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Original Contribution

Using discrete event computer simulation to improve patient flow in a Ghanaian acute care hospital☆,☆☆,★

Allyson M. Best, AB [a], Cinnamon A. Dixon, DO, MPH [b], W. David Kelton, PhD [c], Christopher J. Lindsell, PhD [d], Michael J. Ward, MD, MBA [e,*]

[a] University of Cincinnati, College of Medicine, Cincinnati, OH 45229
[b] Division of Emergency Medicine, Center for Global Health, Cincinnati Children's Hospital Medical Center, University of Cincinnati, Cincinnati, OH 45229
[c] Department of Operations, Business Analytics and Information Systems, University of Cincinnati, Cincinnati, OH 45221
[d] Department of Emergency Medicine, University of Cincinnati, Cincinnati, OH 45267-0769
[e] Department of Emergency Medicine, Vanderbilt University, Nashville, TN 37232

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ABSTRACT

Objectives: Crowding and limited resources have increased the strain on acute care facilities and emergency departments worldwide. These problems are particularly prevalent in developing countries. Discrete event simulation is a computer-based tool that can be used to estimate how changes to complex health care delivery systems such as emergency departments will affect operational performance. Using this modality, our objective was to identify operational interventions that could potentially improve patient throughput of one acute care setting in a developing country.

Methods: We developed a simulation model of acute care at a district level hospital in Ghana to test the effects of resource-neutral (eg, modified staff start times and roles) and resource-additional (eg, increased staff) operational interventions on patient throughput. Previously captured deidentified time-and-motion data from 487 acute care patients were used to develop and test the model. The primary outcome was the modeled effect of interventions on patient length of stay (LOS).

Results: The base-case (no change) scenario had a mean LOS of 292 minutes (95% confidence interval [CI], 291-293). In isolation, adding staffing, changing staff roles, and varying shift times did not affect overall patient LOS. Specifically, adding 2 registration workers, history takers, and physicians resulted in a 23.8-minute (95% CI, 22.3-25.3) LOS decrease. However, when shift start times were coordinated with patient arrival patterns, potential mean LOS was decreased by 96 minutes (95% CI, 94-98), and with the simultaneous combination of staff roles (registration and history taking), there was an overall mean LOS reduction of 152 minutes (95% CI, 150-154).

Conclusions: Resource-neutral interventions identified through discrete event simulation modeling have the potential to improve acute care throughput in this Ghanaian municipal hospital. Discrete event simulation offers another approach to identifying potentially effective interventions to improve patient flow in emergency and acute care in resource-limited settings.

1. Introduction

The challenges of increasing patient volume and decreasing resources facing emergency departments (EDs) in the United States [1–4] are globally ubiquitous, contributing to the current worldwide health care crisis of supply and demand mismatch [5–7]. Developing countries, in particular, are challenged with patient overcrowding, extreme resource limitations, immature emergency care infrastructure, limited training programs [8], and health care workforce shortages [9].

Ghana is a sub-Saharan African country in which patient demand outpaces health care capacity. Although most Ghanaian hospitals are district level hospitals without formal EDs, many of these hospitals have acute care processes [8]. Most of these hospitals have unscheduled visits for acute care throughout the day. Differing from the care in the United States, priority is often given on a first come, first served basis, and there is limited to no formal triage system. This system poses substantial risk of long delays in care despite degree of illness. Contemporary data from a time-and-motion study conducted

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* Corresponding author. Tel.: +1 615 936 8379; fax: +1 615 936 3754.
E-mail address: mward04@gmail.com (M.J. Ward).

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in 1 such hospital found that patients experienced long wait times for evaluation and disposition, independent of their clinical status [10]. Similar to the United States, these health care settings also seek innovative operational interventions in an attempt to improve patient flow and outcomes [8].

Operations management tools familiar in industrial engineering are being effectively used in health care to enhance use of limited resources and improve system efficiency [7,8,11]. Discrete event simulation (DES) is a computer-based methodology capable of modeling complex health care delivery systems like EDs. These models can be used to test common and system-stressing scenarios and to identify strategies to enhance efficiency [11,12]. Discrete event simulation allows users to estimate the likely impact of operational changes before expending resources to implement those changes [13]. When examining international health care systems, it is critical to test operational changes within the limits of the individual system so as to avoid overextending the generalizability of operational changes tried and tested in the United States. Therefore, DES is an especially promising modality to use in developing countries, where patient demand often outstrips medical system capacity and low-cost approaches to improve health care delivery are essential. Discrete event evaluation could be used to identify those resource-neutral strategies most likely to improve patient care in these health systems by testing interventions in safe, simulated, and customized operating environments.

Our goal was to develop a DES model of acute care process in one Ghanaian municipal hospital and compare the effect of operational interventions on patient flow. We hypothesized that interventions that matched demand (ie, patient arrival) with capacity, without increasing resources, would have improved patient flow.

2. Methods

2.1. Study design, setting, and population

The model created in this study depicts a district level hospital in Kintampo, Ghana (Fig. 1). This hospital serves an acute, unscheduled patient population. Unlike the United States, the main acute care facility operates only during daytime. Typical acute care flow consists of patients arriving and queuing for registration, where the patients register and are given their medical record to carry. After registration, patients queue for the history-taking station, where limited vitals (blood pressure and temperature) and the chief complaint are documented. After history taking, patients queue outside of 1 of 4 consultation rooms, where a medical provider (physician or medical assistant) is stationed. The medical evaluation occurs in one of these rooms and depending upon the diagnosis and/or time of day, the patient is sent for ancillary testing (laboratories or radiology) or discharged to the dispensary (ie, pharmacy) to have a prescription filled and subsequently sent home. If a patient is sent for ancillary testing, there is either a second medical consultation with subsequent disposition or the ancillary testing site may send the patient directly to the dispensary for medication provision and discharged home (if the consultation rooms have closed). Patients can be admitted at any point during the hospital course; however, admission commonly occurs after the first medical consult. Patients receiving scheduled parental medications could bypass history-taking and consultation rooms and go directly to the injection room. Those patients seeking care during off hours or still in queue after consultation room closures may not be evaluated and may not have their medical evaluation and care completed.

For this analysis, deidentified observational data were used from a previously conducted quality improvement time-and-motion study [10]. Our institutional review board determined the current study to be exempt from oversight because the data were permanently deidentified. Data included time stamps for when patients entered and exited the various hospital stations during their acute care course. The principal investigator of the prior data collection study served as a member of this study group, providing guidance on hospital operations (ensuring the integrity of the model) and suggestions for operational interventions that could be feasible in this specific clinical environment.

2.2. Measurements and model development

Operational data were available for 564 subjects over a 5-day period; partial or complete flow data were available for 487 of the 564 subjects. As the hospital does not have electronic records, information verifying that these 5 days were representative of, as opposed to an aberration from, normal clinic conditions is not readily available. However, data collected spanned more than 60 hours, and there is no apparent reason to believe that this period would differ significantly from any other 5-day period. Patient flow data were analyzed using Excel 2007 (Microsoft Corporation, Redmond, WA) to determine the acute care path taken by each patient. Potential care paths included multiple combinations of the following stations: registration, history taking, consultation, injection room, laboratory, radiography, and dispensary. All possible pathways through the hospital were used to structure the flow patterns for the clinical environment. The probabilities associated with a patient taking each path were calculated.

Because data were not complete for every patient and variability occurred in flow routes, we used the following approach with existing data to determine patient paths. First, when a patient's path was not indicated by location, arrival times at the various stations were used to define the path. Second, when there was no indication of a patient's next stop, the patient was assumed to have exited the system. Last, when there were conflicting indications of a patient's path, time stamps were used to determine the order and subsequent path.

The observational data were used to parameterize the DES model that was built using Arena Simulation Software v12 (Rockwell Automation, Milwaukee, WI). Patient arrivals were modeled using a

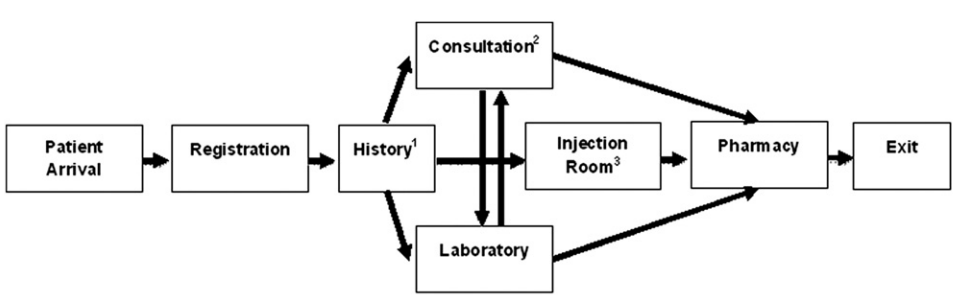

Fig. 1. Simplified model of patient flow in an acute care hospital in Ghana. This diagram represents possible paths taken by patients presenting for care. Notes: [1]Patients' chief complaint and basic vitals (blood pressure and temperature) are collected. [2]Patients assessed by a medical provider; often assessed before laboratory studies, then again afterwards when plan of care made. [3]Patients receiving scheduled medications (eg, tuberculosis treatment).

nonstationary Poisson process because hourly arrival rates were not constant and varied over the course of a day [14]. Mean arrival rates per hour were calculated across the observational period to determine arrival patterns. Probability distributions were fit to service intervals (the amount of time necessary to complete a task, eg, perform radiography) using the Arena Input Analyzer (Rockwell Automation). We used the gamma distribution family as this was found to fit the probability distributions of the measured times well using goodness of fit tests.

Given the acute care process of this hospital is closed in the evening and starts without roomed patients each day, the simulation study began with no patients present in rooms. Simulated patients entered the model according to patient arrival patterns described above. Consistent with the hospital's policies, priority was based upon a first come, first served model, rather than a traditional triage strategy [15]. Staffing schedules were used to specify when clinical and nonclinical staff was available to provide patient care services. The simulation stopped accepting new patients when registration closed at 4:00 PM and ended at 6:00 PM consistent with the practice pattern of the clinic. We defined a patient not receiving complete care as a patient who had not completed their predetermined route by the time the simulation concluded.

2.3. Outcomes

For each scenario, the primary outcome was the length of stay (LOS)—defined as the time (in minutes) between a patient's first recorded arrival at the hospital and their recorded departure from the system after evaluation and care. Patients who were turned away or did not receive complete care due to the closures were not included in LOS calculations.

2.4. Analysis

To assess the validity of our model, we compared the overall LOS for the empirical data with the simulation model output. We also compared the mean and median LOS between simulated and empirical data.

To understand the uncertainty around our model estimates of LOS, we replicated the model using random draws to know how long a specific task takes to be completed. Because randomness occurs in each model run due to the use of probability distributions, additional replication allows the calculation of uncertainty. Each replication of the model generates an estimated mean LOS for that run, and conducting multiple replications allows the calculation of the mean of the individual replications. We determined the number of replications needed for the simulation model by targeting the precision of the LOS confidence interval (CI). Our goal was to achieve a 95% CI half width of less than 1% of the mean LOS. As a rule of thumb, with 300 replications, the central limit theorem is invoked and we have a normal distribution so the use of means to compare time-based data was justified. Initially, we conducted 10 simulations and calculated the need for 300 independent and identically distributed replications to be run. Upon running 300 replications for the base-case scenario, we were able to reduce the half-width CI to 0.28% of the mean LOS.

Variance reduction techniques were used to improve precision of our results and to allow for comparison of different scenarios [16]. We used common random numbers with synchronization to ensure that simulated patients were the same across different scenarios (ie, they arrived at the same time, went to the same care stations, and spent the same amount of time at each care station in different scenarios). Thus, any differences between scenarios would be attributable to operational policies rather than random variation.

Simulations of the current system without any changes were run as the base-case model. The results of this allowed us to assess the model validity in comparison with the empirical data obtained by direct time-and-motion observations and provided a baseline against which we could compare operational changes.

Staffing and operational policy changes were then incorporated into the model. First, because adding extra resources (ie, staff and clinician hours) is often a typical approach to solving flow problems, we explored the effect of increased staffing hours on patient throughput. Specifically, we examined the effect of the following scenarios in which 1 or 2 additional staff was added to the existing work schedule: (1) registration workers, (2) history takers, and (3) physicians. Second, we used a modified staff and clinician scheduling policy in which staff and clinician arrival times at the hospital were coordinated with patient demand (ie, arrivals). Therefore, we staggered arrivals of staff and clinicians to better match patient arrival patterns, while keeping shift lengths and total number of hours the same (unless there were added staff). In particular, we moved the shifts of staff and clinicians earlier in the day when patient flow was higher. We made each shift time change in isolation from other staff members. Finally, given the distinct roles of registration and history taking, we explored the possibility of combining these positions into a single role using the same combined task duration. Because each task typically takes only a few minutes and the combined role would consist of entering a patient into the system, documenting a chief complaint, and taking the limited vitals (blood pressure and temperature), we determined this intervention to be theoretically possible. By doing so, we were able to evaluate the operational benefit of removing an additional waiting period for a separate staff member and its potential effect on patient flow.

A total of 15 scenarios were identified (Table 1) and simulated with 300 replications. We selected these 15 scenarios that represented feasible scenarios given the existing resources, commonly recommended strategies, and hypothesized strategies given the existing resources. The 15 scenarios represent the base case (1 scenario), the addition of 1 or 2 of each staff member in isolation (6 scenarios) and in total (2 scenarios), change in shift start times in isolation (3 scenarios) and in total (1 scenario), combination of history and registration workers (1 scenario), and combination of history and registration workers with shift changes (1 scenario). We compared the scenarios with the base case using an established method for selecting the best simulation system when there are a large number of alternatives [17]. We calculated the difference from the base-case scenario and the 95% CI.

3. Results

3.1. Model validation

The model output from the base-case scenario was compared with those from the data collected from the hospital in Table 2. Mean and median LOS were no different from simulated output. In addition, mean patient arrivals for simulation data (112.78; 95% CI, 112-114) were in the range of the daily values from the empirical data. We concluded that the model was representative of the existing environment and moved forward with scenario testing.

3.2. Main results

Peak arrival time for patients was between 7:00 AM and 9:00 AM. A significant disparity was noted between peak staffing and patient arrival times in the base case (Fig. 2A). As shown in the figure, patient arrivals occur before any staff arrivals and peak while only 1 registration worker is present creating a substantial queue for the history workers and physicians. One intervention to the system involved increasing staffing (Fig. 2B). Model modifications to the system showed improved matching of staff with patient arrivals (Fig. 2C). Most improvement in the matching of staff to arrivals was seen when combining registration and history-taking tasks (Fig. 2D)

Table 1
Scenario characteristics tested in the simulation model, total patient LOS, and mean difference in patient LOS from base case

Scenario no.	Scenario	Additional resource hours	Total LOS in minutes (95% CI)	Difference in minutes from base case (95% CI)
1	Base case	None	292 (291-293)	-
2	Add 1 registration worker[a]	7.5	286 (285-287)	−5.81 (−7.1 to −4.52)
3	Add 2 registration workers[a]	15	286 (285-287)	−6.35 (−7.67 to −5.03)
4	Add 1 history taker[a]	6.5	288 (287-289)	−4.3 (−5.59 to −3.01)
5	Add 2 history takers[a]	13	287 (286-288)	−5.38 (−6.68 to −4.08)
6	Add 1 physician[a]	7	291 (290-292)	−1.65 (−2.85 to −1.65)
7	Add 2 physicians[a]	14	290 (289-291)	−2.2 (−3.42 to −2.2)
8	Add 1 of all resources[a]	21 (7.5 registration, 6.5 history, 7 physicians)	278 (276-280)	−14.2 (−16.19 to −12.21)
9	Add 2 of all resources[a]	42(15 registration, 13 history, 14 physicians)	269 (268-270)	−23.8 (−25.31 to −22.29)
10	Change registration shifts[b]	None	292 (291-293)	−0.6 (−1.89 to 0 .69)
11	Change history shifts[b]	None	323 (322-324)	30.7 (29.37 to 32.03)
12	Change physician shifts[b]	None	279 (278-280)	−14.0 (−15.69 to −12.31)
13	Combine registration and history[c]	None	267 (266-268)	−26.1 (−27.81 to 24.39)
14	Change all shifts[b]	None	197 (196-198)	−95.9 (−97.54 to −94.26)
15	Combine registration/history and change physician shifts[d]	None	141 (140-142)	−152.0 (−153.63 to −150.37)

[a] Resource-additional changes consisted of adding the specified number of shifts to the model using time schedules for staffing.
[b] Resource-neutral shift changes consisted of moving shifts earlier in the morning to better align with increased patient arrival patterns.
[c] Combining registration and history taking consisted of functionally combining the role of registration and history worker into 1 position in such a way that each registration-history worker would be able to perform both functions for each patient.
[d] Consisted of combining registration and history workers as well as making resource-neutral shift changes for physicians.

Results for each scenario are given in Table 1. Fig. 3 provides the estimated mean LOS for each operational scenario. The addition of resources (increased staffing) minimally improved LOS or even worsened LOS, as noted in the case of the history-taking shifts. Although most resource-additional scenarios resulted in only marginal improvements in patient LOS, the addition of up to 2 registration staff, 2 history-taking staff, and 2 medical providers (an additional 42 hours of staffing total) resulted in the largest decrease in mean patient LOS of 23.8 minutes (95% CI, 22.3-25.3) among resource-additional scenarios. When schedule modifications for all 3 staffing resources were coordinated with patient arrivals, mean LOS was reduced by 95.9 minutes (95% CI 94.3, 97.5). Combining registration and history taking into a single role with simultaneous coordination of staffing and patient arrivals resulted in a reduction in mean patient LOS by 152.0 minutes (95% CI, 150.4-153.6).

4. Discussion

Simulating the acute care process at one Ghanaian district level hospital strongly suggests that matching staff resources with patient arrival patterns can result in potentially substantial patient throughput improvements as compared with simply adding resources (eg, staff and medical providers). This finding underscores the benefit of modeling operational changes before implementation, especially in resource-limited settings, which includes both developed and developing countries. Such an approach allows for the identification of which strategies are most likely to be effective and the potential magnitude of effect. Furthermore, this study underscores the benefit of using limited resources in a strategic approach that matches demand with capacity. This policy, rather than adding the most expensive resource (ie, staffing) was found to have the greatest reduction in overall throughput.

Our study also identified potential resource-neutral strategies that could enhance the performance of the system. Combining staff responsibilities from 2 positions (registration and history taking) into a single position along with coordinating staffing with patient arrivals resulted in the largest reduction in LOS. Despite the theoretical nature of this combined registration/history-taking position, this example further emphasized the value of computer-based simulation by allowing us to ask "what-if" questions for situations that might challenge current operational constraints.

Similar to our study, prior research has used DES to model and examine potential interventions to health care settings to inform future implementations. For example, one study used DES to prioritize interventions and identified that decreasing boarding time would have a larger effect on LOS than adding beds [18]. Another study found that moving the time of elective cardiac catheterizations would have a larger effect on ED boarding for telemetry beds than building

Table 2
Comparison of the original hospital time-and-motion data with simulated base-case scenario

Outcome metric	Hospital collected data					Simulation model output data
	Monday	Tuesday	Wednesday	Thursday	Friday	Daily
Mean LOS	311 (293, 329)	292 (274, 310)	276 (261, 291)	296 (273, 319)	334 (312, 356)	292 (291, 293)
Median LOS	333 (316, 348)	296 (272, 308)	280 (267, 294)	311 (264, 347)	350 (315, 371)	295 (294, 296)
No. of patient arrivals	155	107	82	112	108	113 (112, 114)

All times are in minutes.

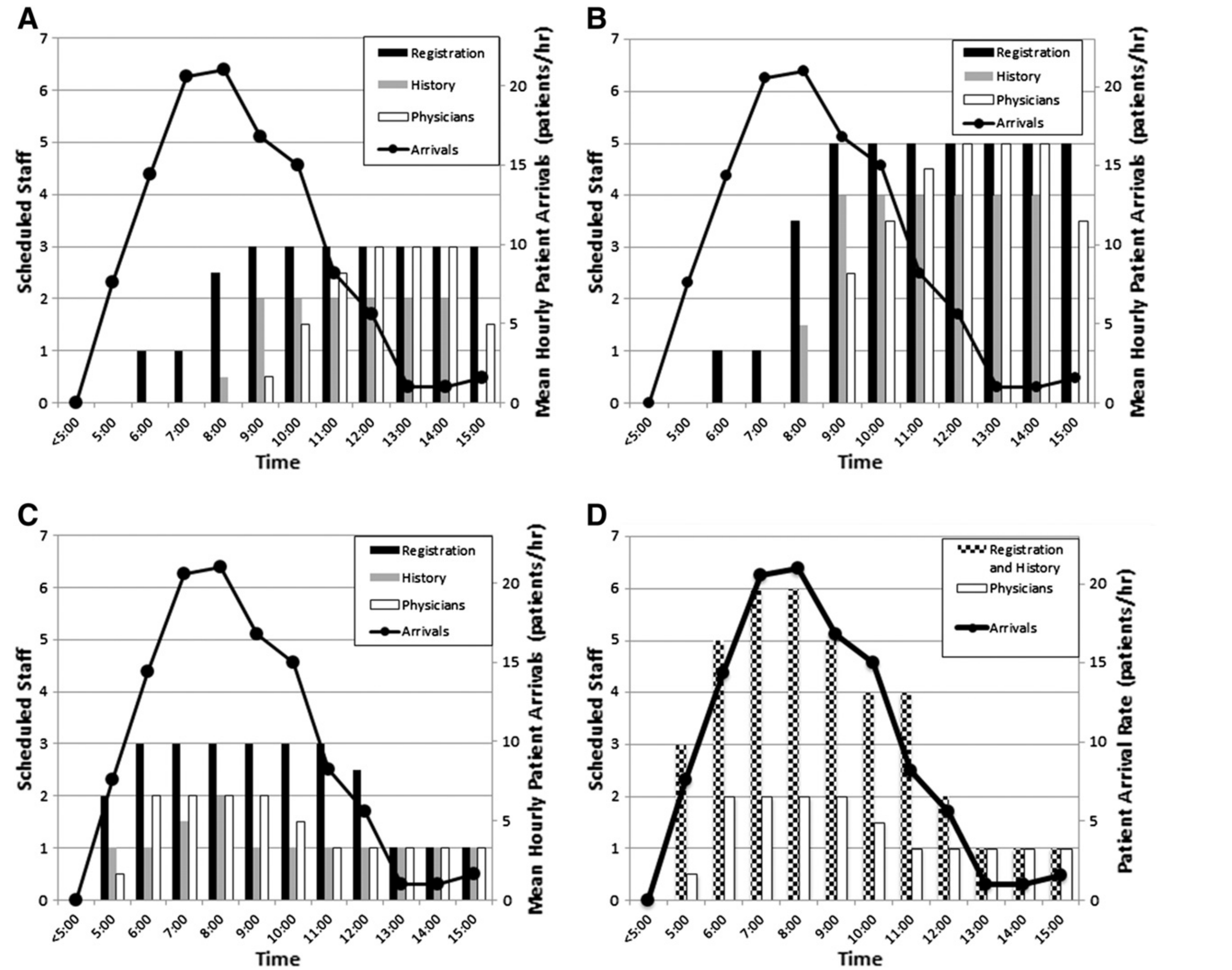

Fig. 2. Patient arrival rates compared to staffing and physician schedules in the current system (A), the additional staffing system (B), the altered (staggered) staffing schedule system with separate registration and history takers (C), and the combined registration/history system (D).

additional beds [19]. Discrete event evaluation has also been used in international settings comparable with the acute care hospital used in this study by simulating the efficiency of human immunodeficiency virus screening in outpatient health services [20]. Beyond the evaluation of potential policy changes, DES can help to guide implementations in a variety of complex health care settings evaluating nurse scheduling, LOS, patient satisfaction, and need for operational interventions [21–24].

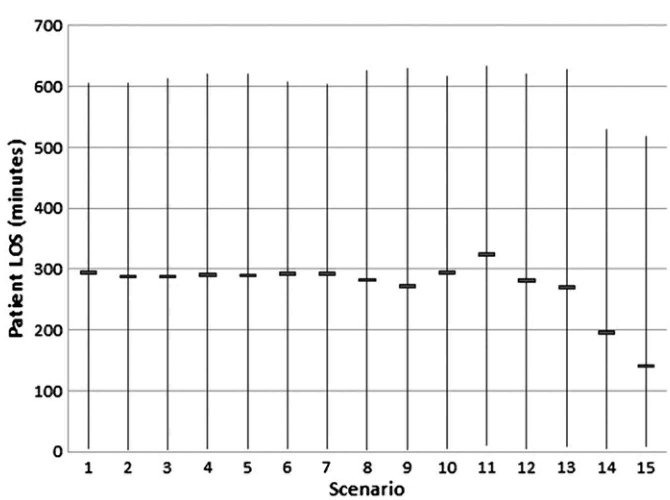

Fig. 3. Mean patient LOS by scenario. Scenarios 1 to 15 are described in Table 1. Boxes represent 95% CIs for each scenario, and whiskers represent the minimum and maximum mean LOS across the 300 simulation replications.

Although this study provides useful information about system changes in one Ghanaian acute care hospital, the true value of our findings can only be realized with implementation and subsequent evaluation. Operational changes require close collaboration with members of the Ghanaian health care team to best determine what changes appear beneficial in the structured simulation environment versus what is feasible in real-life conditions, considering practical implementation and cultural norms. To enhance the system, we propose working with Ghanaian health care administrative leaders to solicit feedback regarding other possible interventions that may not have been realized in our simulation model. Furthermore, although our approach is adequate for enacting 1-time process changes, training the Ghanaian health care team in operational principles (eg, coordination of demand and capacity) would elicit greater potential for ongoing system performance improvement.

Last, our simulation underscores the potential performance benefits of planning and modeling health care operations before implementation of significant operational changes so as to maximize the efficiency of limited resources. The benefit of this methodology exists both in the United States and in international settings. Although our study was designed to evaluate flow in one Ghanaian acute care hospital, lessons learned from applying DES can be applied in other domestic or global acute care settings.

5. Limitations

Although our results suggest that DES can be an important tool for estimating potential effects of operational policy changes and coordination of staffing with patient arrivals, there are several important limitations to discuss. First, data used to parameterize our simulation model came from a limited sample. Although the data had been collected during a typical work week at this hospital, it represented a small sampling period, and it is unknown if these data were representative of normal operations and potential seasonality changes. In addition, data entailing patient-dependent factors such as patient acuity and chief complaint were not available, so it is unknown whether these data represented the hospital's typical patient population. Despite these limitations, we used probability distributions to model service times, allowing the system to retain its inherent random variation.

Furthermore, these data were insufficient to quantify the number of patients who left without receiving complete care, which represents a potential limitation to both the model validation as well as the proposed changes. The number of patients not receiving complete care is a critical indicator of system performance that should be addressed when implementing a new system, and the suggested scenarios do not alleviate the problem of patients leaving before they receive care. One possible approach to this problem is to implement set closing times to deter patients from arriving when they are not likely to receive complete care. However, such a policy still could not guarantee complete care for everyone in an environment in which there are set closing hours due to the variability of time it takes to care for patients.

The operating characteristics of the facility (eg, opening and closing hours, patient arrival patterns and staff start and stop times) varied daily. Therefore, when building our model scenarios, we had to create a "typical day" using the estimated arrival patterns and task durations calculated from the empirical data. Although not exactly duplicative of the existing environment, we used simplifying assumptions to facilitate model building and scenario comparison to estimate the likely difference between changes in operational policies.

Finally, results of our simulation model provide only an estimation of how changes could potentially affect this Ghanaian municipal hospital's operations. Actual implementation of any of the suggested changes might be affected by unmeasured and uncontrolled factors such as cultural norms, staff understanding and buy-in, and other implementation barriers. Therefore, before implementation, it would be important to have key informant meetings to see what is feasible in this setting.

6. Conclusions

Using DES, we identified resource-neutral capacity allocation interventions that could potentially improve patient flow in one Ghanaian acute care setting. Specifically, interventions designed to maximize the efficiency of existing resources to meet patient demand could significantly decrease patient LOS in this already overextended health care setting. Expanding the use of computer-based modeling tools such as DES to other resource-restrained settings has the potential to accelerate the identification of effective interventions, test implementation in simulated environments, and improve clinical operations domestically and abroad—thus, helping to address the global acute care challenge of supply-demand mismatch.

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