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MODELING CARE TEAMS AT MAYO CLINIC

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ABSTRACT

At Mayo Clinic, care teams are being evaluated as a means to improve health care staff productivity and patient service. Traditional care in outpatient practices has health care staff working independently of each other with little coordination. Initial feedback by participating practices support the value of care teams. Our research focuses on a quantitative analysis of the care teams approach. By collecting detailed task data related to patient visits we then use discrete-event simulation to design alternative care team configurations, analyze staffing cost options, and compare these to traditional outpatient care delivery.

1 INTRODUCTION

Mayo Clinic has over 500,000 patient visits annually at its three sites in Rochester, Minnesota; Scottsdale, Arizona; and Jacksonville, Florida. A significant proportion of these are outpatient visits to consulting physicians in a variety of general medical disciplines (e.g., family practice, internal medicine) and specialties (e.g., endocrinology, neurology). Throughout its history, Mayo Clinic has been an innovator in how care is delivered to patients. Working through the Center for Innovation at Mayo Clinic an initiative: *Re-Imagining Integration in the Outpatient Setting* (RIOS) suggests the use of Care Teams as a way to more productively use health care human resources. Health care reform in the U.S. further underscores the need and potential value for such innovations.

One of the major objectives of Mayo Clinic is to improve the value of the healthcare it provides. Value is defined as the Quality of Care (i.e., outcomes, safety, service) divided by Cost. Historically, the physicians in outpatient practices have seen patients in a relatively independent manner of other supporting staff. The creation of Care Teams, where physicians are more directly supported by staff in a coordinated manner is seen as a potential mechanism to increase value. The intent of the approach is to allow physicians to see patients in higher volumes without sacrificing the quality of the health care delivered.

Simulation modeling was proposed as a way to quantify the cost savings that might result from the Care Teams concept. While creating a well-functioning team is a key to the concept and modeling cannot consider the human dynamics of a team, it could be used to explore the reallocation of patient-care and administrative tasks and the implications of these work changes on patient flow, travel distances, and similar issues that affect cost.

The remaining sections of this paper will provide a more detailed discussion of care teams, present an overview of the simulation model building process, present preliminary results, and discuss conclusions and practice implications.

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2 AN OVERVIEW OF CARE TEAMS

In this section we will provide an overview of care teams and related simulation modeling research.

2.1 Literature Review

In the literature review we will present some of the research regarding the care teams approach and simulation modeling work related to outpatient health services.

2.1.1 Healthcare Services Literature

The use of multidisciplinary groups of care providers ("care teams") has been employed in part to efficiently distribute health care human resources and provide high-quality patient care. Much of that work has focused on worker reallocation among specific positions. One recent example is shifting or "matching" work from physicians to nonphysician clinicians (Druss 2003). Grzybicki et al. (2002) studied the capabilities of physician assistants and Mundinger et al. (2000) examined the outcomes of utilizing nurse practitioners. Ideal task alignment is now thought to be as important as ever; almost half of the physician workday, on average, is spent outside of the patient encounter (Gottschalk and Flock, 2005). The outcomes assessed in recent work-shifting studies have included costs (Roblin, Howard, Becker et al. 2004, Grzybicki et al. 2002), patient-reported outcomes (Mundinger et al. 2000), and, more specifically, patient satisfaction (Roblin et al. 2004).

A primary goal of work reallocation is to free up physician time so that it can be focused on treating patients; it may also better match worker skill sets. The former is important from the modeling perspective, however, the latter is also valuable for staff satisfaction. Berry (2003) argues that health care access is improved when team members do work commensurate with their "maximal" training, skills, and experience. Further, Wagner (2000) finds that patients who require behavioral counseling, such as those with chronic illnesses, are more appropriately served by non-medical staff that have more specialized training in patient education. Similarly, Palmer and Midgette (2008) found that some medical assistants are appropriately trained to play a larger patient education role in health care teams. All of these studies support the concept of work reallocation in a team environment.

2.1.2 Simulation Modeling of Outpatient Practices

The use of simulation as a tool to analyze and improve outpatient health services is a growing research area. Simulation's use to consider outpatient scheduling issues is particularly prevalent (see the review article of Cayirli and Veral 2003 for many examples). There are also studies where simulation is used in a broader way to model outpatient flows. Chand et al. (2009) report on a case study where simulation was used in an outpatient clinic to reduce patient waiting time and increase physician utilization. Their use of simulation identified problems with variability in the clinic and assisted in recommending several implementation options.

Studies related to determining the best staffing mix in healthcare environments are less common, however, there are some examples. Mukherjee (1991) uses simulation to test staffing mix options that reduces patient waiting time at a pharmacy. Hashimoto and Bell (1996) vary the number of the different staff in the general internal medicine clinic they studied. Similar to our work they captured detailed task data via a time and motion study. They identified that having the right balances of staff in the clinic was important to efficient patient flow. However, they did not explore the potential value of reallocating tasks within a team structure. Finally, Sendi, et al. (2004) use the discrete event simulation capabilities of colored petri nets to identify the best number of senior physicians to staff in an outpatient clinic where resident physicians are also part of the staffing mix. Again, the potential teamwork among the staff was not explored.

2.2 Care Teams at Mayo Clinic

At Mayo Clinic, care teams are being explored as a new approach to delivering outpatient health services. It is one of the initiatives being explored within the Re-imagining Integration in the Outpatient Setting (RIOS) Project. This project was set up to address the unique and challenging aspects of providing health care in an integrated practice like at Mayo Clinic. Some of the challenges RIOS is meant to address are:

- Managing complex episodes
- Prioritizing orders
- Distinguishing patient paths

A prototyping lab was set up to test out alternative health care delivery modes and technologies. Care teams were one of the approaches tested in this lab.

Several advantages to care teams were reported by the staff testing the care team approach in the lab. All staff levels reported better communication and coordination and the physicians noted smoother patient flow. Anecdotally, the staff in the care teams reported that their days were easier than in the previous configuration where each worked independently from the others. The role of the simulation modeling effort is to support the value of care teams quantitatively and to assist in identifying the best team configurations from an efficiency perspective.

3 SIMULATION MODEL DEVELOPMENT

3.1 Process Flow and Human Resources

Patients in the outpatient practices at Mayo Clinic have a relatively standard sequence as described in Table 1. (The list of sub tasks is a sample of the tasks for each step).

Table 1: Listing of Activities and Staff Responsibilities

	Staff Currently Responsible	
Major Activity (with some sub tasks listed)	**Clinical Assistant/LPN**	**Physician/NP**
Check In	x	
Rooming		
Call and room patient	x	
Check vitals	x	X
Signal patient is ready	x	
Pre-Consult		
Medicine reconciliation	x	
Document health concerns		X
Consultation		
Patient dresses/undresses		
Examination		x
Discuss additional tests		x
Prescriptions		x
Post-Consult		
Patient education		x
Place medical orders		x
Place non-medical orders	x	x
Clean room	x	
Check Out	x	

The staff member that is most commonly responsible for each task is also noted. The clinical assistants (CAs) and licensed practical nurses (LPNs) do much of the check in and check out activities while the physicians and nurse practitioners consult with the patients. Not all tasks are performed during each patient visit, and some tasks are revisited within the major activities.

The staff also do additional activities that are outside of the patient flow. The physicians/NPs do much of the documentation (e.g., medical notes dictations, correspondences) and the CAs/LPNs handle patient phone calls, schedule patients, and other administrative tasks identified as continuing care.

The GIM area modeled for this study is a subgroup of the department, but constitutes a mostly independent group of staff (i.e., little sharing of duties elsewhere). In this group there are eight physicians, 3 CAs, and 2 LPNs. Additional staff such as medical secretaries, transcriptionists, and administrators were not included in the model since they were not directly involved with patient visits.

3.2 Data Collection and Input Analysis

To build a valid model of patient visits and create the flexibility needed to consider the reallocation of tasks between staff, very detailed timings of the activities in the medical areas were required. Medical staff activities were broken down into about 60 different tasks and then evaluated to determine which ones either had to be done together or would sensibly be done together. This led to 15 separate timings being done across the 6 major activities listed in Table 1 and for the physician documentation activity described in section 3.1.

Dedicated data collectors were assigned to track physicians, CAs, and LPNs. No patient information was included in the data collection, however, consent was required from the patients to have the data collectors present for the timings. Data collectors used a sheet with special bar codes that corresponded to tasks. Timings for tasks were done with a special wand that read the codes for the tasks and recorded the start and stop times. Post analysis was done to test the inter-rater reliability between data collectors to ensure that all observers had consistent views of the individual tasks being performed. Post analysis was also performed to determine if there was a physician difference. Analysis showed that while some tasks differed between practices, differences between physicians within a practice were not statistically significant. Initial data collection of the task data resulted in about 1800 individual task observations for the 15 grouped tasks. Additional data on patient arrival times were accessed from existing data sources to develop an early/late time arrival time distribution. For the tasks and arrival times traditional distribution fitting was used to determine good choices of mathematical functions to use in the simulation model. Distance data were also collected using a distance measurement wheel and detailed schematics of the buildings.

Several challenges were identified in the process of incorporating the data for use in the simulation model. Most notably, for some of the tasks there was a tendency for the staff to move back and forth between several of them with very short durations. As an example, for the consultation activity, the physician may move from the physical exam, to a discussion of additional testing, back to the exam, then to a medication reconciliation, back to the exam, and so on. To keep the model reasonably simple we decided to aggregate the tasks as opposed to modeling the back and forth behavior. We used a Poisson distribution to determine the frequency of the tasks. For tasks that had to have at least one occurrence a zero-truncated Poisson distribution was used. Total task times were then generated by randomly drawing values from the appropriate fitted task time distribution and adding them together. This modeling approach was compared to the original aggregated data. The results were very good for both the mean and variance. Table 2 shows the analysis results for the physical examination task of the consultation activity.

Table 2: Verification analysis of multiple step task physical examination

		Mean	Std	Min	Max
Frequency of Task	Simulation	4.09	2.24	1	13
	Observed	4.08	2.42	1	12
Total Time of Task	Simulation	22.83	17.98	0.29	110.95
	Observed	22.46	18.78	0.82	112.88

3.3 Model Structure

The data were incorporated into a simulation model using the Arena software (Rockwell 2009). The program was modularized into the major activities: patient arrival/check in, rooming, consultation, and so on. The following list identifies several of the key measures tracked:

- Number in waiting room
- Patient waiting time for resources (e.g., CA, Room, Physician)
- Staff/Resource utilization
- Number of patients seen in appointment period
- Time that appointment period was complete (i.e., end of day)
- Staff distance traveled

The last measure was included to consider possible layout changes based on the care teams structure. That analysis is proposed for future study.

3.3.1 Simulation Model

Because visual representation was important in selling the care team concept to potential medical areas, a detailed animated version of the model was required. To show the movement of staff as well as patients, transporters were used. Thus, staff would move to pick up patients and transport them to the appropriate locations in the model. In addition, staff were included as resources to properly track their usage for tasks and utilization measures. The CFI staff who commissioned the model agreed that the animated version of the model was effective in representing the actual system studied. Figure 1 shows a snapshot of the simulation model.

It is not a trivial endeavor to create a model that both looks realistic and also creates output data that is useful for analysis. One particularly difficult aspect of the model was the correct allocation of resources that also served as transports of the patients. In order to create the most realistic movement of patient throughout the area we used the actual distances between each location on the floor. This required the use of transfers to accurately reflect the time it would take for a patient to move to any specific location.

Properly modeling the LPN/CA staff posed additional challenges beyond proper animation of their movement. These two resources perform several functions on the clinical floor, many of which were outside the scope of the simulation model. While their basic duties for these patient visits were considered to be the same, we were not able to collect information on all of the other duties that they perform away from the patient visit. Discussion with nurse managers from the area and from other similar roles at Mayo Clinic resulted in an estimate that about 50% of nurse time is not directly related to the patient visit.

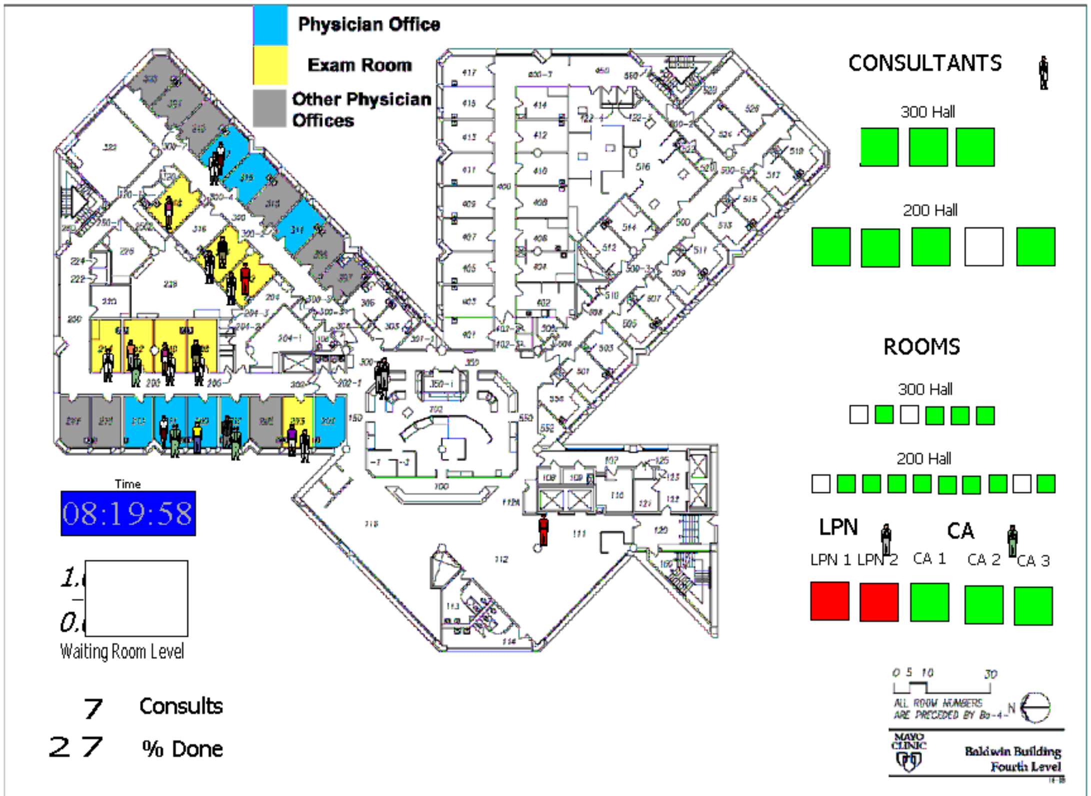


Figure 1: Animation from BA4 base simulation model.

Additionally, we also tested our model while adjusting this ratio and found that a 50% ratio seemed to be reasonable for the number of patients and physicians on the floor at one time with the assumed nurse staffing of 3 CA's and 2 LPN's. To represent the 50% effort each nurse was given a failure of Expo(15 minutes) up and Expo(15 minutes) down. The 15 minute time was chosen because the first two tasks (which are always done by CA's and LPN's) should be easily completed without causing extended delays of waiting for the next downtime (failure) to occur.

In order to keep track of the CA and LPN they were treated as a set which was dynamically linked to a group of transfers, with transfers having different visual representation to indicate if they were a CA or LPN. The LPN/CA also performs the task of cleaning the room after the patient departs which required the use of dummy entities to properly animate the LPN/CA transfer/resource moving empty to a room, cleaning the room, and then returning to the nurses' station.

The physicians had some of the same logistical problems as the LPN/CA's however they were also limited to specific rooms to which they would see patients. Also, during the initial stages we kept track of the total distance traveled by each physician. However, this was very complicated because of the way they moved about the floor, and became more so as the scope of the simulation grew. Since physicians did not always perform some tasks which required movement it was necessary to always check to see if they would have actually moved, and from what areas they were moving. If we would have been able to assume that physicians always moved about in a consistent manner it would have been possible to easily estimate distance based on the number of patients they saw. Additionally Arena uses station numbers as internally to track location. The resulting matrix of distances between locations became exceedingly difficult to track as the number of physicians, and therefore the number of exams, increased. The internal calculations being done to check locations and calculate distances also seemed to substantially slow down the simulation as the distance matrix became larger. As a result we decided to leave out distance traveled from the primary analysis at this time.

Patient arrival patterns were physician specific. Each physician could be viewed almost as a separate practice, thus in order to more accurately represent the way the floor operates, patients were generated for each physician separately based on actual arrival patterns. While this more accurately represented the real state, it also caused some unintended analysis problems which we will discuss later.

The results of these efforts did, however, prove to be very valuable. Demonstrations of the model to nurse managers and operations administrators of the area quickly recognized how the model represented what was happening in real life. The detailed animation also quickly identified errors in the animation, and therefore the logic, which made corrections to the model much easier than would have been the case if we had simply relied on the basic statistical output from the model.

4 ANALYSIS RESULTS

4.1 Experimental Design

The primary approach to analysis was to look at the effect of work shifting from the physician to an LPN after the basic consultation is completed. The belief is that an LPN would be capable of handling medical review and prescription ordering. The shifting of work required some minor modifications to the base simulation model. While in general LPN's and CA's perform many similar functions relative to the patient visits we observed, the transfer of some tasks can not be equally split between the two resources. CA's would not be able to perform most of the tasks to be shifted from the physicians. As a result we also looked at the ratio of LPN's to CA's.

The primary metric used to evaluate the models was patient throughput. Since the general hypothesis was that shifting of work would free physician time and allow them to see additional patients it seemed logical to look at total number of patients making it through the system. This metric, however, is not always easily or accurately captured within this environment. One problem is how to handle the noon break accurately. The way the nursing staff handles their lunch breaks can be a difficult process to simulate, so for the purposes of this model we focused only on the morning shift.

As mentioned earlier, the arrival patterns for patients among the eight physicians also caused analysis problems. Because patient arrivals were stochastic in nature it was very possible for a physician to have very few, if any, patients arrive within the simulation. Initially the model was validated in part based on having the floor on average complete the morning by noon, and while this validation worked well, it made it difficult to see exactly how the shifting of work was actually affecting the floor.

In order to get a better understanding of how work shifting was working, we created unrealistic patient arrival patterns in order to ensure that physicians would be more likely to have a full morning's slate of patients. We then capped the day at noon to see how many patients could be seen during the morning during both the base model and the work shift model. While not a completely realistic view of the floor, this does give us a sense of what the capacity of each model it, and the benefits, if any, of shifting work away from physicians.

4.2 Results

Simulation models were run as 100 replications of one single morning shift. Patients were to start arriving at 7:00AM with a random distribution around this arrival time allowing patient to arrive early or later with a 30 minute time between arrivals. This would simulate the real world environment of most patients arriving prior to their scheduled arrival time but also allow patient to arrive late. Patients began rooming at 7:45AM. Physicians would begin seeing patients at 8:00AM and continue through early afternoon, however statistical results ignored patients that did not complete their visit by noon.

Because the simulation was overloaded to ensure that most physicians would see patients until noon the results should not be interpreted as actual values. The base model was validated backwards using the known number of patients seen during a morning shift and then patient numbers increased dramatically in order to get a better understanding of the magnitude of work shifting effects. To better illustrate the differences between the base model and the test model percent differences are included. All results were output to flat files and statistical analysis was performed using SAS 9.1

Table 3 shows the theoretical maximum number of patients that could be seen by 8 physicians on average under various LPN and CA configurations. One interesting observation from this table is that it shows a nice correlation between the current practice and the theoretical maximums. Currently the floor works under a model with approximately 5 total LPN/CA, and we can see from the simulation that this number holds even under increased patient load stresses

Table 3: Simulation results from base model.

Total LPN/CA	LPN	CA	Mean	10%	Median	90%	Std
3	1	2	24.9	21.0	25.0	28.5	3.10
4	2	2	29.3	26.0	29.0	33.5	2.93
5	2	3	30.5	27.0	30.0	34.0	3.05
6	3	3	31.4	27.5	31.0	36.0	3.32
7	3	4	31.1	28.0	31.0	35.0	2.97
8	4	4	31.3	28.0	31.0	35.0	2.83

Table 4 shows the same theoretical maximums under a possible work shift environment. There were a greater number of work shift models tested because the relationship between LPN and CA is more of a determining factor. When LPN's perform some of the tasks currently done by the physicians it results in large differences when the ratio between the two are changed, particularly when the total number of LPN's and CA's increase. As we would expect, under models with few LPN's and CA's, the shifting of work has a negative effect, while as the total number of LPN's and CA's increase the benefits of work shifting are shown. We also see that the benefits of work shifting are maximized around 7 total LPN/CA's.

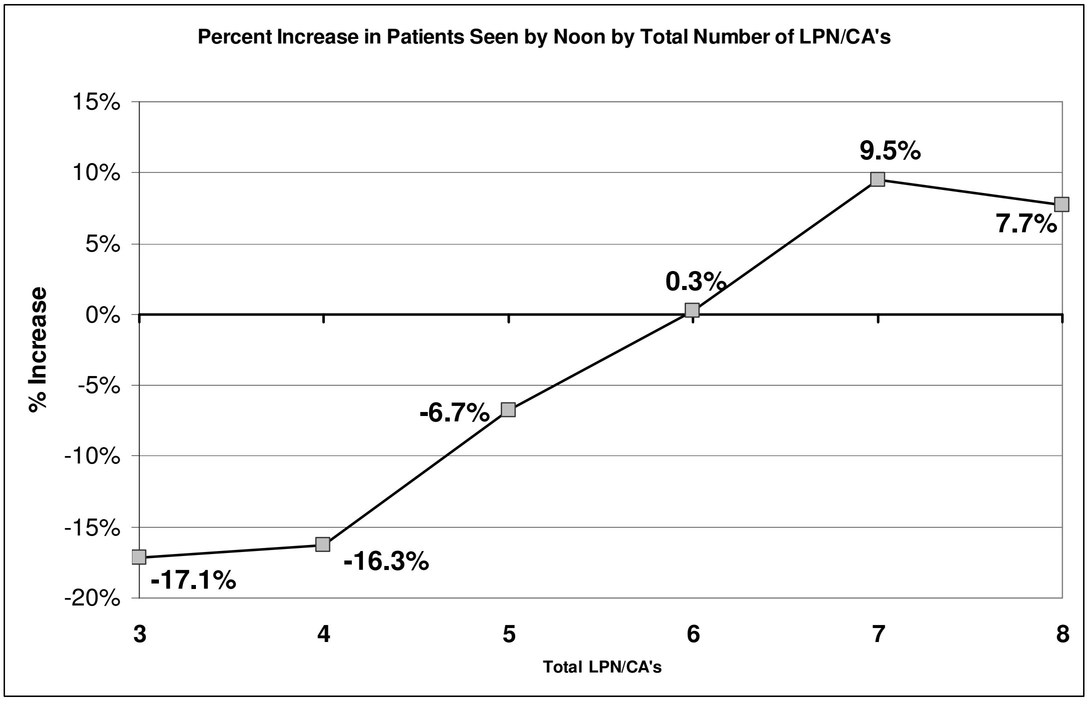
Table 4: Simulation results from test model.

Total LPN/CA	LPN	CA	Mean	10%	Median	90%	Std
3	1	2	19.9	17.0	20.0	22.0	1.99
3	2	1	20.6	18.0	21.0	23.0	1.95
4	1	3	21.6	19.0	21.0	24.0	1.83
4	2	2	24.5	22.0	24.0	27.5	2.41
4	3	1	23.3	20.0	23.0	26.0	2.53
5	2	3	27.1	23.5	27.0	31.0	2.95
5	3	2	28.4	25.0	29.0	32.0	2.66
6	2	4	28.4	25.0	28.0	32.0	2.41
6	3	3	31.4	28.5	32.0	34.5	2.60
6	4	2	30.6	27.0	30.0	35.0	3.13
7	3	4	33.0	29.0	33.5	37.0	2.87
7	4	3	34.1	31.0	34.0	38.0	2.71
8	3	5	32.4	28.5	32.0	36.0	2.98
8	4	4	33.7	30.0	34.0	37.0	2.58

*Shaded columns to be used for comparison testing.

Using the results from table 3 and the results from the shaded rows of table 4 we can get a feel for the impact of reallocating the tasks from physicians to LPNs/CAs. The shaded rows from table 4 were selected because they showed the largest improvement in the mean number of patients seen. Figure 2 shows these results, and we can see how the percentage increase in patients seen as the total number of LPN/CA's increase to a point.

Figure 2: Effects of work shifting.



We also decided to look at the floor from another point of view. Based on work shifting it appears that we could achieve a theoretical maximum of 34.1 patients per day. We were curious how many physicians would be required to reach the same throughput under current work rules. Table 5 shows the results from increasing the number of physicians to 9, 10 and 11 physicians while keeping the number of LPN/CA's at the nominal level of 5. We can see that one additional physician will almost obtain the same level of throughput and each additional physician thereafter does increase the number of total patients seen by noon. However, the average number of patients seen decreases at a steady rate indicating the stress on the LPN/CA resource resulting in approximately a 3% decrease in average efficiency per physician.

Table 5: Simulation results from base model with increased physicians.

Total Physicians	LPN	CA	Mean	10%	Median	90%	Std	Avg # of Patients
8 Base	2	3	30.5	27.0	30.0	34.0	3.05	3.81
9 Base	2	3	33.3	30.5	33.0	37.0	2.81	3.70
10 Base	2	3	36.2	31.5	36.0	41.0	3.58	3.62
11 Base	2	3	38.5	34.5	39.0	43.0	3.55	3.50
8 Work Shift	4	3	34.1	31.0	34.0	38.0	2.71	4.26

5 CONCLUSIONS

Care Teams are being explored as an alternative health care delivery model at Mayo Clinic. We showed how the use of a discrete-event simulation modeling could be used to quantify the value of this approach and in the design of the best staff structure for these teams.

A highly detailed animated simulation model was developed. The animation was important to the verification and validation processes because it provided an easy means for staff involved in the studied practices to identify key aspects the model was properly or improperly incorporating. In the end the model validated well to the real system and was used to test alternative team configurations.

The results show that by reallocating work from physicians to the supporting Licensed Practical Nurses and Clinical Assistants may allow higher patient volumes to be seen in the General Internal Medicine practice studied. With two additional LPN/CA staff and the same number of physicians, the work reallocation allows about 12% more patients to be seen per session. However, under current or lower LPN/CA staffing levels reallocating work to the LPNs and CAs results in lower volumes because these staff are the primary bottleneck in the system.

Also, if the goal is to increase overall patient throughput, it would appear that work shifting, if viable, is preferred over simply increasing the number of physicians available. Since the costs of support staff are lower than that of physicians, there is little to gain from increasing the number of physicians at a reduced patient load without hiring additional support staff at which point work shifting would again show to be a better use of resources.

Immediate future work associated with our model is to consider the value of using teams to intervene with complex/time consuming patients. This may also involve factoring in new resources such as registered nurses to the team. The model may also be used to evaluate alternative uses of space and associated efficiencies that the Care Teams concept promotes. Shared work spaces that are closer to where patients are treated may significantly reduce space requirements and travel distances/times for staff. The model can be used to help predict the latter, in particular. In addition, with the acceptance of the simulation approach financial models can be developed in conjunction with the simulation analytics to consider the benefits of making the transition to a care-team approach for Mayo Clinic.

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