.14	4.01	0.54	4.64	0.15	4.28	0.23

Table 8: Average values and confidence interval for each hospitalist and nurse response.

				visit with nurse (%)		hospitalist cycle		hospitalist waiting		patients served	
Strategy	Capacity	Arrivals	Demand	average	half width	average	half width	average	half width	average	half width
N	N	N	N	80.17%	0.82%	3.03	0.16	1.02	0.21	15.53	0.87
N	N	N	H	80.08%	0.79%	3.20	0.27	1.00	0.14	17.92	0.75
N	N	H	N	80.60%	0.84%	3.05	0.20	0.99	0.21	16.09	0.85
N	N	H	H	80.58%	0.95%	3.03	0.23	0.98	0.18	18.35	0.87
N	H	N	N	79.54%	0.88%	2.15	0.22	1.47	0.23	10.78	0.65
N	H	N	H	79.03%	1.06%	2.46	0.11	1.64	0.22	11.83	0.63
N	H	H	N	79.80%	0.57%	2.32	0.15	1.71	0.35	11.23	0.53
N	H	H	H	79.99%	1.13%	2.30	0.15	1.58	0.26	12.07	0.52
H	N	N	N	95.80%	0.76%	3.40	0.18	0.04	0.06	15.53	0.74
H	N	N	H	96.23%	0.59%	3.73	0.21	0.02	0.03	17.62	1.08
H	N	H	N	95.80%	0.50%	3.46	0.19	0.01	0.01	16.33	1.33
H	N	H	H	95.95%	0.60%	3.40	0.16	0.01	0.01	17.54	0.70
H	H	N	N	92.47%	0.79%	2.29	0.13	0.37	0.15	10.53	0.40
H	H	N	H	92.38%	1.15%	2.42	0.14	0.26	0.09	11.85	0.45
H	H	H	N	92.50%	1.33%	2.24	0.15	0.26	0.15	10.61	0.89
H	H	H	H	91.87%	1.22%	2.35	0.10	0.53	0.21	11.80	0.80

The results show that by increasing the hospitalist capacity from 2 to 3, then each physician will spend less time in the hospital per day. This makes sense as the more hospitalist there are to preform rounds the smaller the individual workload. The combination that lead to the smallest cycle time was (NHNN) leading to a cycle time of 2.15 hours, showing that increasing capacity was needed to reduce the individual time in system. In addition to the benefits of decreased cycle time, the number of patients assigned to each physician and visits each day is also reduced proportionally. The HHNN combination achieved the fewest patients per day with the new strategy and increased capacity but most drops in this measure were due to the capacity.

Having the hospitalist arrive earlier in the day increases the time a patient will generally have to wait to see the physician. Most patients arrive mid-day so if the physician arrives before the patient does the patient will have to wait to the following day in order to meet with the hospitalist. The shortest waiting time was the HNNH combination of factors where the constant 11:00 AM arrival time was not altered. Increasing the hospitalist from 2 to 3 each day negatively impact the hospitalist waiting time on the nurse. The largest contributing combination was the NHHN, where the hospitalist capacity was increased to 3 and the hospitalists' arrival time was fixed to an earlier time (8:00am). This is due to the fact that if more physicians are seeking nurses all at once the nurse availability will decrease. Inversely if there are few nurses being seized at once then their availability will be increased. For the strategy factor the hospitalist will never wait for the primary nurse. If the nurse is busy he will immediately seize the charge if available. Since there are two resources available at once and only two physicians able to seize them, this would explain the very small wait time incurred in the 2 doctor strategy runs.

The arrival time played the largest role in the patient discharge time. The earlier the hospitalist arrived to the hospital the sooner the hospitalist would meet with the patient, allowing them to be issued a discharge earlier in the day. The earliest time of discharge was achieved by a HHHN combination where doctors did not visit a room without a nurse, they arrived earlier to the hospital, and had and increased physician capacity. The largest indicator of earlier discharge time was the doctor's arrival; the earlier a physician arrived at the hospital the earlier a patient would be discharged that day.

Increasing nurse availability would maximize the percentage of times a physician would meet with a nurse. The choices for the hospitalist are to seize the patient's primary nurse and, if they are not available then, the doctor will automatically go to the charge nurse. Entering the room without either is not an option for the hospitalist. Therefore, entering a room with a nurse is increased from 80% to mid-95% range. The percentage stayed low at 80% until the hospitalist was forced to enter the room with one of the hospital staff members in which case the percentage increased to more than 90%'s.

6 Conclusion

Schedule planning to improve patient experience of care can be a very challenging problem and has only just begun to receive attention from the researching world. Hospitals must find new methods to improve quality of care in order to maximize the incentive payouts received from the HCAHPS survey. In this paper, we have modeled a system to maximize the intersection of time and place to increase the number of times a hospitalist performs his or her rounding with an attending nurse. In addition to the model we have developed a discrete event simulation to test the various outcomes from variability in the system. A 2^k factorial experiment was used to test the significant factors that can affect the workings of the hospital system. The simulation also shows effects that can further enhance patient satisfaction such as earlier discharge times for patients and decreasing the time waiting for the first visit with a hospitalist. This research has not only shown that it is mathematically possible to schedule around doctor and nurse visits but it has also shown that this schedule can be maintained even in a dynamic system.

Future work will be directed towards finding methods to decrease the variation in hospitalist arrival at a constant 8:00 AM. By reducing the variation of arrivals, further process improvement measures will be more easily adopted and implemented. In addition to adoption benefits, improved physician time management can lead to improved work moral, and improved cognitive ability that can lead to increased clinical outcomes.

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