Predicting the Future: Using Simulation Modeling to Forecast Patient Flow on General Medicine Units

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BACKGROUND: Hospitals are complex adaptive systems within which multiple components such as patients, practitioners, facilities, and technology interact. A careful approach to optimization of this complex system is needed because any change can result in unexpected deleterious effects. One such approach is discrete event simulation, in which what-if scenarios allow researchers to predict the impact of a proposed change on the system. However, studies illustrating the application of simulation in optimization of general internal medicine (GIM) team inpatient operations are lacking.

METHODS: Administrative data about admissions and discharges, data from a time-motion study, and expert opinion on workflow were used to construct the simulation model. Then, the impact of four changes – aligning medical teams with nursing units, adding a hospitalist team, adding a nursing unit, and adding both a nursing unit and hospitalist team with higher admission volume – were modeled on key hospital operational metrics.

RESULTS: Aligning medical teams with nursing units improved team metrics for aligned teams but shifted patients to unaligned teams. Adding a hospitalist team had little benefit, but adding a nursing unit improved system metrics. Both adding a hospitalist team and a nursing unit would be required to maintain operational metrics with increased patient volume.

CONCLUSION: Using simulation modeling, we provided data on the implications of four possible strategic changes on GIM inpatient units, providers, and patient throughput. Such analyses may be a worthwhile investment to study strategic decisions and make better choices with fewer unintended consequences. Journal of Hospital Medicine 2018;14:9-15. Published online first November 28, 2018. © 2019 Society of Hospital Medicine

Hospitals are complex adaptive systems within which practitioners, technology, physical resources, and other components adapt interdependently to attempt to best meet the needs of patients.[1] Hospitals must provide a stable, dependable level of care while also surging to respond to times of high demand, such as patient emergencies or swells in patient volume. Given the critical and resource-intensive nature of this work, optimizing the system is essential; however, because of the complexity of the system, making changes can result in unexpected and possibly deleterious effects. We need to approach change in hospital processes carefully and thoughtfully.

The Institute of Medicine, the National Academy of Engineering, and the President's Council of Advisors on Science and Technology have recommended the application of systems engineering approaches to improve health care delivery.[2,3] Systems engineering seeks to coordinate, synchronize, and integrate complex systems of people, information, materials, technology, and financial resources.[4,5] To determine how complex systems can be improved, engineers apply analytic methods to describe how such systems operate and what the impact of changes might be. These methodologies have improved patient care and reduced costs at several hospitals.[6] For example, a decision support system that combined simulation, optimization, and machine learning methods in an emergency department (ED) resulted in a 33% reduction in length of stay (LOS) and a 28% decrease in ED readmissions.[7] Other strategies to improve patient flow include shaping demand (decreasing variation in surgical scheduling, relocating low acuity care ED visits to primary care, etc.), redesigning systems (early discharges, improving efficiency, and coordination of hospital discharge process, decreasing care variation, etc.), or aligning capacity and demand. Another approach, real-time demand capacity (RTDC), is based on management principles

and queuing and constraint theory and has been implemented successfully in a variety of healthcare organizations. RTDC represents a promising approach to improve hospitalwide patient flow and can be integrated into current bed management processes.[8] Unfortunately, many of these approaches are not well known to clinicians and would benefit from greater awareness and input from healthcare practitioners.

One systems engineering tool that can be used to describe, analyze, and evaluate proposed changes in care is simulation.[9] Simulation creates a model within which what-if scenarios (ie, adjusting various inputs into the simulation) allow researchers to define the likelihood of consequences from various courses of action and determine the optimal change to a system. Such analyses can predict the impact of a proposed change on patients and healthcare practitioners.[10-13]

A critical concern for hospitals that simulation may help address is managing the volume of inpatients. A high inpatient census is necessary for financial solvency, yet too high a census of inpatients or an unexpected surge in acuity can overwhelm hospital resources. Many hospitals, pressured by growing numbers of increasingly complex patients, have seen medical inpatients spread across multiple nonmedical nursing units (NUs) of their institution such that a particular medical team may have only a couple patients assigned to each nursing unit.[14] This dispersion may hinder communication between physicians and nurses and limits the time physicians have to interact with patients.[15] Additionally, coordination of care may become more challenging for discharge planning.[16] Aligning medical teams with NUs may benefit the quality and efficiency of care or may create a barrier to patient flow, which worsens these problems.[15,17] Alternatively, hospitals might meet the increasing demands for care by choosing to add capacity by opening new NUs or hiring additional healthcare providers. We identified no studies in the literature that applied simulation modeling to general medicine inpatients to evaluate the impact of these different decisions.

This article describes the application of simulation to model the interconnected variables and subsequent future states created by several possible strategic decisions around the care of general medicine inpatients. Through the application of systems engineering techniques, we modeled four future states that illustrate the following: (1) the complexities of a large health delivery system, (2) the intended and unintended consequences of implementing different changes in the process of care delivery, and (3) how the simulation modeling might be used to inform decision making.

METHODS

Setting and Present State

Virginia Commonwealth University (VCU) is a 865-bed tertiary academic medical center, with inpatient care activities spread between four connected buildings and 50 different NUs. The occupancy rate had been over 92% during the time period of this project with admission volume limited primarily by the capacity of the facility. Three of the NUs were primarily allocated to general medicine (GIM) patients. However, over the years, GIM inpa-

tients grew to over 7,500 admissions annually, resulting in nearly 50% of GIM patients being admitted to a non-GIM nursing unit.

Additionally, patients on each medical team had a high degree of spread across NUs due to several factors. Admissions and discharges from the hospital did not align across the day. While discharges clumped in the late afternoon, admission occurred throughout the day with a surge in the later afternoon. This mismatch frequently led to patients waiting in the ED for a bed, medical team, or both, and patients were typically assigned to the first available bed and team. For medical team assignments, newly admitted patients were distributed relatively equally across five hospitalist teams and five housestaff teams (that include residents, interns, and medical students). This steady distribution of patients through the day supported meeting housestaff work-hour restrictions of 80 hours each week.[18] Yet, as a result of the high occupancy rate, the patterns of patient admissions and discharges, and the distribution of patients among medical teams and across NUs, medical teams and NUs rarely shared more than a few patients.

Leaders at our institution outlined several possible options to address these challenges, including aligning medical teams with NUs, adding an additional hospitalist team, or adding an additional nursing unit. In addition, institutional leaders were concerned about the impact of continued growth in admission volume and the impact of patient dispersion on trainees and students. The overall goal of creating a simulation model was to determine the impact of an increased volume of patients and these possible strategic decisions on operational metrics, including number of patients waiting in the ED, ED boarding time per patient, time in system per patient (ED boarding time plus inpatient LOS), team utilization, and rounding travel time.

Simulation Modeling

To model the impact of some possible system changes on patient care, we applied Kelton and Law's simulation study framework;[19] including data collection, model building and validation, and what-if scenario testing (Figure 1).

Data Collection

Process Flow Map

We created a complex process flow map of patient care activities on medical teams. The map was developed by four general medicine physicians (R.C., H.M., V.M., and S.P.T.) who all provided medical care on the hospital-based services and ensured expert input on the patient care activities captured by the simulation modeling.

Time and Motion Studies

Time and motion study is a well-established technique used to evaluate the efficiency of work processes.[20,21] Originally applied to increase productivity in manufacturing, this technique uses first-hand observations to measure the time allotted to different work tasks to systematically analyze workflow.[22] Workflow in healthcare, like manufacturing tasks, tends to have a repetitive pattern, making time and motion studies a highly applicable tool.
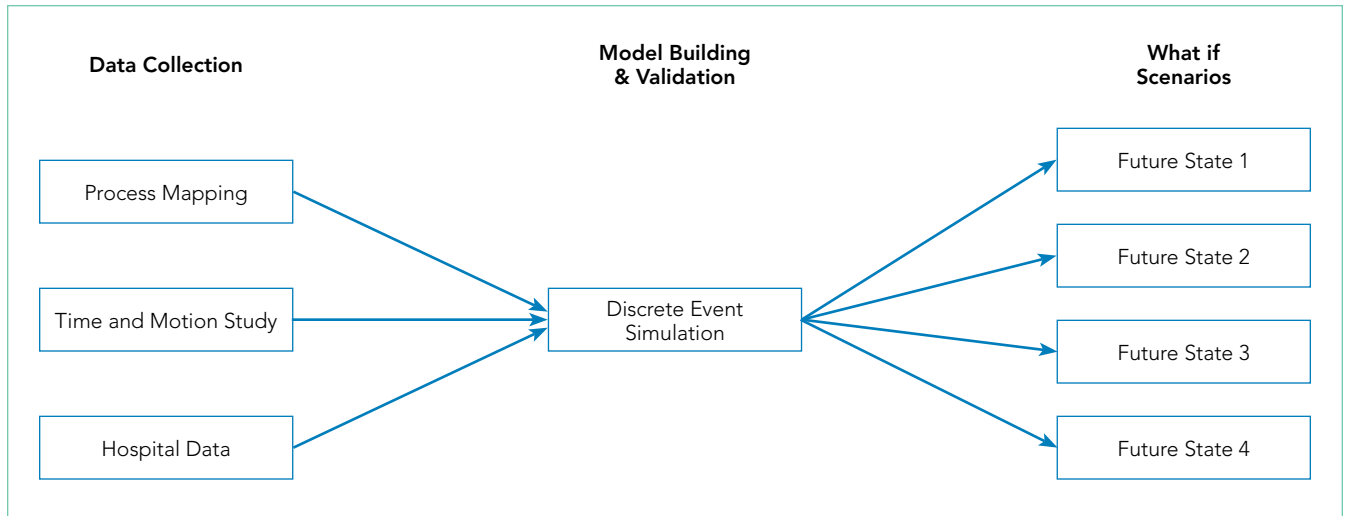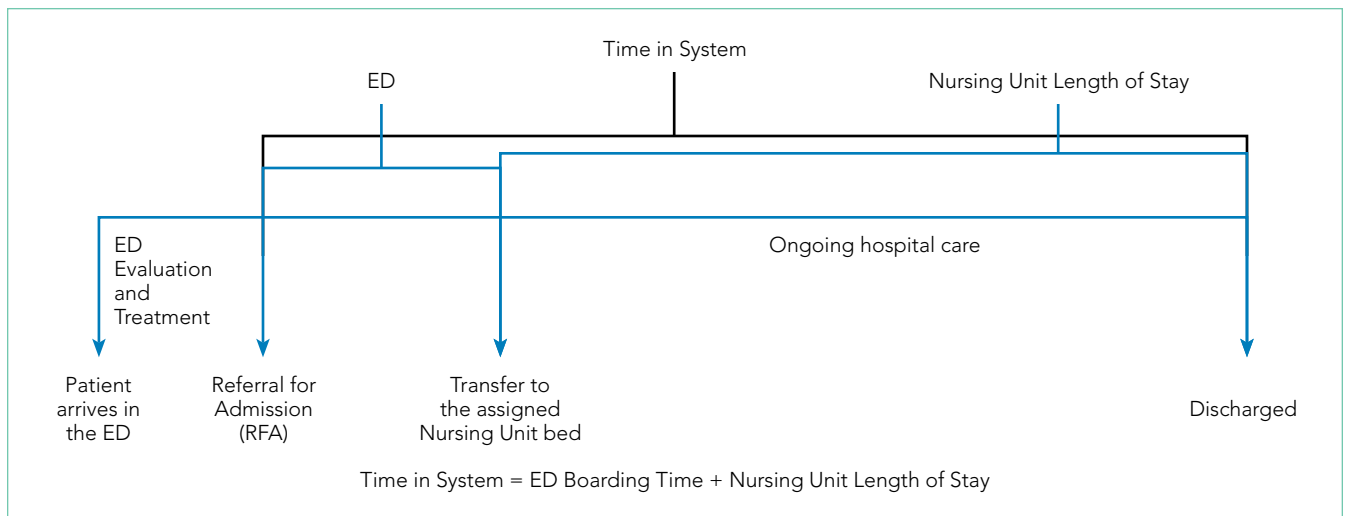
FIG 1. Model of Study Design

FIG 2. Simulation Model.

A research assistant observed a total of 30 hospitalist work cycles to describe the work of our inpatient clinicians. A work cycle, defined as one complete process flow,[23] began when the hospitalist started a daytime shift of patient care and concluded after the physician "signed out" to the physician who was assuming responsibility for ongoing medical care of the patients (ie, cross-coverage). Time spent on different activities identified by the process flow map was captured throughout the cycle. These activities included time spent traveling to evaluate patients located on different NUs. To minimize disruptions in patient care and adhere to privacy standards, no observations were conducted in patient rooms, and details of computer work were not recorded. To ensure stable estimates of the mean and standard deviation of the time spent at each step, at least 30 cycles of observation are recommended. Thus, 300 hours of observations over the course of 30 separate days were collected.

Hospital Data
We extracted admission and discharge data from the electronic health records (EHR) for general medicine patients admitted from the ED for the calendar year 2013. These records were used to establish means and standard deviations for admission date and time, distribution of patients across NUs, and LOS.

Model Building and Internal Validation
On the basis of these data inputs and using SIMIO® Simulation Software version 7, we constructed a discrete event simulation (DES) model representing the patient care activities of general medicine teams. Each patient was assigned a bed on a nursing unit through a probability distribution based on prior EHR data and then randomly assigned to a general medicine team. We replicated the model 200 times, and each model ran for 365 days. Each team was limited to 16 assigned patients, the maximum number of patients per housestaff team allowed by VCU protocol; henceforth, this number is referred to as team-patient

TABLE 1. **Simulation Models Input Data**

	Present State	Future State 1 Geography	Future State 2 + 26 beds	Future State 3 + Team 6	Future State 4 + 26 beds + Team 6 + ↑ Admit Rate
No. of Teams	10	10	10	11	11
Team Assignment	Random	Geographic assignment*	Random	Random	Random
Patient Generator	Actual admission data (ADD) ~21.6 pts/day	ADD ~21.6 pts/day	ADD ~21.6 pts/day	ADD ~21.6 pts/day	Derived admission 25 pts/day
Duration of Run (days)	365	365	365	365	365
Nursing Unit Distribution of Patients	Probability distribution from dataset (PDD)	PDD	PDD + added unit	PDD	PDD + added unit
Nursing Unit Length of Stay (hrs. per original data)	Random exponential with mean of 133 hrs.	Random exponential with mean of 133 hrs.	Random exponential with mean of 133 hrs.	Random exponential with mean of 133 hrs.	Random exponential with mean of 133 hrs.

*Constraining patients on housestaff (but not hospitalist) teams to the three general medicine nursing units

capacity. The model assumed patients remained on the assigned nursing unit and medical team for the entirety of their hospital stay and that each patient was seen by their assigned medical team every day. The results of the present state model, including mean number of patients on each nursing unit, mean team census, patient dispersion (ie, the number of NUs on which each medical team had patients), and team utilization (ie, mean team census divided by team patient capacity), were compared with actual data from 2013 to internally validate the model.

What-If Scenario Testing

We constructed four what-if scenarios based on possible strategic directions identified by leadership. These models evaluated:

- constraining patients on housestaff (but not hospitalist) teams to the three general medicine NUs (Future State 1),
- increasing bed capacity for general medicine patients by adding one additional nursing unit of 26 beds (Future State 2),
- increasing the number of general medicine teams by adding one additional hospitalist team of up to 16 patients (Future State 3),
- modeling the impact of increased patient admissions from 21 per day to 25 per day while also adding a nursing unit and an additional medical team (Future State 4).

For Future States 1-3, admission volume was held constant. The model generated nursing unit LOS using a random continuous exponential probability distribution with a mean of 133 hours to match the LOS distribution derived from health system data. As patients entered the system for admission, the model assigned a bed to the patient, but the patient could not move to the assigned bed until a bed and care team were both available. We were only interested in the steady-state behavior of the system, so collecting performance statistics only after the model had been populated and steady state had been achieved was important.

Table 1 summarizes the input data and the fixed and dynamic variable for each future state model.

We examined the impact of these scenarios on the follow-

ing variables (Table 2): (1) average time in system; (2) average number of patients waiting for a bed; (3) average ED boarding time; (4) total daily general medicine census; (5) average housestaff team census per team; (6) average hospitalist team census per team; (7) average combined housestaff and hospitalist team census per team; (8) average housestaff team utilization (ie, mean team census divided by team patient capacity of 16); (9) average hospitalist team utilization (ie, mean team census divided by team patient capacity of 16); (10) average nursing unit utilization (ie, mean nursing unit census divided by maximum number of patients that can be cared for on each nursing unit); (11) patient dispersion to NUs (ie, average number of NUs on which each general medicine team has patients); 12) estimated average rounding time per general medicine team.

Of note, the average time in the system included time patients spent waiting for bed and team assignments (ED boarding time) in addition to the time they spent in the assigned nursing unit (nursing LOS). The difference between the nursing LOS (ie, time on the nursing unit) and total time in the system is one indicator of system efficiency around hospital admission.

The Institutional Review Board of Virginia Commonwealth University approved this study.

RESULTS
Time and Motion Data

The mean time spent with each patient was nine minutes. The mean time traveling between NUs Healthcare Quality for Children and Adolescents with Suicidality Admitted to Acute Care Hospitals in the United States was five minutes. Average rounding time was noted to be two hours, 53 minutes. Thirty-seven minutes, about ~21% of the time, was wasted in traveling. Each team, on average, traveled to seven different NUs to round on their daily census, averaging 1.6 patients in each nursing unit.

Hospital Data

Between January 1, 2011 to December 31, 2013, a total of 7,902 patients were admitted to the general medicine teams,

TABLE 2. **Summary of Results from Simulation Model**

	Present State	Future State 1 Geography[a] (95% CI)	Future State 2 + 26 beds (95% CI)	Future State 3 + Team 6 (95% CI)	Future State 4 + 26 beds + Team 6 + Increase Admit Rate[b] (95% CI)
Total Pt Admissions[c] per Year	7222.00	7222.00	7222.00	7222.00	8301.68 (8314.14–8289.02)
Average Time in System[d] Hrs./Pt	147.37	149.72 (148.35–151.09)	137.51* (137.22–137.80)	147.34 (146.16–148.52)	144.89* (144.28–145.50)
Average Number of Pts waiting for a bed	11.31	13.18 (12.03–14.37)	1.99* (1.85–2.13)	11.30 (10.30–12.29)	9.94 (9.33–10.54)
Average ED Boarding Time (Hrs.)	12.39	14.42 (13.14–15.71)	2.19* (2.03–2.34)	12.37 (11.28–13.46)	9.49* (8.93–10.06)
Total Daily General Medicine Census Pts/Day	119.26	119.01* (118.98–119.05)	119.59* (119.57–119.60)	119.25 (119.23–119.27)	137.19* (137.17–137.22)
Average House Staff Team Census (Pt/Team)	12.17	9.96* (9.58–10.34)	12.20 (12.00–12.39)	11.11* (10.93–11.29)	12.73* (12.56–12.90)
Average Hospitalist Team Census (Pt/Team)	11.68	13.85* (13.46–14.18)	11.72 (11.53–11.91)	10.66* (10.49–10.84)	12.30* (12.05–12.47)
Average Internal Medicine Team Census (Pt/Team)	11.93	11.90 (9.58–14.18)	11.96 (11.53–12.39)	10.84* (10.40–11.29)	12.47 (12.05–12.90)
Average House Staff Team Utilization % of max # Pts/Team	76.06	62.22* (62.02–62.42)	76.22 (76.10–76.35)	69.42* (69.30–69.54)	79.56* (79.41–79.71)
Average Hospitalist Team Utilization % of max # Pts/Team	73.02	86.55* (86.31–86.79)	73.26 (73.14–73.38)	66.65* (66.52–66.77)	76.87* (76.72–77.02)
Nursing Unit Utilization % of max # Pts/NU	62.29	62.19 (61.82–62.55)	51.75* (51.41–52.09)	62.28 (61.93–62.63)	59.49* (59.11–59.86)
Patient Dispersion (NU)[e,f]	7.30	4.27	7.40	6.95	7.65
Rounding Travel Time (min)/day[f]	36.50	21.35	37	34.75	38.25

*Statistically significant difference from present state at the 0.05 level
[a]Geography = Pts selectively assigned to 3 NUs for Housestaff Teams
[b]Increased admission rate = from 21 Pts/day to 25 Pts/day
[c]Sum of all patients admitted to general internal medicine team (housestaff as well as hospitalists)
[d]Average Time in System = Average ED boarding time + Average Nursing Unit length of stay
[e]Distribution of patients among medical teams across nursing unit
[f]Values were averages of the collection of teams, so confidence intervals were not available. These were calculated values and not direct results of the simulation model.
Abbreviations: Dept, department; Hrs, hours; min, minute; NU, nursing unit; Pt, patient; Pts, patients.

spanning 23 NUs. The average number of admissions per day was 21.6, and the average nursing unit LOS was 133 hours. Average team census was derived from historical data across all GIM teams for 2013 and was noted to be 11.5 patients per team, and these patients were spread over seven NUs.

Model Validation
The mean number of patients admitted to different NUs was estimated from the simulation model then compared with the EHR data from 2013. None were statistically different (*P* > .05), which signified that the validated simulation model is similar to the EHR data from 2013 despite the underlying assumptions.

Model Outputs
Analysis of the models indicated that steady-state (based upon hospital census) was realized at approximately 800 hours or after 680 patients were admitted to the GIM teams. Statistics collection, therefore, was started after 800 hours of simulated time and reflected the admission of the remaining 7,222 patients in the model validation sample (Table 2).

In the model, the total daily general medicine patient census was 119.26. Average time in the system per patient was noted to be 147.37 hours, which was 14.37 hours more than the average nursing unit LOS of 133 hours. Average number of patients waiting for a bed was noted to be 11.31, while the

average wait time for a patient to get a bed was 12.39 hours.

Average housestaff team and hospitalist team utilization were 76.06% and 73.02%, respectively, with average team utilization of 74.54% (range: 72.88%-76.19%). Housestaff teams and hospitalist teams averaged 12.17 and 11.68 patients per care team, respectively. General medicine teams had patients on 7.30 NUs on average. GIM teams rounding travel time was 36.5 minutes.

What-If Scenario Testing
Simulation outputs for the four future states are summarized in Table 2. With Future State 1, through which patients were selectively assigned to housestaff teams aligned with three NUs, the average time in the system per patient increased by 2.35 hours, with 1.87 more patients waiting for a bed and waiting for 2.03 more hours as compared with the present state. A marked disparity was observed in hospitalist and housestaff team utilization of 62.22% and 86.55% respectively. Patient dispersion to various NUs significantly decreased, and rounding time correspondingly decreased by approximately 41%.

Future State 2, adding a nursing unit, decreased average time in the system per patient by 9.86 hours, with 9.32 fewer patients waiting for a bed as compared with the present state. A slight increase in patient dispersion and rounding time was observed. Overall, patients spent 137.51 hours in the system, which demonstrated improved efficiency of the system.

Future State 3, adding an additional medical team, interestingly did not have a significant effect on patients' average time in system or the number of patients waiting for a bed even though a decrease occurred in average team census, team utilization, and patient dispersion.

Finally, Future State 4, increasing admissions while also adding a nursing unit and a hospitalist team, resulted in an increase in admission volume while maintaining similar utilization rates for teams and NUs. Patients spent about 2.48 hours less in the system, while only 9.94 patients were noted to be waiting for a bed as compared with 11.21 patients in the present state model. The total daily general medicine patient census was noted to be 137.19. Average team census and average team utilization were noted to be similar to those of the present state model, while admissions were up by approximately 1,080 per year. Both patient dispersion and rounding were slightly worsened.

Sensitivity Analysis
Overall, average time in system was most affected by the number of patient arrivals. This became particularly significant as the volume of patient arrivals approached and exceeded the capacity of the rounding teams. Adding a nursing unit had more impact on decreasing average time in the system than adding a medical team or aligning teams with NUs under the conditions defined by the model. However, under different conditions, such as increasing admission volume, the relative benefit of different approaches may vary.

DISCUSSION
Given that hospitals are large, complex systems,[2] the impact of system-level changes can have unpredictable and potentially deleterious effects. Simulation provides a technique for modeling the impact of changes to understand the ramifications of these interventions more thoroughly.[3] In this study, we describe the process of building a simulation model for the admission and discharge of patients from general medicine services in a tertiary care hospital, internally validating this model, and examining the outcomes from several potential changes to the system.

The outcomes for these what-if scenarios provided some important insights about the secondary effect of system changes and the need for multiple, simultaneous interventions. Given that hospitals often function at near capacity, adding a hospitalist team or nursing unit might be seen as a reasonable strategy to improve the system metrics, number of patient discharges, or average LOS. On the basis of our analysis, adding a nursing unit would have more benefit than adding a hospitalist team. Leaders who want to increase capacity may need to consider both adding a hospitalist team and a nursing unit, and model the impact of each choice as described with a simulation.

Additionally, assigning patients to medical teams aligned with NUs seems theoretically appealing to improve interprofessional communication and decrease the time spent in transit between patients by physicians. While our findings supported a decrease in rounding time and patient dispersion, the teams not aligned with a nursing unit (ie, the hospitalists) exceeded 80% utilization, the threshold at which efficiency is known to decrease.[24] Potentially, benefits resulting from teams being aligned with NUs were offset by decrements in performance of the teams not aligned with NUs. If medical teams and NUs become aligned, then a higher number of teams may be necessary to maintain patient throughput.

Simulation models identify these unexpected consequences prior to investing resources in a significant change; however, modeling is not simple. Simulation models depend on the characteristics of the model and the quality of the input data. For example, we used an expert approach to map physician workflow as an underpinning of the model, but we may have missed an important variation in physician workflow. Understanding this variation could strengthen the model and provide some testable variables for future study. Likewise, understanding nursing workflow and how variation in physician workflow shapes nursing workflow, and vice versa, is worth exploring.

Other data could also be added to, and help interpret, the outputs of this model. For example, the impact of various levels of team and unit utilization on diversion time for the hospital ED may help determine whether adding team capacity or unit capacity is more beneficial for the system. Likewise, aligning medical teams with NUs seems to hinder patient throughput on this analysis, but benefits in patient satisfaction or decreased readmissions might improve reimbursement and outweigh the revenue lost from throughput. Underpinning each of these types of decisions is a need to model the system well and thoughtfully choose the inputs, processes, and outputs. Pursuing a new strategic decision usually involves cost; simulation modeling provides data to help leaders weigh the benefits in terms of the needed investment.

The major limitations of the study stem from these choices. Our study focused on matching capacity and demand while limiting other changes in the system, such as changes in nursing unit LOS. Future work to quantify the relationship of other variables on parameters, such as the impact of decreased team dispersion on LOS, early discharges, and decreasing care variation, would make future models more robust. This model does not consider other strategies to improve patient flow, such as shaping demand, adaptive team assignment algorithms, or creating surge capacity. We also used only hospitalist time and motion data in our model; housestaff workflow is likely different. In addition, we modeled all patients as having a general level of nursing care and did not account for admissions or transfers to intensive care units or other services. These parameters could be added in future iterations. Finally, the biggest limitation in any simulation is the underlying assumptions made to construct the model. While we validated the model retrospectively, prospective validation and refinement should also be performed with attention to how the model functions under extreme conditions, such as a very high patient load.

CONCLUSION

Major system changes are expensive and must be made carefully. Systems engineering techniques, such as DES, provide techniques to estimate the impact of changes on pertinent care delivery variables. Results from this study underscore the complexity of patient care delivery and how simulation models can integrate multiple system components to provide a data-driven approach to inform decision making in a complex system.

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